Spatio-temporal variation of dugongs’ habitat use and vessel traffic revealed by underwater acoustics information: Toward harmonized coastal management

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"... This may raise a question; which is more important, life of a dugong or livelihood of villager A? I cannot answer this question now — nor do I expect to be able to answer it one day in future..." (Ichikawa 2014, originally in Japanese and translated by author). This is a line concerning dilemma about dugongs' conservation written by Prof. Kotaro Ichikawa. This is, at the same time, an eye-opening line where this study all began. I cannot thank more to him for his support and advice in and out of lab, in Japan and abroad, above and below the sea. My skill and my attitude toward the ocean would not be here without meeting him.

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Ethics statement

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Publications

Chapter 2

<u>Kotaro Tanaka</u>, Kotaro Ichikawa, Kongkiat Kittiwattanawong, Nobuaki Arai, and Hiromichi Mitamura. (2021) "Automated Classification of Dugong Calls and Tonal Noise by Combining Contour and MFCC Features", Acoustics Australia, Springer, https://doi.org/10.1007/s40857-021-00234-5

(Conference Presentation) **<u>Kotaro Tanaka</u>**, Kotaro Ichikawa, Kongkiat Kittiwattanawong, Nobuaki Arai and Hiromichi Mitamura. (2021). "Development of detection and classification method for vessels around the marine protected area in the southern part of Thailand, using underwater acoustic information". Spring Meeting of the Japanese Society of Fisheries Science., Mar 26–29, 2021 (in Japanese)

Chapter 3

<u>Kotaro Tanaka</u>, Kotaro Ichikawa, Kongkiat Kittiwattanawong, Nobuaki Arai & Hiromichi Mitamura (2022) "Spatial variation of vocalising dugongs around Talibong Island, Thailand", Bioacoustics, https://doi.org/10.1080/09524622.2022.2058614

Chapter 3 (partly), 4 and 5

<u>Kotaro Tanaka</u>, Kotaro Ichikawa, Tomonari Akamatsu, Kongkiat Kittiwattanawong, Nobuaki Arai and Hiromichi Mitamura. (*in press*) "Spatio-temporal variation of dugong's acoustic presence and vessel traffic around Talibong Island, Thailand: Inputs for local coastal management from passive acoustical aspect" Ocean & Coastal Management.

Other relevant publications

<u>Kotaro Tanaka</u>, Kotaro Ichikawa, Hideaki Nishizawa, Kongkiat Kittiwattanawong, Nobuaki Arai, and Hiromichi Mitamura (2016) "Effects of environmental factors on vocalization pattern of dugongs revealed by generalized linear model", Proceedings of Techno-Ocean2016, Kobe, Japan, October 6–8, (non-reviewed)

<u>Kotaro Tanaka</u>, Kotaro Ichikawa, Hideaki Nishizawa, Kongkiat Kittiwattanawong, Nobuaki Arai, and Hiromichi Mitamura. (2017) "Differences in vocalisation pattern of dugongs between fine-scale habitats around Talibong Island, Thailand", Acoustics Australia, Springer, 45, 243–251. DOI 10.1007/s40857-017-0094-7

Chiaki Yamato, Kotaro Ichikawa, Nobuaki Arai, **<u>Kotaro Tanaka</u>**, Takahiro Nishiyama, and Kongkiat Kittiwattanawong. (2021). "Deep neural networks based automated extraction of dugong feeding trails from UAV images in the intertidal seagrass beds", Plos one, 16(8), e0255586. DOI 10.1371/journal.pone.0255586

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Abstract

In coastal seas, human and ecological elements closely interact and are strongly interlinked. Thus, considering proper Marine Spatial Planning (MSP) to foster harmonized and sustainable ocean management, based on the scientific knowledge of socio-ecosystem, is essential. Conservation of marine megafauna is recognized as one of the key elements in MSP, given that not only their unique role in coastal ecosystem but also their iconic status in public consciousness and local cultures, as well as the economic importance in ecotourism. Although habitat use of marine megafauna is one of the important layers in consideration of MSP, most of them are limited in spatial or temporal scale, or based on snapshot survey. Furthermore, among human activities, spatio-temporal characteristics of vessel traffic is a baseline information to assess the potential risk of noise pollution and physical collision. However, as such knowledge has been mostly collected in industrialized area or from large ships, those efforts in local coastal area is relatively limited. Filling those gaps is expected to contemplate effective and less burdensome costal management strategy in the habitat of endangered marine megafauna.

Dugong (*Dugong dugon*) is a herbivorous marine mammal which is listed as Vulnerable in IUCN Red List, and they spend most of their time in coastal seas as they exclusively feed seagrass. Examining the spatio-temporal habitat use of dugongs and local human activity in fine scale would provide the important inputs for a harmonized management measure to mitigate conflict between dugong conservation and the restriction of human activity. In this context, Passive Acoustic Monitoring (PAM) can provide unique layer of such information in continuous manner, by observing dugongs' social call and the sounds generated by motorized vessels. The objective of this study is, in Talibong Island, Thailand, to visualize the spatio-temporal pattern of dugongs' acoustic presence and vessel traffic in fine scale, and to provide an implication to the harmonized coastal management measure.

To expand the spatial and temporal scales of PAM, automatically detecting and classifying target sounds from large amount of audio data is essential but challenging. A classification method between dugong calls and tonal noise, which is the main cause of false detection, was developed, to properly extract target sound in the noisy shallow waters. Mel-Frequency Cepstral Coefficients (MFCC) were extracted to characterize background sounds along with a few parameters of the signal contour, and a support vector machine was trained for binary classification. The classifier achieved an 84.4% recall and a 93.5% precision on the testing dataset. In addition to the dugong calls, broadband vessel sounds were detected by entropy threshold filter. Furthermore, as a referential information at one location, vessel type classification was attempted with frequency characteristics and passage duration. As a result, 89.8% recall and 90.7% precision were obtained. The developed software was used in the data analysis subsequently.

Underwater recorders were deployed at 11 locations around Talibong Island, through one-month period in both rainy and dry seasons (Sep. 2019 and Feb.-Mar. 2020, respectively). From the recorded sound stream (1933 h in rainy season and 2719 h in dry season), dugong calls (21,340 calls in rainy season and 16,337 in dry season) were detected and then the spatio-temporal variation of them were visualized. An elevated rate of detected calls was consistently

observed at a few certain monitoring locations in both seasons, and some of them are outside of existing community-based protected area. Furthermore, temporal patterns of their vocalization varied among locations. These locations and times should be paid attention in the process of marine spatial planning for their conservation, in addition to the examination of their distribution by visual observation.

In parallel with dugong calls, vessel sounds were automatically detected (1,968 min in rainy season and 4,265 min in dry season). Unlike dugongs' vocalization, the distribution of vessel traffic was spatially and temporally stable, and active passage was observed around the ports and the sea route. From the classification result of vessel types at a location in the north of the island, speedboat, which potentially has large disturbance risk (e.g. vessel strike and noise pollution), mostly passed between 1 pm and 3 pm. This result suggested that vessel operators should pay attention to dugongs' presence in the surroundings or lower speed around those hours.

The relationship between dugongs' vocalization pattern and environmental/anthropological factors was estimated by generalized additive model (GAM), in order to enhance the generic understanding of their acoustical habitat use. There were significant correlations at some locations, while those factors varied among locations. Furthermore, the relationship between dugongs' spatial preference for their vocal behavior and the fine-scale geographical feature, e.g. distance to the shore and seagrass bed, was not obvious. Therefore, it was suggested that generalizing dugongs' acoustic presence with environmental and anthropological factors is not adequate. The necessity of fine-scale monitoring to examine their habitat use was highlighted.

Based on those findings, this study implies that (1) spatial management measure is primarily effective to conserve dugongs' social behavior via vocalizations (2) temporally dynamic restriction may reduce the potential disturbance risk while reducing the restriction of human activity, but fine-scale investigation would be required. This study also demonstrated that, toward harmonized marine spatial planning in local coastal area, continuous PAM approach can provide unique layer of the habitat use of vocalizing animals and motorized vessel traffic in fine scale. Generally, MSP primarily focuses on the spatial allocation by drawing lines of a given area. However, taking the findings of this study into account, i.e. temporal variation of the socio-ecosystem in a coastal area, this study implies the importance of envisaging the temporal dynamics of MSP in fine scale.

要旨

海洋の中でも活発な人間活動と高い生物多様性が併存する沿岸域では、社会・生態系双方に関する科学的知見を根拠とした意思決定を実施し、調和のとれたかつ持続的な海域マネジメントのための海洋空間計画の策定が求められる。沿岸生態系において重要な役割を担うとともに文化的・経済的にも重要性の高い海産哺乳類の保全は、沿岸域マネジメントの中でも優先度の高い項目である。対象動物の生息地利用特性は海洋空間計画を検討する上で重要な情報の一つであるが、それらはこれまで時空間スケールにおいて限定されているか、スナップショット的な観察をもとにしたものに限られていた。また、人間活動の中でも船舶航行の時空間的な特徴は海中騒音や衝突リスク評価のための基礎情報となるが、大規模港湾周辺や大型船に関する知見が多く、地方沿岸域における情報は十分であるとはいえない。これらの課題を克服した情報を提供することにより、希少海産哺乳類が生息する地方の沿岸域においてより効果的かつ現地住民の負担の少ないマネジメントが検討することができると考えられる。

ジュゴン（*Dugong dugon*）は IUCN レッドリストにおいて危急種に指定されている草食性の海産哺乳類であり、浅海域に繁茂する海草を餌とすることから沿岸域を主な生息域としている。ジュゴンの保全と人間活動を両立させる沿岸域マネジメント方策について検討するためには、ジュゴンと人間活動両方の生息地利用特性を可能な限り詳細な時空間スケールで継続的に観察する必要がある。昼夜連続観察を実現する手法として、ジュゴンが発する鳴音ならびに船舶音を記録する受動的音響観察が有効であると考えられる。本研究の目的は、タイ国のタリボン島において詳細なスケールかつ連続的な音響観察を実施することでジュゴンの生息地利用と船舶航行を時空間的に可視化し、それをもとに有効な沿岸域マネジメントの方策を提案することとした。

長期・多地点における音響観察を実施する上では、記録された大量の水中音から対象となる音を自動的に検出・分類することが最初のステップとなる。雑音の多い沿岸域で対象となる対象音を適切に検出するため、機械学習を用いてジュゴン鳴音と誤検出の原因となる狭帯域ノイズを分類する手法を開発した。特徴量として対象信号のコンター（スペクトログラム上の軌跡）に関するパラメータに加え、メ

ル周波数ケプストラム係数（MFCC）を抽出して分類に用いることで、再現率 84.4%、適合率 93.5% という分類性能を得た。広帯域音である船舶音については周波数方向のエントロピーを用いて自動検出を行った。また、ある一地点における参考値としてではあるものの、検出した船舶音の周波数特性と持続時間から船舶種の分類も試み、頻繁に観察された船舶種に対して再現率 89.8%、適合率 90.7%という分類性能を得た。これらの開発した手法をデータ解析に用いて、音響観察を実施した。

雨期・乾期それぞれの約 1 か月間、タリボン島周辺ののべ 11 地点に水中録音機を設置し、取得した水中音（雨期 1933 時間、乾期 2719 時間）から上述した手法を用いてジュゴン鳴音（雨期 21,340 回、乾季 16,337 回）を検出した後、時空間変化を可視化した。ジュゴン鳴音について、雨期・乾期ともに観察範囲内の限られた 3–4 地点において頻繁に観察され、そのうちの数地点は現行の地域ベースの保護区の外側に位置することが分かった。また、時間変化のパターンは生息地内で同一ではなく、観察地点ごとに異なることが明らかになった。目視観察などほかの調査手法から得られる情報とも組み合わせたうえで、これらの時間・場所にも保護努力を分配することが期待される。

ジュゴン鳴音と同時に船舶音（雨期 1,968 分、乾期 4,265 分）も検出し、その時空間分布を調べたところ、港周辺や航路にあたる地点において活発な航行が見られた。ジュゴンとは異なり時間変化については雨期・乾期ともに地点間でおおむね共通していた。また、島北部の 1 地点において船舶種の分類を行ったところ、潜在的な攪乱のリスク（騒音・衝突など）が大きいスピードボートは 13 時ごろから 15 時ごろに航行が集中していることが分かった。この時間帯においては、航路付近にジュゴンが存在しないか注意を払う、速度を落とすなどの対応が攪乱リスク低減のために有効となる可能性がある。

ジュゴンの発声行動について、地点ごとに一般化加法モデルを用いて環境要因と船舶航行との関係を調べたところ、発声頻度の変化と有意に関係する要因は異なっていた。また、多くの鳴音が観察された地点と海草藻場や岸との距離といった要因の影響は明確に認められなかった。この結果から、活発に発声行動を行う時間・場所を環境要因や人的要因から一般的な知見として推定することは適切ではないことが示唆された。別の言い方をすれば、詳細なスケールで生息地利用特性の観察を実施することの重要性が提起された。

以上の結果から、ジュゴンが生息する沿岸域においては(1)活発に鳴音を用いた社会行動を行う場所を保全するための空間計画は効果的であり、優先的に取り組まれるべきであること(2)時間的な変動を考慮することで保全策の有効性を高めながら人間活動に対する制限もある程度軽減できる可能性があること が示唆された。この研究を通して、水中音響を用いた連続観察は、地方の沿岸域における調和のとれた海洋空間計画を検討するうえで、発音性海洋生物と船舶航行の海域利用特性に関する時空間情報を連続的かつ詳細なスケールで提供できる独自かつ有効な手法であることが示された。海洋空間計画はその名の通り区画設定のような空間的側面が注目される傾向にあるが、希少生物と人間活動それぞれにおいて時間的な変動がみられたことを踏まえると、今後詳細なスケールでの時間的な可塑性も検討に含められるべきであるし、本研究はその重要性を投げかけるものであるといえる。

Spatio-temporal variation of dugongs' habitat use and vessel traffic revealed by underwater acoustics information: Toward harmonized coastal management

Contents

List of Acronyms

AIC	Akaike Information Criterion
AIS	Automatic Identification System
CBD	Convention on Biological Diversity
DEMON	Detection of Envelope Modulation On Noise
EBM	Ecosystem Based Management
FFT	Fast Fourier Transform
GAM	Generalized Additive Model
GPS	Global Positioning System
ICM	Integrated Coastal area Management
ICT	Information and Communication Technology
IMMA	Important Marine Mammal Areas
IMO	International Maritime Organization
IUCN	International Union for Conservation of Nature
ISO	International Organization for Standardization
MFCC	Mel-Frequency Cepstral Coefficients
MPA	Marine Protected Area
MSP	Marine Spatial Planning
PAM	Passive Acoustic Monitoring
RMS	Root Mean Square
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SDM	Species Distribution Model
SNR	Signal-to-Noise Ratio
SOLAS	Safety Of Life At Sea
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
UNESCO	United Nations Educational, Scientific and Cultural Organization
VMS	Vessel Monitoring System

Chapter 1 Introduction

1.1 Social background

1.1.1 Ocean and coastal management

Oceans cover more than 70% of the Earth's surface. They provide human beings with food, energy, transportation, sense of identity, spiritual and cultural values, as well as regulating the climate (Barbier, 2017). Oceans and coasts support the livelihoods of hundreds of millions of people and contribute more than 60% of the total economic value of the biosphere (Martínez et al., 2007). However, oceans and marine ecosystems are some of the most heavily impacted systems on the planet from anthropogenic pressure (Nicholls and Cazenave, 2010). More than 40% of the world's 7.5 billion people live within 200 km of the coast, and this number is expected to rise (Neumann et al., 2015). On the other hand, coastal area is a home to abundant marine ecosystem and high biodiversity. Near-shore environments are estimated to be responsible for 38% of ecosystem-derived benefits to human society (Domínguez-Tejo et al., 2016). Planning a sustainable future for our sea-bounded society requires improved management over multiple human uses of the ocean, particularly coastal seas, and improved knowledge of the current status and the responses of natural systems to anthropological activities (Domínguez-Tejo et al., 2016).

Marine Spatial Planning (MSP) is recognized as an important management tool that provides a comprehensive framework for managing multiple activities within the marine environment (Schaefer and Barale, 2011). It is defined by UNESCO as a "public process of analyzing and allocating the spatial and temporal distribution of human activities in marine areas to achieve ecological, economic and social objectives that are typically specified through the political process". MSP provides the appropriate framework for public authorities and stakeholders to coordinate their action across sectors and administrative boundaries, and to optimize the use of natural resources (Schaefer and Barale, 2011). MSP is also one of the key tools in Ecosystem Based Management (EBM), an approach that recognizes human society as an integral part of ecosystems. EBM is widely accepted as a key framework for delivering sustainable development in the marine environment. Integrated Coastal Management (ICM) is another approach to manage such multi-faceted use of coastal area, based on multidisciplinary information from the land, shoreline and the sea (Taijaard and Adams, 2021). During the planning phase in those MSP, EBM, and ICM, the spatial and temporal data of the biological aspects and the anthropogenic pressures should be mapped and their interactions should be understood as baseline information of any strategy consideration (Coomber et al., 2016). In this context, large-scale (continental, worldwide) studies are now commonly conducted while local studies (regional, local) are lacking (Holon et al., 2015). In addition to the gap between the global-scale analysis and what can really be done in the field, there is a paradox between the international scale of political will and the local scale of biodiversity conservation (Holon et al., 2015). There is a need to provide managers and stakeholders with local fine-scale information.

As its name indicates, MSP primarily considers spatial aspect, i.e. "drawing lines" on the sea, as restricting access or activities in a certain area is a critical measure to reduce anthropological pressure to marine ecosystem. On the other hand, given the temporal dynamics of coastal ecosystem, static spatial management might not be always optimal to balance the conservation efficiency and restriction of human activity. Dwyer et al. (2020) examined the habitat use of common dolphin (*Delphinus* sp.) in New Zealand, and suggested that static spatial exclusion zones are a non-optimal management tool based on their movement. Another issue is that, considering the complexity of ecosystem and human activity in coastal area, the characteristics of those elements could vary among fine-scale habitat. Skov and Thomsen (2008) highlighted fine-scale spatio-temporal dynamics in the distribution of harbor porpoise (*Phocoena phocoena*), while examining the potential relationship with small-scale local currents reflecting upwelling. Nakamura and Saleh (2015) examined the fine-scale characteristics of fisheries in Dungonab Bay MPA, Sudan, to assess the risk of dugong (*Dugong dugon*) bycatch problem. In those contexts, scientific baseline information needs to be accumulated based on the monitoring in continuous and fine-scale manner.

1.1.2 Coastal management and marine megafauna

Marine megafauna comprise all large-bodied organisms (body mass, ≥45 kg) inhabiting the coastal and open oceans, including bony fishes, elasmobranchs (sharks and rays), mammals (whales, seals, sea cows, and the polar bear), reptiles (sea turtles), a species of sea bird (i.e., the emperor penguin), and a few species of mollusks (clams, squids, and octopuses) (Estes et al., 2016). Megafauna affect ocean ecosystems by (i) consuming large amounts of biomass; (ii) transporting nutrients within and between habitats via excretion; (iii) connecting ocean ecosystems via long-distance migration; and (iv) physically modifying habitats by way of their feeding, locomotion, and mortality (Pimiento et al., 2020). Furthermore, marine megafauna includes many charismatic species that are socially, economically, and culturally important (Estes et al., 2016). Despite their profound ecological and societal value, marine megafauna are currently threatened by human exploitation, habitat loss, pollution, fisheries bycatch, maritime development and climate change, which together have triggered population declines and local extinctions of many species over just the past century (Estes et al., 2016; Pimiento et al., 2020). Thus, science-based management measure, such as MSP of their habitat, is strongly required for their conservation.

Among marine megafauna, marine mammals can play important ecological roles in aquatic ecosystems, and their presence can be key to community structure and function (Nelms et al., 2021). Consequently, marine mammals are often considered indicators of ecosystem health and flagship species (Nelms et al., 2021). However, historical population declines caused by anthropological factors listed above continue to impact many marine mammal species, and at least 25% are classified as threatened (Critically Endangered, Endangered or Vulnerable) on the International Union for Conservation of Nature (IUCN) Red List (Nelms et al., 2021). Conversely, some species have experienced population increases/recoveries in recent decades, reflecting management interventions (Nelms et al., 2021). To continue these successes and reverse the declining trend of the at-risk species' population, it is necessary to evaluate the threats faced by marine mammals and to consider the conservation mechanisms available to address them.

Plant-eating marine megafauna, or marine megaherbivores, is another group that the attention should be paid. They typically move between foraging and breeding grounds in the coastal area, and their movements are largely influenced by environmental and biological drivers, such as the availability of shelter and food resources that are often spatially explicit (i.e., seagrass meadows, and macroalgal beds) (Bakker et al., 2016; Khamis et al., 2022). The spatio-temporal dynamics of environmental drivers and anthropogenic stressors over marine megaherbivore lead to a significant challenge for conservation spatial planning and effective management interventions (Khamis et al., 2022). Many marine megaherbivores often spend large periods of time around one or multiple feeding grounds that can be relatively stable and predictable as long as resource stocks last (Sheppard et al., 2010, 2006). Thus, focusing on examining their habitat use and designing conservation measures that are cost effective and tailor made for these specific locations is important (di Sciara et al., 2016; Khamis et al., 2022).

To proceed the conservation management of marine megafauna, the process of demarcating marine protected areas (MPAs) is being supported by spatial designations, including ecological or biologically significant areas of the Convention on Biological Diversity (CBD), the International Maritime Organization's particularly sensitive sea areas, IUCN's key biodiversity areas, and biologically important areas adopted by the United States and Australia (di Sciara et al., 2016). Recently, the important marine mammal areas (IMMA) designation has been introduced by the IUCN Task Force on marine mammal protected areas (Hoyt and Sciara, 2021). Such approaches have the potential to enhance the protection of marine megafauna within the overarching approach of systematic marine spatial planning. On the other hand, such protected areas in coastal seas tend to be difficult to implement and manage, since it imposes restriction on the active and complex human activity for some amount, and crosses several different authorities. Thus, those protected areas often end up to be "paper parks" (i.e., legally gazetted protected areas with insufficient management or enforcement) (Khamis et al., 2022; Wells et al., 2016). To overcome this, examining habitat use of both marine megafauna and human activity in fine scale and proposing reasonable and harmonized management measure is expected.

A case study to tackle those issues is needed. To conduct a case study, there is one species which has the aspect of both marine mammal and marine megaherbivore, inhabits in coastal area, and thus effective and harmonized coastal management plays essential role to maintain their population—dugongs (*Dugong dugon*).

1.1.3 Anthropological activity and vessel traffic

As stated in section 1.1.2, several anthropological activities have been recognized as potential threats to marine megafauna in coastal area. Thus, quantitative layers and subsequent impact assessment of those activities provide scientific evidence for making decision of MSP. Vessel traffic is one of those anthropological factors that heavily contribute to the local livelihood in coastal area but have high potential disturbance risk at the same time.

The continued increment of vessel traffic for fisheries, tourism and transportation around the world, and increased recognition of the direct and indirect impacts of vessel activities to marine fauna, has prompted interest in better understanding vessel operations as a baseline information (Robards et al., 2016). The impacts to the wildlife are considerably diverse; fatal strikes or collisions (Delory et al., 2007; Schoeman et al., 2020), noise pollution to their vocal communication or echolocation (Duarte et al., 2021), habitat damaging (especially on corals) through anchoring (Flynn and Forrester, 2019), introduction of pathogens or invasive species (Keller et al., 2011; Yang et al., 2022) and carbon emissions (Wang et al., 2017). Among those impacts from maritime traffic, noise pollution and vessel strike are reported to be main threats to marine mammals (Coomber et al., 2016).

In terms of noise pollution, the number of studies which reported the significant effect was the largest among other noise sources, such as sonar or seismic air-gun (Duarte et al., 2021; Harding et al., 2021). The effects considerably diverse, for example multiple behavioral impacts, compromised anti-predator response, sensory processing and cognition, vocalization behavior, presence/absence, or altering hearing ability (Duarte et al., 2021). Those threats have been recognized in the shipping community and countermeasures have steadily been proposed. In 2014, the International Maritime Organization (IMO) approved voluntary guidelines for reducing underwater noise from commercial ships (IMO 2014). These guidelines focused on design features that could reduce the primary sources of underwater noise, namely the propellers, hull form, and on-board machinery. While this guideline is applied to "any commercial ship", a previous study reported that small recreational vessels dominate anthropogenic noise contributions to a shallow water soundscape (Hermannsen et al., 2019). Particularly in coastal area, in this context, further assessment on the traffic of small vessels and consideration of further management guideline or policy would be expected.

A vessel strike or collision is defined as any impact between any part of a watercraft (most commonly bow or propeller) and a live marine animal (Peel et al., 2018). Collisions often result in physical trauma to- or death of the animal (Moore et al., 2013; Neilson et al., 2012; Schoeman et al., 2020) and may cause serious damage to the vessel, while people on board are at risk of injury and mortality (Neilson et al., 2012). To date, most scientific publications on collisions have focused on the interactions between large vessels and large whales (Schoeman et al., 2020). On the other hand, data on collisions between smaller marine species and smaller vessels is relatively scarce, which is likely more a result of reporting biases than a reflection of the true extent of the collision problem (Schoeman et al., 2020). Species that occur in coastal waters are specifically at risk of collision with small- and medium-sized vessels that occur in high densities near urbanized coastal regions. Efforts should therefore also be put into the identification of high-risk areas based on small vessel traffic, especially in areas where these dominate collision reports (Neilson et al., 2012). While multiple mitigation measures, e.g. re-routing measures (Frantzis et al., 2019), speed restrictions (Conn and Silber, 2013), and early warning system (Niezrecki et al., 2003) have been conducted, further efforts to identify high-risk areas for species other than large whales, would provide fundamental information toward the mitigation of collisions with smaller species (Schoeman et al., 2020).

To assess those potential risks and to create harmonized MSP consequently, visualizing spatio-temporal variation of vessel traffic plays critical role to provide a baseline information. In parallel with the habitat use of marine megafauna, such layer should be examined through fine-scale continuous monitoring.

1.2 Scope and Objectives

1.2.1 Framing of this study

Based on the social background described above, as a case study, this thesis aims to propose the conservation and management implication of the dugong (*Dugong dugon*) around Talibong Island, Thailand, an important population in Andaman sea. Baseline information is collected using underwater acoustics information. The remainder of this introductory chapter provides a background on the issues associated with dugong conservation, a brief overview of dugong ecology, adopted methodology, and the current situation of the study site. I then identify key information gaps required to enhance the conservation of species in this region. Finally, I present the objectives of my research and explain the structure of this thesis, as well as the contribution to the social informatics.

1.2.2 Dugong

The dugong, Dugong dugon, is the only herbivorous mammal that is strictly marine and a seagrass community specialist (Marsh et al, 2002) (Fig. 1.1). Dugongs are classified as Vulnerable in IUCN Red List (IUCN, 2019). They occur in tropical and subtropical coastal waters from east Africa to Vanuatu, and the largest population is found in Australian waters (Fig. 1.2). Local populations in other areas are reportedly decreasing (Kayanne et al., 2022; Marsh et al., 2002), and such is the case with the population along the coast of the Andaman Sea (Hines et al., 2005). Because of their dependence on seagrass meadows that are restricted to coastal habitats, they play a unique functional role among marine megafauna in tropical and sub-tropical coastal ecosystem (Hays et al., 2018; Nowicki et al., 2021; Pimiento et al., 2020). On the other side of coin, this dependence makes dugongs vulnerable to anthropogenic influences (Marsh et al., 2011b). There are several threating processes which derive from anthropological activities, such as fishing pressure (e.g. trawling), accidental bycatch, habitat loss/degradation, hunting, chemical pollution, noise pollution and vessel strike (Marsh et al., 2002; Petcharat and Lee, 2020).

Fig. 1.1 Dugong (*Dugong dugon*) in Talibong Island, Thailand (left) and in Toba Aquarium, Japan (right). Photo courtesy: Kotaro Tanaka

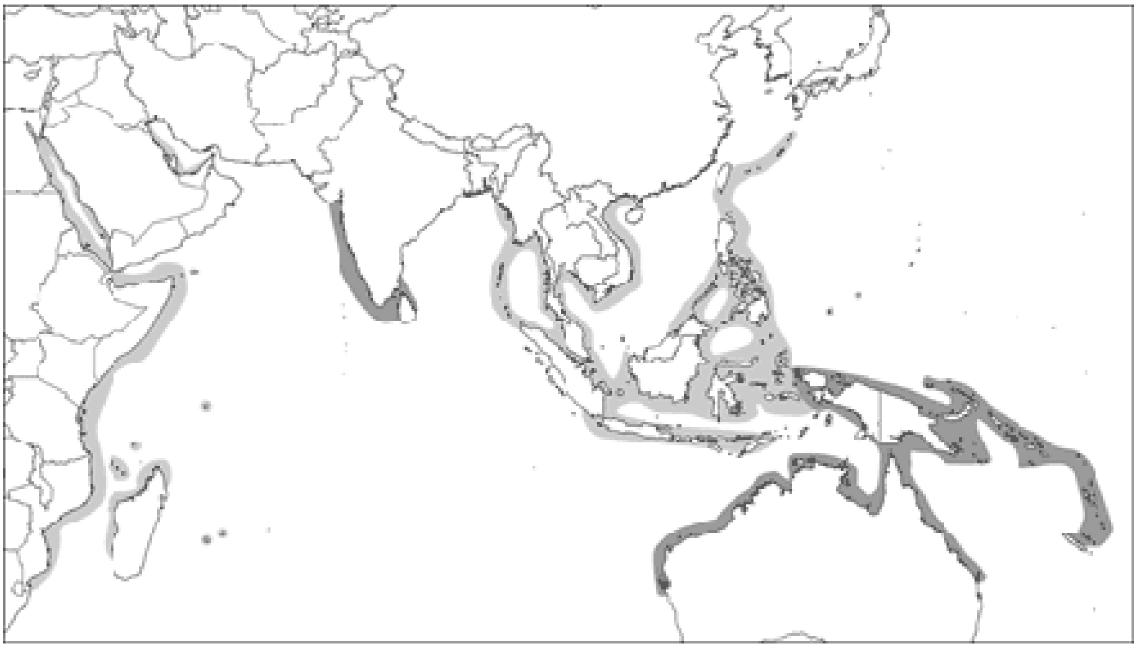

Fig. 1.2 The distribution of dugong (Marsh et al., 2002).

1.2.3 Passive acoustic monitoring

Passive Acoustic Monitoring (PAM) is getting attention as an emerging approach to provide unique information toward the conservation and appropriate MSP for vocalizing marine megafauna, aided by recent advances in technology and analytical approaches (Dutton et al., 2019; Marques et al., 2013; Roch et al., 2016). Since many of marine megafauna rely on acoustic cues for navigation, foraging and communication with conspecifics due to poor visibility and the fast speed of the sound in the water, PAM approach has an advantage in enabling continuous monitoring particularly for rare and elusive species (Marques et al., 2013). PAM for marine megafauna's conservation have mostly carried out to measure species presence or distribution (Romagosa et al., 2020; Thomisch et al., 2019, 2016; Verfuß et al., 2007) and density (Kimura et al., 2010; Marques et al., 2009; Rogers et al., 2013), which are fundamental and primary information for management measures. Those study has been conducted for species producing echolocation clicks in many cases, which is emitted in high rate for navigation so that they often correspond with animals' presence/absence patterns (Mellinger et al., 2007). Social calls, which are used for inter-individual communication, are less frequently produced than echolocation clicks, but their observation is still powerful tool to examine the habitat use of data-deficit cryptic species although it cannot detect non-vocalizing individuals (McCauley et al., 2018). Thus, the presence elicited by monitoring social calls are referred as "acoustic presence", in order to distinguish from animals' presence/absence (Romagosa et al., 2020). Further potential of social call monitoring has been proposed to elaborate conservation measures, since it can provide spatial and temporal information of animals' key life events, namely those associated with reproduction and recruitment, alarm and defense, and social behavior (Teixeira et al., 2019). In addition to the animals' habitat use, sound-producing human activities, i.e. traffic of motorized vessel, can be monitored by PAM (Hermannsen et al., 2019; Kline et al., 2020). Overlapping those ecological and anthropological layers examined by PAM would contribute to the effective and harmonized MSP between ecosystem conservation and local livelihood, by indicating the prioritized location and time in their habitat from the perspective of animals' behavior and potential threats from human activity. The advantage of PAM, namely enabling continuous monitoring, is expected to be particularly suited to the survey in coastal area which requires high spatio-temporal resolution of those layers because of the complex usage from wildlife and local residents.

1.2.4 Dugong and acoustics

PAM studies have also been conducted for dugongs, which produce a 'bird-like' tonal sound (Anderson and Barclay, 1995). Chirps and trills, which are frequency-modulated calls in the range of 3 kHz to 18 kHz, and classified by their duration (chirp: duration shorter than 300 ms, trill: duration longer than 300 ms) (Ichikawa et al., 2006). Although the functional role of their vocalization is not fully understood yet, given the fact that they showed callback response to conspecific chirp playbacks and that source level and duration of dugong chirps increased significantly as distance increased, it is suggested that their vocalization have functions for exchanging information and ranging between individuals (Ichikawa et al., 2011). Another study reported that, from the observation in an aquarium, their call might reflect their mating status (Hishimoto et al., 2005). From the previous PAM studies conducted in Thailand, the existence of a 'vocal hotspot' had been reported (Ichikawa et al., 2012, 2009). Vocal hotspots are areas of approximately 1 km^2 where dugongs show active vocal behavior compared to those of other locations within their daily home range (Ichikawa et al., 2012). Considering visually-detected distribution of dugong herds did not overlap with that of the vocalizing dugongs (Ichikawa et al., 2012, 2009), vocal hotspot is assumed to be an important location primarily for their socializing via vocalization. Thus, allocating a higher conservation priority to such area for coastal management would be expected. However, temporal variation of them at multiple locations in their habitat have not been examined so far. Furthermore, relationships of their acoustic presence with environmental and anthropologic factors, e.g. tidal current, season, geographical features and vessel traffic, were little studied, although such information is beneficial to generalize knowledge obtained in a local habitat to other habitat. This is because analyzing large acoustic data collected from long-term monitoring was challenging due to the technical problem, i.e. detecting tonal dugong calls out of noisy background sound in coastal seas.

1.2.5 Talibong Island, Trang, Thailand

Talibong Island (Koh Libong) in Trang province is located near the border of Thailand and Malaysia in the side of Andaman Sea (Fig. 1.3). The livelihood of local residents mostly comprises tourism (resort facilities, souvenir shop, or dugong watching), small-scale fisheries or rubber plantation (Ando-Mizobata 2014). Approximately 120–150 dugongs were estimated to inhabit this area, representing the largest population in Thailand (Adulyanukosol and Poovachiranon, 2006; Hines et al., 2005), and thus Trang is nationally recognized as "Home of dugongs".

In Thailand, the dugong has been legally protected under the Thai Fisheries Act since 1947, and they are one of the fifteen designated reserved animal species, which are defined by the Wild Animal Reservation and Protection Act of BE 2535 (1992). After the launch of this fisheries act, reportedly there was no dugong hunting (Adulyanukosol et al., 2010). The flora (mangroves and seagrasses) around Talibong Island is protected by the Botanical Department as the Libong Archipelago Wildlife Reserve (Ando-Mizobata 2014). Furthermore, this area is designated as Ramsar site No. 1182; Hat Chao Mai Marine National Park -Ko Libong Non-Hunting Area -Trang River Estuaries (Ramsar Sites Information Service). While hunting of vulnerable and endangered species are prohibited, inshore and offshore fisheries are locally important (Ramsar Sites Information Service). Since 1980s, non-governmental organizations and research organizations have been working to enhance the awareness for sustainable management of natural resources. Because of those efforts and the relevance to local livelihood, local residents and municipalities have relatively high interest and motivation toward environmental issues including dugong conservation (Ando-Mizobata 2014). Even internationally, coastal seas in Trang province is considered as “candidate of IMMA“ by IUCN, and waiting for the confirmation with the further assessment at time of writing (IUCN-MMPATF). This area is also known as a habitat for other marine mammals such as Indo-Pacific humpback dolphins (*Sousa chinensis*), Indo-Pacific bottlenose dolphins (*Tursiops aduncus*) and Irrawady dolphins (*Orcaella brevirostris*) (IUCN-MMPATF). In 2019, dugong calf was found without its mother in the coastal waters of Krabi (Fullerton 2019). The female dugong was nicknamed “Mariam”, and relocated to the sheltered area around Talibong Island. Her behavioral interactions with her human caretakers, such as being orphaned by veterinarians, captured the attention of many people (Ponnampalam et al., 2022). This seemingly fueled the momentum toward dugong conservation in local and national level more than before. After her death assumingly from infections resulting from plastic ingestion, Thai government declared 17 August as National Dugong Day (Ponnampalam et al., 2022). This is also an example showing the cultural and social importance of dugong in this area.

Over the past 20 years, there has been an average of five dugong mortalities annually (IUCN-MMPATF). Due to the fact that seagrass beds embrace abundant fishery resources, potential threats to dugongs therefore often come from coastal fisheries, from the use of fishing gears, such as drifting nets and gill net to catch fish and the use of the bamboo fish-trap (Wongsuryrat et al., 2011). In addition, since various sized vessels from speed boat to cargo ship are observed in this area, noise pollution and boat strike could be another potential threat for local population. Given that such usages of coastal area by dugongs and local residents around Talibong Island is highly overlapped, collecting information of their habitat use in fine spatio-temporal scale will be valuable to elaborate coastal management measure. Although community-based dugong protected area was already set around this Island (Marine National Park Operation Center 3 Trang 2018, see Chapter 3), this was based on the input from visual survey, and thus temporal flexibility has not been incorporated. Incorporating fine-scale spatio-temporal variation about dugongs’ acoustic presence and vessel traffic into existing management measure would be beneficial, and PAM should have the capacity to provide such information. Based on the high awareness and motivation of local community toward ecosystem conservation including dugong, case study in this area could play a representative role as a good practice to demonstrate the effectiveness of PAM approach for coastal management.

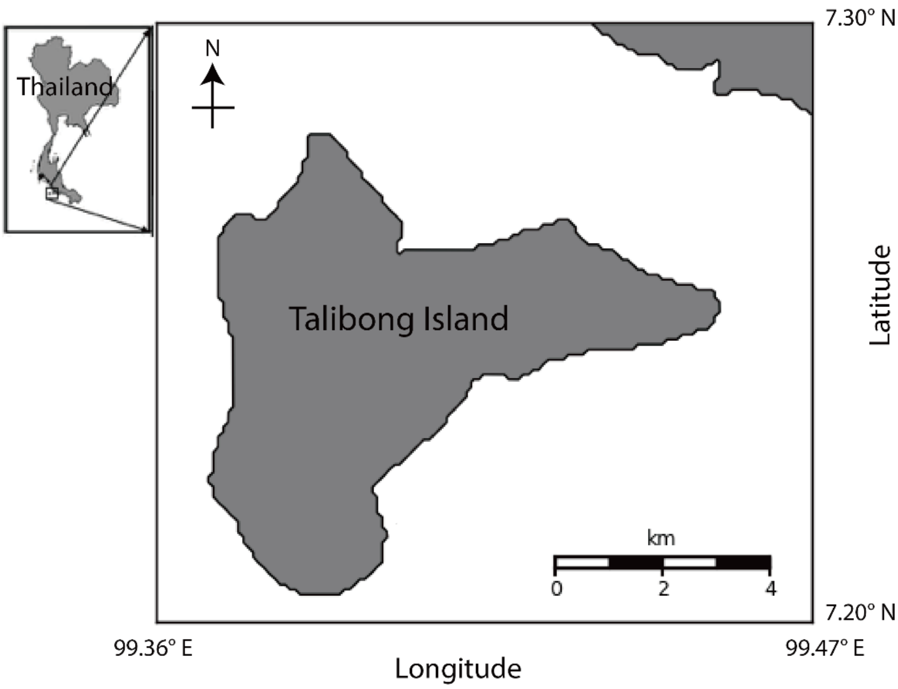

Fig. 1.3 Map of Talibong Island, Trang, Thailand.

1.2.6 Objectives

The ultimate goal of this study is to illustrate the spatio-temporal usage of endangered marine megafauna and local residents in fine scale and to provide an insight into harmonized coastal management. To pursue that, in this study, underwater acoustic information is adopted as a methodology to enable continuous monitoring, and vocalizing dugongs and motorized vessels around Talibong Island are targeted.

Here, it has to be noted that the output of this study is one of the inputs to a coastal management, not as a whole. MSP is not considered only by the habitat use of endangered species and vessels. There are many other elements in social-ecological-economical system around coastal area. Nevertheless, this study provides unique layer in the coastal social-ecosystem and thus would contribute to elaborating the coastal management.

1.2.7 Thesis structure

This thesis consists of six chapters (Fig. 1.4). **Chapter 1** is devoted to introduce the social background of coastal management, to justify dugongs and vessels as study targets and to highlight the necessity and the aim of this study to fill the knowledge gap. As a methodology, passive acoustic monitoring was adopted since it is beneficial to continuously monitor both vocalizing dugongs and motorized vessels. However, manual detection process of target sounds limits the scale of acoustic observation, and this raises the necessity to automate this process. In **Chapter 2**, I described how I developed the automated detection and classification method to monitor dugong calls and vessel sound out of noisy environment in coastal waters. Developed software was then utilized in the following chapters to extract target sounds from large amount of acoustic data obtained from multiple recorders. In **Chapter 3**, I conducted acoustic survey to investigate where and when dugongs actively vocalize in their habitat. This information is expected to identify prioritized time and space in the consideration of conservation management and MSP. In **Chapter 4**, in order to quantify local maritime activity, the vessel traffic around Talibong Island was illustrated from the same dataset in **Chapter 3**. The vessel type passing at one of the monitoring locations was classified from the recorded sound, although it is still limited to a reference result. In **Chapter 5**, I examined the relationship between dugongs' acoustic habitat use and environmental/anthropological factors, e.g. tidal current or vessel traffic. This analysis was intended to enhance the generic understanding of dugongs' acoustic presence. In **Chapter 6**, I discussed the obtained results in relation to their capacity to recommend dugong conservation and coastal management in Talibong Island. Furthermore, the implication to other habitats was considered, and future perspectives were outlined.

1.3 Contribution to social informatics

"Information is born where human lives—internet is not the only source which give a birth to information about our society" — Prof. Nobuhito Ohte (Kyoto University)

Social informatics is generally recognized as an approach for understanding interactions between various social systems and information and communication technologies (ICTs) (Smutny and Vehovar, 2020; Vehovar et al., 2022). Given the cultural, social, economic, and scientific circumstances are highly distinctive in different social systems, the corresponding conceptualizations of social informatics also differed (Smutny and Vehovar, 2020; Vehovar et al., 2022). The efforts, activities, and outputs of these research communities were clustered into five to seven clusters, which Smutny and Vehovar (2020) characterized as "schools" of social informatics. While each school focuses on slightly different aspects of social informatics, they all provide a conceptual basis for understanding the problems and challenges of integrating ICTs into society (Smutny, 2016).

The presented study ultimately pursues, among complex and diverse social systems where human beings live, sustainable and harmonized management of a coastal sea. There, not only social aspect, but also ecological system needs to be well considered given their deep connection and interaction. To understand current situation and to identify potential challenges and solution there, underwater acoustic information was collected as one of the ICTs, since it offers cost-effective continuous monitoring of both human activity and the ecology of endangered marine mammal in the coastal area. In this sense, this study aims to expand the coverage of social informatics into socio-ecological informatics. Coastal area plays a unique role, as a case site, to demonstrate this potential.

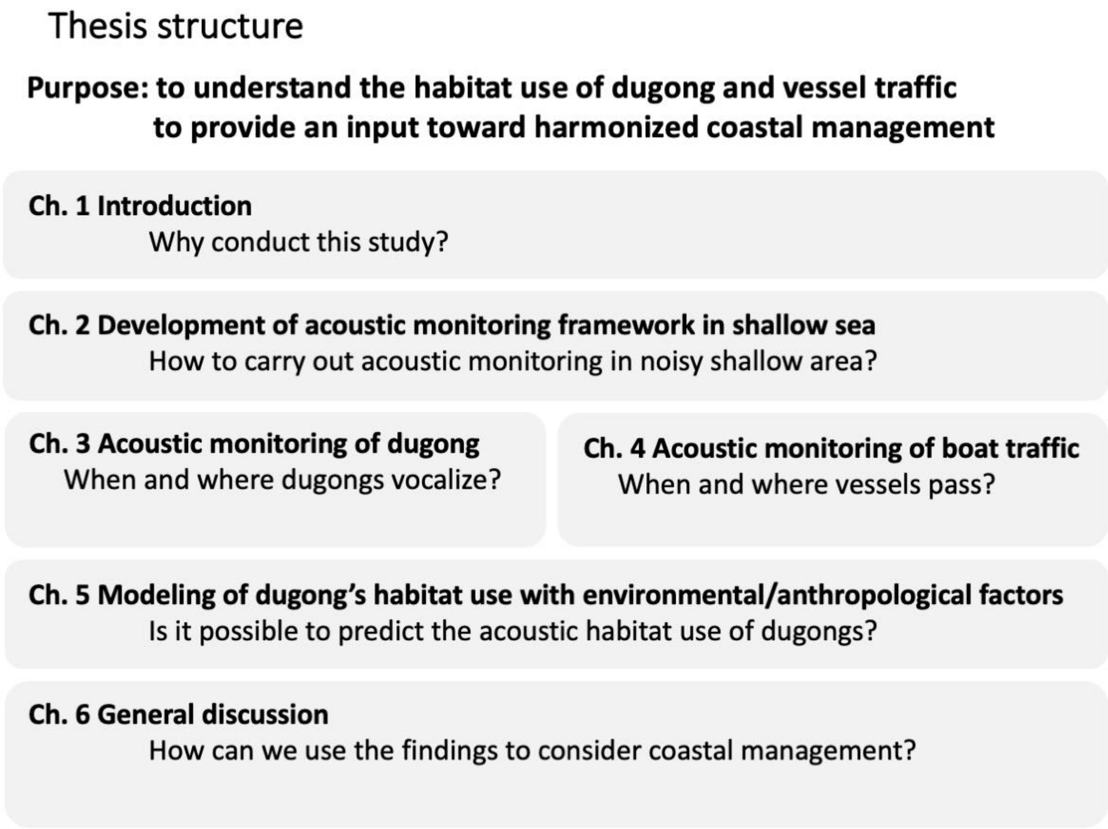

Fig. 1.4 Conceptual image of the structure of this thesis.

Chapter 2 Development of automated detection and classification method for dugong call and vessel sound in shallow waters

2.1 Detection and Classification of dugong calls

2.1.1 Introduction

Passive acoustic monitoring (PAM) is a method used to observe sound signals produced by animals. It is particularly suitable for studying the distribution and behavior of cryptic species. It has been successfully used for nocturnal species (Zwart et al., 2014) and species inhabiting dense forests (Wrege et al., 2017). PAM has also been widely employed for observation of marine mammals and can potentially play a key role in the monitoring of these animals, including their habitats, distribution, and social interaction (Marques et al., 2013; Mellinger et al., 2007; Mellinger and Barlow, 2003). Large spatial scale and long-term acoustic monitoring are required to estimate the geographical and temporal variations in animal distribution, habitat use and behavior, which should be understood to establish effective conservation measures. The use of acoustic surveys has become more feasible with advanced recording technology, that is, with longer battery life and larger memory capacity. As a result, the amount of sound data is steadily increasing (Sousa-Lima, 2013). Manual sound detection with such a large amount of data is extremely time-intensive and costly, limiting the amount of sound that can be reviewed and the scope of the questions that can be answered using the data (Keen et al., 2017). To deal with this issue, multiple techniques have been proposed to enable the automated detection of vocalizations of marine mammals within sound streams (Baumgartner and Mussoline, 2011; Bittle and Duncan, 2013; Lin and Chou, 2015; Niezrecki et al., 2003; Yan et al., 2005).

Long-term and wide-range observations of dugong calls are required to explore and gain a deeper understanding of their habitat use; however, such large-scale acoustic monitoring subsequently yields a large acoustic dataset. Although an automated detection algorithm for dugong calls has been proposed (Ichikawa et al., 2006), the overlap of vocalization frequencies with tonal noise that lies in the same frequency band makes the application of such algorithms challenging. Dugongs mainly inhabit shallow and warm waters, spending 72% of their day in waters less than 3 m deep (Louise Chilvers et al., 2004). Such waters exhibit various sound sources, for example, boat engines, biological sounds, and sound of waves and rain, and some of them show tonal frequency characteristics. Separating pure tonal sound from tonal noise within the same frequency band is a universal problem in tonal sound detection, not just in the specific problem of dugong call detection. Tonal sound detectors generally search for consecutive tonal spectral peaks in the time–frequency domain with either bandpass energy (Ichikawa et al., 2006; Lin and Chou, 2015; Mellinger, 2004; Niezrecki et al., 2003; Zaugg et al., 2012) or entropy (Erbe and King, 2008) after denoising and emphasizing processes. However, undesirable tonal noise often meets those criteria if its frequency band overlaps with that of the target signals; hence, they can be detected as false positives. In the case of the West Indian manatee, which is another member of Sirenians, the harmonic structure of the vocalization helps distinguish the manatee sound from noise (Niezrecki et al., 2003). However, dugong vocalizations often do not have a harmonic structure (Ichikawa et al., 2006), and this makes their calls difficult to distinguish from other tonal noise. Because manual removal of false positives is a burdensome task when the amount of data increases, those sounds need to be effectively classified using additional information after the detection process. Distinguishing dugong calls from tonal noise, which is mainly generated by motorized vessels, is a major challenge of their acoustic monitoring, given dugongs inhabit coastal waters where marine traffic is generally heavy due to local fisheries and tourism.

The objective of this section is to develop a classification method for dugong calls and tonal noise, which is the main cause of false positives in the conventional detection method (Ichikawa et al., 2006). This section is expected to contribute not only to the acoustic monitoring of dugongs, but also to the acoustic monitoring of other animals that produce tonal vocalization under the existence of tonal noise. A supervised machine learning technique was employed, because it is assumed to be more effective than a combination of filters when the characteristics of target signals in the frequency domain are similar. The proposed method is expected to be used in a long-term and wide-range acoustic program for monitoring of vocalizing dugongs to enable further investigation into their habitat use. Thus, the following information, which is useful to conduct such surveys, was examined:
(i) Effective features for classification (ii) Necessary amount of training data (iii) Compatibility of classifiers among recording locations.

To minimize the risk of misguiding estimations of the habitat use of dugongs, prioritized improving precision, thereby reducing the need for manual inspection. Given that dugongs often produce multiple calls successively (Hines et al., 2005), missing a few calls may not significantly affect the estimation of their presence.

2.1.2 Materials and Methods

Data collection

Underwater sounds were recorded in the south of Talibong Island, Thailand, from February 6 to 15, 2015 (Fig. 2.1). For the recordings, three underwater recorders (AUSOMS, AquaSound Inc., Kobe, Japan) were deployed on the seafloor at locations where dugong vocalizations were frequently observed in previous acoustic surveys (Ichikawa et al., 2006). The locations where the three AUSOMS (A, B, and C) were deployed were approximately 600 m, 1000 m, and 1300 m offshore, respectively (Fig. 2.1). The AUSOMS had a single hydrophone (AQH20k, AquaSound Inc.) with a sensitivity of − 195 dB re 1 V/ μPa. The hydrophone had a flat frequency response within 2 dB between 20 and 96 kHz. Because the amplifier gain was 60 dB and the internal noise floor of the AUSOMS was ~ 70 dB re 1 μPa, the dynamic range was 70–135 dB re 1 μPa. The sampling frequency was 48 kHz with a 16-bit resolution. Underwater sound data were stored in eight flash memory cards (32 GB microSD cards). At the deployed locations, few obstacles, such as rocks and sandbars, in the path of sound waves in the focal area were observed. The depth of the deployed locations varied between 2.5 and 5.5 m due to tidal shift (Tanaka et al., 2017).

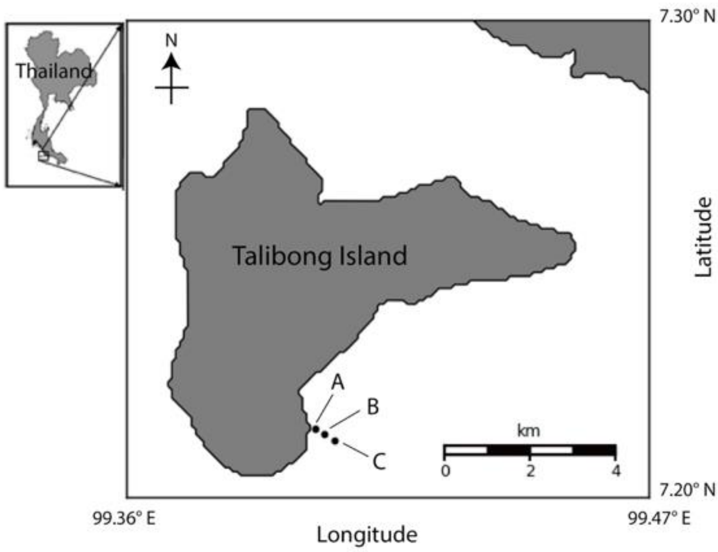

Fig. 2.1 Study area and locations of deployed recorders in Talibong Island, Trang, Thailand. Three AUSOMS (A, B, C) were deployed on the seafloor. Circles indicate their deployed locations.

Acoustic Characteristics of Target Signals

In Australian dugong populations, Anderson and Barclay (Anderson and Barclay, 1995) categorized dugong calls into three types: chirps (frequency-modulated signals in the 3–18 kHz range with two or more harmonics, lasting less than 60 ms), trills (frequency-modulated calls lasting up to 2.2 s in the 3–18 kHz range), and barks (broadband signals between 500 Hz and 2.2 kHz, lasting up to 120 ms).

Dugong calls in southern Thailand have also been categorized into short and long-duration calls (Ichikawa et al., 2006), which seem to correspond to chirps and trills, respectively. To date, no vocalizations corresponding to barks have been recorded from the Thai population of dugongs, the two dugongs kept in the Toba Aquarium in Japan (Hishimoto et al., 2005), or the one in Underwater Seaworld in Singapore (Okumura et al., 2006). Thus, this section focused on dugong chirps and trills. In many cases, dugong calls have no harmonic structure. Tonal noise, which is mostly produced by motorized boats, is the main cause of false positives for dugong calls (Fig. 2.2).

Design of Automated Detection Algorithm

The proposed algorithm is created to automatically detect dugong calls by separating them from tonal noise in recordings. This process includes three main steps: tonal sound detection, feature extraction, and classification (Fig. 2.3). All computations were implemented in MATLAB (R2016a, The MathWorks, Inc., Natick, MA).

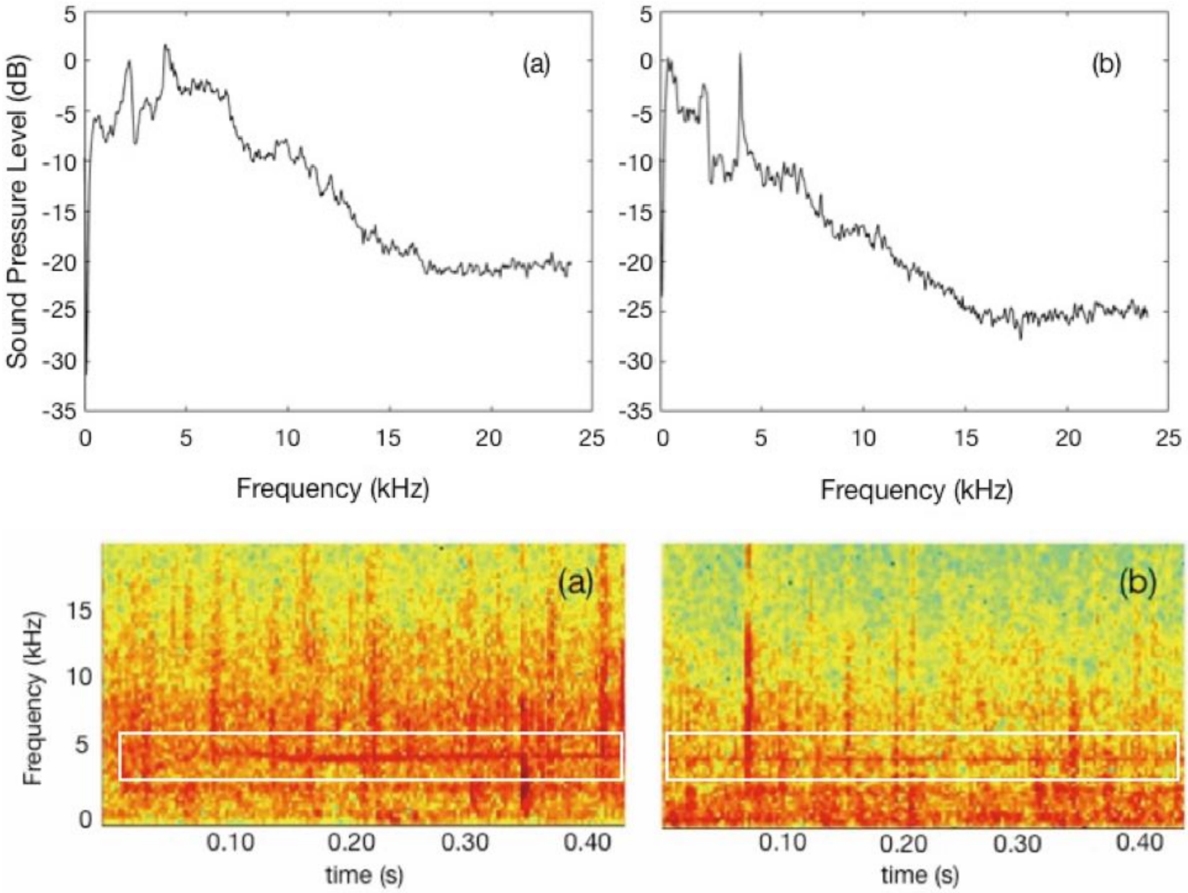

Fig. 2.2 Example of spectrum (upper) and sonogram (lower) of a dugong call and b tonal noise. The sonogram shows that both signals are tonal, and their frequency bands approximately overlap at 4 kHz. The white boxes in the sonograms indicate where the dugong call and tonal noise are shown

i. Tonal sound detection

Tonal sounds, including both dugong calls and noise, were automatically detected out of the sound stream based on the algorithm proposed by Ichikawa (2006). The root mean square (RMS) source levels of dugong calls are 130–140 dB re 1 μPa (Ichikawa et al., 2011; Parsons et al., 2013). Based on Ichikawa (2006), which developed the detection algorithm with the data obtained at the same location of this study, the detection range using this software was assumed to be approximately 200 m from the recorder (Ichikawa et al., 2006). Within that range, the recall (number of true detections / number of true examples) of this detector was 75%, and the precision (number of true detections / number of all detections) was 100% under the condition of no tonal noise for a randomly selected 15 min sound clip (Japan Ministry of Defense, 2015). However, in the presence of tonal noise, the precision dropped to 4%, whereas the recall was 100%. Detected candidates were manually labelled as either dugong call or tonal noise by listening to the sounds and through visual inspection of spectrograms and were used as ground truth data to train a classifier. The number of labelled calls and noises were different for each recorder (Table 2.1).

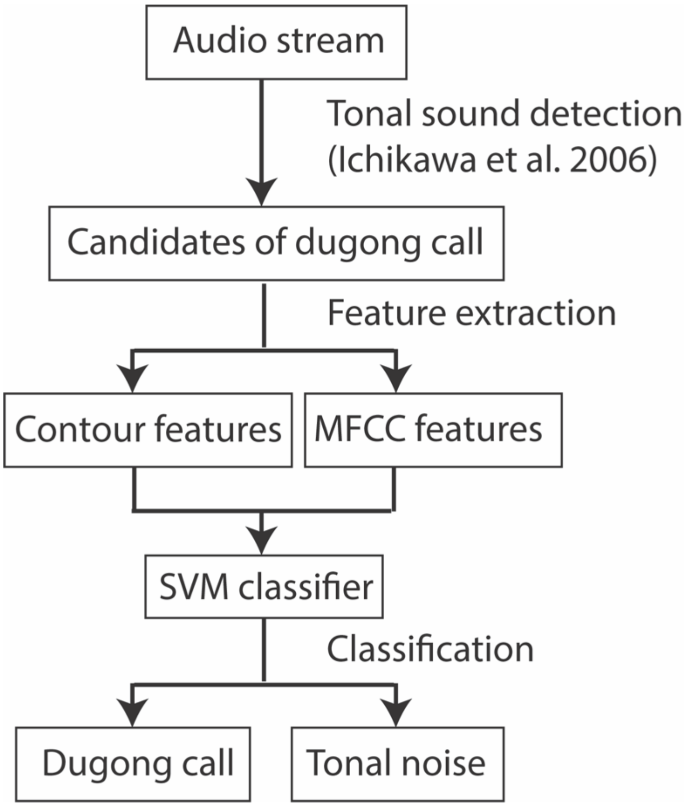

Fig. 2.3 Flowchart of the proposed method

Table 2.1 Number of labelled signals recorded by each recorder. Both signals were outputs of a conventional tonal sound detector, and then they were labelled as calls and noises by manual inspection.

Recorder	Number of Calls	Number of noises
A	1417	11793
B	4428	3464
C	5450	1242

ii. Feature Extraction

Two sets of feature measurements were extracted from each detected signal: contour features, which quantify the shape of the signal contour on spectrograms; and Mel-frequency cepstral coefficient (MFCC) features, which measure the spectral envelope of a time window to consider the characteristics of the background sound. When these two sets were combined, the combined feature vector had a total of 15 dimensions for each signal.

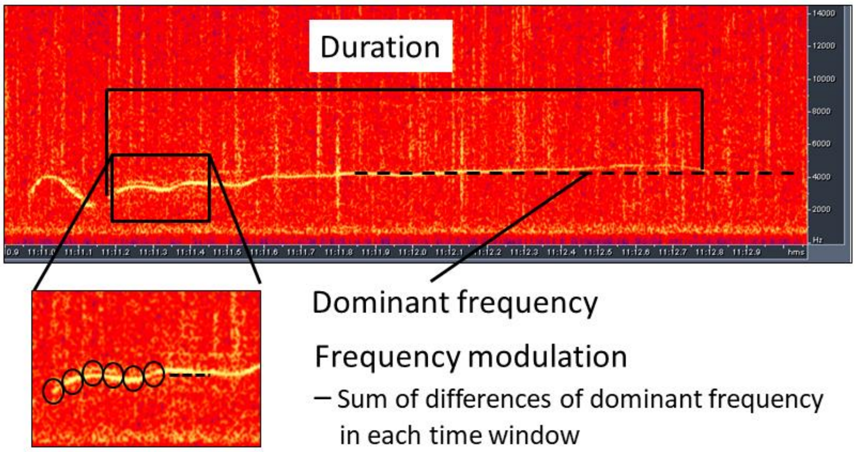

Fig. 2.4 Contour features. Duration (ms), Dominant frequency (Hz) and Frequency modulation (Hz) were extracted from each signal

ii.a Contour Features Duration, dominant frequency, and frequency modulation, which are feature sets representing signal contour, were extracted from each detected signal in the detection step (Fig. 2.4). Frequency modulation involves summing of the differences of the adopted frequencies in each time bin. Tonal noise tends to have a longer duration and smaller frequency modulation than dugong calls. Other parameters, such as the time interval from the previous signal, magnitude of dominant frequency, or coefficient of frequency modulation (frequency modulation divided by duration), were tested; however, they were excluded from the feature set, because the classification performance did not improve when these features were included.

ii.b MFCC Features Measuring accurate contour information using an automatic detection step is difficult under a low signal-to-noise ratio (SNR) environment in many cases. Thus, I assumed that considering the overall spectral characteristics of a time window including the background sound would help in the appropriate classification of dugong call and tonal noise given that tonal noise is often generated by boats; thus, the power of the low frequency band tends to be high. To parameterize this, MFCCs were employed (Fig. 2.5). The MFCC represents the short-term power spectrum of a sound on a scale that attempts to mimic the human perception of pitch. The MFCC is an example of commonly used features in audio-related similarity tasks and is often applied in speech recognition research. More recently, MFCCs have been employed in bioacoustics research, such as in the recognition of birdsongs and primate calls (Koops et al., 2015; Mielke and Zuberbühler, 2013), and music information retrieval applications, such as genre classification and instrument recognition (Gaikwad et al., 2014; Tzanetakis and Cook, 2002).MFCCs are based on the Mel scale, which matches the pitch perception of the auditory system of terrestrial vertebrates. MFCCs are much better at discerning small changes in pitch at low–mid frequencies than at high frequencies. Incorporating this scale makes the features sensitive to low frequency, which is the strongest frequency band of both dugong calls and tonal noise. The extraction of MFCC features from signals begins with segmenting the waveform into frames. The fast Fourier transform (FFT) is calculated from the pre-emphasized and hamming-windowed signal frame. Pre-emphasis is a step to balance the frequency spectrum by amplifying the high frequencies in time domain (Yucesoy and Nabiyev, 2013). The widely used pre-emphasis filter for signal x is given as,

$$y(t) = x(t) - \alpha x(t-1) \tag{2.1}$$

In this study I took α = 0.97 (Table 2.2). Then, the FFT magnitude is input to a series of Mel scale spaced filter banks (Eq. 2.2).

$$F_{mel} = 2595\log_{10}\left(1 + \frac{F_{Hz}}{700}\right) \tag{2.2}$$

Finally, the log filter bank amplitudes are used to calculate the MFCCs using the discrete cosine transform (Chou and Ko, 2011) (Eq. 2.3),

$$c_i(m) = \sum_{j=0}^{J-1} \cos\left\{m\frac{\pi}{J}(j+0.5)\right\}\log_{10}(E_j), 0 \le m < 12 \tag{2.3}$$

where ci(m) denotes the mth order MFCC of the ith frame, while J is the number of filterbank channels and Ej is the energy of the jth filter band. In the following experiments, a frame size of 20 ms and step size of 10 ms were employed, based on the study of Mirzaei et al. (2012) (Table 2.2). The coefficients were averaged at each order in a signal. For implementation, I employed HTK MFCC MATLAB toolbox in MATLAB to calculate MFCCs (https://jp.mathworks.com/matlabcentral/fileexchan ge/32849-htk-mfcc-matlab).

iii. Classification and Validation

A support vector machine (SVM) was employed to classify dugong calls and tonal noise (Cortes and Vapnik, 1995). The SVM is chosen for the following reasons: (i) the training and testing speeds are high, (ii) the parameter tuning strategy is easy and well known, and (iii) it is widely used in the field of bioacoustics classification (Jarvis et al., 2013; Roch et al., 2007; Yovel and Au, 2010). Other classifiers, for example, artificial neural networks (Zaugg et al., 2010) or random forests (Risch et al., 2013) were preliminarily tested; however, their performances were highly similar to the SVM. Thus, these methods were viewed as being interchangeable for this application. The radial basis function kernel, a representative kernel function, was used to address nonlinearly separable data. For the box constraint (C) and the kernel scale parameter (gamma), the default values of MATLAB (both were 1) were used.

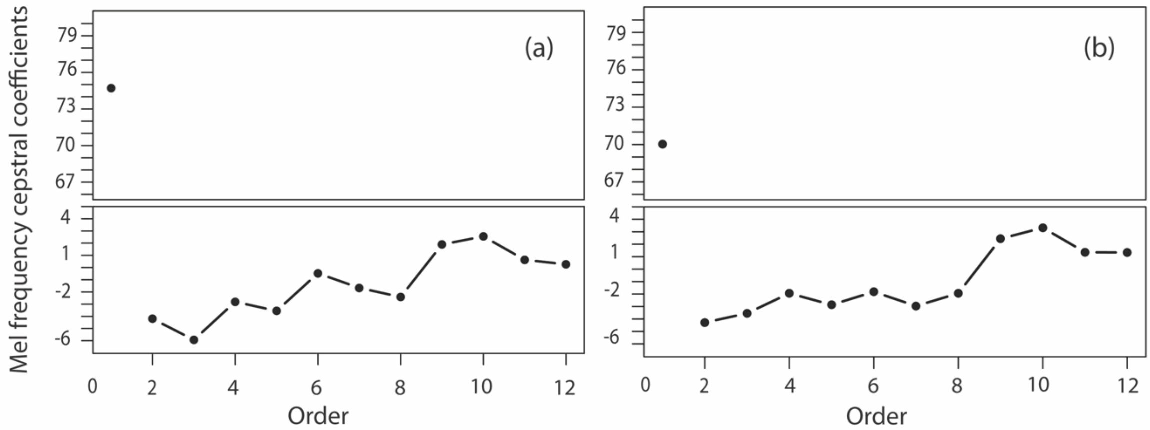

Fig. 2.5 Example of extracted MFCCs of a dugong call and b tonal noise, which are displayed in Fig. 2.2. There was a large gap between the first coefficient and the others, thus that gap was omitted.

Table 2.2 Parameters used for MFCC extraction

Parameter	Values
Window type	Hamming
Frame length (ms)	20
Frame overlap (ms)	10
Pre-emphasis coefficient	0.97
Number of filterbank channels	20
Feature vector length	12
Liftering parameter	22

The SVM classifier model was trained using labelled signals and two feature sets. At first, every parameter was standardized, and the numbers of each class were equalized to that of the class with fewer samples by random down sampling. The performance of the classifiers was examined by cross-validation, trained using 90% of the dataset and tested using 10% of the dataset. The sequence of training and testing was repeated 10 times, and training and testing data were randomly chosen each time. The average of the recall and precision were calculated as follows (Eq. 2.4, 2.5), where each term is defined in Table 2.3:

$$\text{Recall} = \frac{\text{Number of True positives}}{\text{Number of True positives} + \text{Number of False negatives}} \tag{2.4}$$

$$\text{Precision} = \frac{\text{Number of True positives}}{\text{Number of True positives} + \text{Number of False positives}} \tag{2.5}$$

Table 2.3 Confusion matrix of the tonal sound classification

		Predicted class	
		Dugong call	Tonal noise
Actual Class			
	Dugong call	True positive	False negative
	Tonal noise	False positive	True negative

The classification performances of the three feature sets, contour, MFCC, and contour + MFCC were tested and compared. To explore the relationship between training data amounts and classification performances, classifiers were trained using 0.05%, 0.1%, 1%, 5%, 10%, 50%, and 90% of the datasets and tested using 10% of the data that did not overlap with the dataset used for the training procedure. Finally, to evaluate the compatibility of classifiers between the recording locations, training and testing were performed for several combinations of recorders, for example, trained by recorder A and tested by recorder B, and so on. In this evaluation, training/testing was always carried out with 90%/10% of the dataset.

2.1.3 Results

i. Effective Features for Classification

The combination of contour and MFCC features provided the highest precisions for all recorders (A: 96.1%, B: 92.1%, C: 92.1%, Table 2.4) among all the features, whereas the recalls were not the highest (A: 77.6%, B: 92.1%; C: 83.5%). When the recall was considered, the MFCC features contributed to the highest recall on recorder A and B (A: 81.0%, B: 93.0%) and contour features on recorder C (90.3%) among all feature sets. Because the combination of contour and MFCC features demonstrated the highest precision, both were used as features to consider the necessary amount of training data and the compatibility of classifiers among locations.

ii. Necessary Amount of Training Data

Although there was some variation among recorders, the precision achieved was more than 90% when 1000 samples were used for training and remained high beyond that (Fig. 2.6). In the AUSOMS A and C, less training data were required to improve the precision to above 90% than AUSOMS B: the precision was 90.6% when the classifier was trained using 142 samples in AUSOMS A and 92.3% when the classifier was trained using 249 samples in AUSOMS C. Along with the increased precision, the recall also improved; in other words, no trade-off between the recall and the precision was observed.

Table 2.4 Performances and features used for training each recorder. For each feature set, 90% of the data were randomly selected and used to train the classifier, and the remaining 10% data were used for testing.

A		
Feature set	Recall (%)	Precision (%)
Contour	79.4	80.7
MFCC	81.0	92.1
Contour + MFCC	77.6	96.1

B		
Feature set	Recall	Precision
Contour	84.1	84.9
MFCC	93.0	90.5
Contour + MFCC	92.1	92.2

C		
Feature set	Recall	Precision
Contour	90.3	79.8
MFCC	86.1	90.9
Contour + MFCC	83.5	92.1

iii. Compatibility of Classifier Among Recorded Locations

In terms of the compatibility of classifiers, both recall and precision were optimal when the classifiers were trained using the same recorder that was used for testing (Table 2.5). When classifiers were trained using different recorders from those used for testing, that is, datasets obtained at different locations were used, the quality of the performance was reduced.

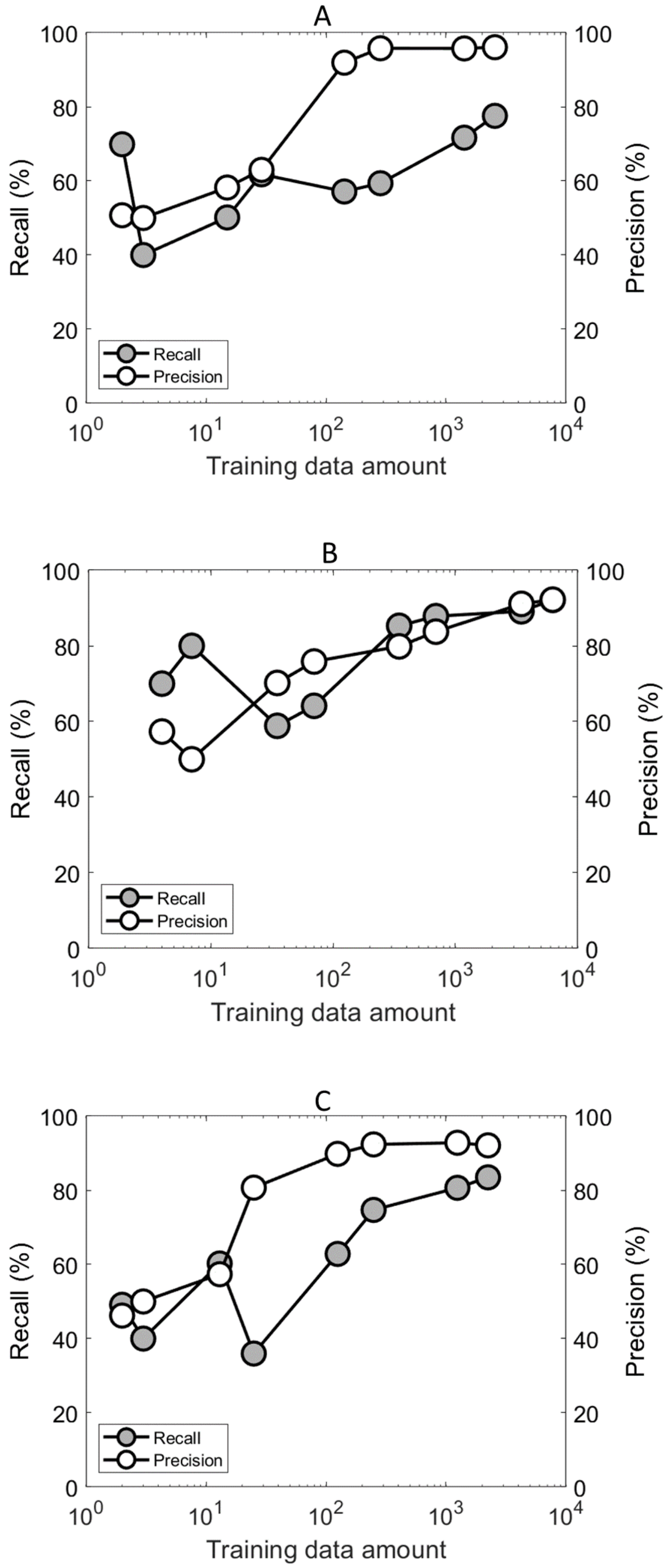

Fig. 2.6 Classification performance versus training data amount. Classifiers were trained using 0.05%, 0.1%, 0.5%, 1%, 5%, 10%, 50%, and 90% of the dataset obtained by each recorder and were tested using the remaining data. The X-axes represent the number of training data (log scale) corresponding to those percentages of the dataset. Training and testing were performed for each recorder, and both contour and MFCC features were used.

2.1.4 Discussion

The proposed algorithm, which uses two feature sets and an SVM for classifying dugong calls and tonal noise, represents a tool that enables efficient automated call detection of dugongs in noisy, shallow waters. The proposed algorithm improved precision from below 10% to above 90% in a noisy environment. The novel approach of the proposed algorithm is that it considers characteristics of background sounds in addition to the target signal, and it contributes to discriminating false detection caused by tonal noise. In a previous study, tonal sounds were mostly detected only using contour information or entropy (Erbe and King, 2008; Zaugg et al., 2012). However, in the case of PAM of dugong, which is conducted in noisy coastal waters, separating target calls from background sounds and precisely extracting contour information are challenging tasks. Tonal noise is mostly generated by boats, especially when they travel away from the recording location. Thus, low frequency bands usually have high energy with reverbs of engine sound. The MFCC is sensitive to the low- to mid-frequency band of approximately 1000 Hz (Mielke and Zuberbühler, 2013), which is the main difference in the background sound between dugong calls and tonal noise (Fig. 2.2), and thus it could have contributed to effective classification.

Table 2.5 Recall (upper) and precision (lower) of classifiers trained and tested using datasets from different recorders. Both contour and MFCC features were used for training; 90% of the data were randomly selected from each dataset and used to train the classifier, and the remaining 10% were used for testing. Values on the diagonal line, i.e. performances of classifiers trained and tested by the same recorders, are the same as the values shown in Table 2.3.

Recall (%)		Testing		
		A	B	C
Training	A	77.6	62.7	71.7
	B	57.8	92.1	74.3
	C	47.3	47.1	83.5

Precision (%)		Testing		
		A	B	C
Training	A	96.1	72.5	88.5
	B	95.6	92.1	88.4
	C	90.3	82.9	92.1

For all recorders, 1000 samples were sufficient to train the classifiers to achieve a precision of more than 90%, even though in AUSOMS A and C, the precision was above 90% at the point where less than 300 samples were used for training (Fig. 2.6). Classification performance was reliable when the classifiers were trained and tested using datasets obtained at the same location. However, the performances were degraded when the classifiers were trained and tested using datasets obtained at different locations. Based on this, our algorithm is sensitive to acoustic variations between the recorded locations. Recently, it was reported that the acoustic environment is remarkably different between adjacent coral reef habitats on a small spatial scale (Radford et al., 2014). This fine-scale difference of soundscape was also observed in our study site; i.e. the component ratio of energy in several octave bands was different between locations (K. Ichikawa pers. comm.), although there were no coral reefs within the monitoring area. Because the proposed algorithm considers the characteristics of background sound, such spatial differences in the soundscape may have led to poor classification performance.

As another scenario, the proposed method can be applied to the alert system of vocalizing dugongs, achieved by the real-time detection of their call. This was already implemented to the alert system of manatee (Niezrecki et al., 2003; Yan et al., 2005), which is another member of Sirenia. In this situation, high recall will be prioritized more than the precision, especially in areas where the population of dugongs is endangered. From our results, combining contour and MFCC features did not always contribute the highest recall, and less training data was required to achieve 90% recall than the amount of training data to achieve 90% precision in AUSOMS B. The proposed classification algorithm improved the efficiency of dugong call detection, thus, enabled us to handle large datasets obtained by long-term and wide-range acoustic observation. To date, acoustic monitoring of dugongs has been limited to short-term, stationary acoustic recordings (up to 20 days) (Matsuo et al., 2013; Tanaka et al., 2017) or towed acoustic surveys conducting during the daytime (Ichikawa et al., 2012, 2009). Given the spatial distribution and species composition of seagrass changes, between dry and wet seasons, affected by environmental factors in the study site (Khogkhao et al., 2017) and considering that the amount of marine traffic also changes with fluctuations in tourism, temporal and spatial patterns of dugongs' habitat use could undergo seasonal variation. To examine this, acoustic observations covering different seasons need to be conducted by deploying recorders at multiple locations. Data from such surveys is expected to expand the accumulated knowledge base of the spatio-temporal distribution of dugongs and will contribute to the management of space-based conservation measures on a local scale. The work conducted during this study involved distinguishing between tonal target signals and similar noise, which could potentially be applied to PAM of another species. Many other marine mammals are known to produce tonal vocalizations for communication, such as killer whales and other small odontocetes (Deecke et al., 1999; Lin and Chou, 2015), and manatees (Niezrecki et al., 2003; Yan et al., 2005). Particularly for species distributed in shallow waters, where the SNR is generally low, characterising background sound, in addition to target sounds and employing supervised machine learning, as has been done in this study, is likely to be a worthwhile pursuit.

In this section, datasets were collected over only 20 days in November. Thus, the seasonal and inter-annual variations in the characteristics of target signals and background sound were not considered. It has been reported that dugong call characteristics do not dramatically change within a habitat between years (K. Ichikawa pers. comm.); however, the characteristics of other sounds, for example, boat type or traffic amount, may change, and more extremely, the beginning of a coastal construction could affect the condition of the background sound. To consider the divergence of background sounds, classifiers should be trained on a yearly basis, or at least compatibility should be tested.

2.2 Detection and Classification of vessel sounds

2.2.1 Introduction

As the potential negative impact of vessel traffic to marine ecosystem has been recognized, the demand for consistent and quantitative method of data collection is increasing (André et al., 2011) (further discussion on the importance of vessel traffic will be presented in Chapter 4). Autonomous underwater recorders offer a cost-effective method for a continuous ocean monitoring in order to identify the spatio-temporal occurrence of motorized vessel traffic, which could then play a role as a baseline information for the assessment of undesirable or threatening impacts (Reis et al., 2019). This vessel monitoring can be often carried out in parallel with the animal bioacoustics observation (André et al., 2011; Zaugg et al., 2010), which was described in section 2.1. Similar with the challenges in PAM for marine mammals, manual inspection of acoustic recordings obtained over extensive time periods is not practical, in terms of required time and human labors. This has motivated many research efforts towards devising methods to automatically detect the presence of vessels in underwater acoustic recordings. In addition to the detection, classification of vessel types (e.g. ferry, speed boat, or fishing boat) is expected as the potential risk and impact could vary among those types, as well as their role in social and economic system. In this sense, the classification would contribute to the science-based decision making in the coastal management.

Numerous algorithms had been proposed to automatically detect and classify vessel sound (Meir et al., 2012; Pollara et al., 2017; Reis et al., 2019). Nonetheless, improving detection accuracy in noisy conditions and reducing the rate of false positives remain as challenges (Reis et al., 2019). The Detection of Envelope Modulation On Noise (DEMON) is one of the most reliable methods for ship detection and classification (Chung et al., 2011). However, it is reported to yield poor results on noisy signals. In addition to the output of FFT, wavelet packet coefficients were utilized to detect certain types of vessel in recordings with background noise (Averbuch et al., 2011; Reis et al., 2019). The method by Yan et al. (2017) uses a combination of resonance-based sparse signal decomposition and Hilbert marginal spectrum analysis to recognize certain types of vessels, defined a priori (Yan et al., 2017). However, those algorithms may require complex transformations of the original signal compared to the FFT frequency spectrum (Reis et al., 2019). In terms of the vessel type classification, supervised machine learning techniques have been employed, such as artificial neural networks and support vector machines, using max peak, energy values and central frequency (Leal et al., 2015).

In the shallow water environment of coastal seas, propagating sounds are complicatedly influenced by the refraction, reflection, scattering or interference at sea surface and sea floor (Au and Hastings, 2008). This makes the detection and classification of vessel sounds less straightforward than that in the deep offshore environment. In the International Organization for Standardization (ISO), standardizing procedures for measurement of sound radiated by vessels in shallow water is still under development in the underwater acoustics committee at the time of writing (ISO 2023). This implies that generalization of the detection/classification process requires precise observation of the sound characteristics and complicated computation. However, classification even at single but key location is still beneficial to assess the maritime activity, and the technical barrier could be lower. It would be possible to classify the vessels from their sound at one location using machine learning technique with effective input features, rather than establishing 'universal' detection and classification method.

The objective of this section is to develop automated and "handy" detection and classification method of vessel sound in the shallow waters. It must be noted, however, that the outputs derived from those methodology are limited to the reference results rather than precise products.

2.2.2 Materials and Methods

Data Collection

Data collection was conducted around Talibong Island, Thailand (7.2151°N, 99.4012° E, Fig. 2.1), in September 2019 and from February to March 2020. Five to seven SoundTrap HFs (Ocean Instruments, New Zealand) were deployed to record underwater sounds (Fig. 2.7), and after seven to ten days of recordings, they were re-deployed to the different locations. Underwater sounds were recorded continuously with a sampling frequency of 48 kHz with 16-bit resolution (preamplifier gain was on and sensitivity was 173 dB). SoundTraps were anchored by rope to the seafloor using two or three sandbags and suspended in the water column at a depth of 1 m to 1.5 m above the seafloor. The detailed information, e.g. observation periods, coordinates and the water depth at the deployment, is described in chapter 3 and 4.

While underwater sound was continuously recorded, passing motorized vessels nearby the recording location B was visually observed from the research boat to conduct vessels classification by their sounds (Fig. 2.7). For each passing vessel, the time of passage and vessel type were recorded, photograph was taken to confirm the vessel type, and distance from the observer was measured by laser distance meter (KLR-600A, KenkoTokina Corporation, Japan). Visual observation was conducted in various tidal depth, in order to consider several reflection and reverberation conditions affected by sea surface and sea floor. Thus, training data was assumed to have the variation of received sound. Vessel classes were subsequently categorized based on their structure, size and objectives. Those classes were used as the ground truth data.

Acoustic Characteristics of Target Signals

The sound from a vessel consists of a broadband component and narrowband tones (Matzner et al., 2010) (Fig. 2.8). Particularly in shallow water, the broadband sound appears as a U-shaped feature on spectrogram, commonly referred to as a "bathtub" pattern. The apex of the U corresponds to the closest point of approach of the vessel to the hydrophone (Matzner et al., 2010).

Multiple papers have investigated the physical mechanism of underwater sounds produced by large vessels (Pollara et al., 2017, 2016). The main engines and auxiliary systems on a vessel produce tones at frequencies related to their operation. The hull of the vessel radiates sound from on-board sources into the water. Vibrations from the main engines of a vessel usually occur at frequencies related to the firing rates of individual cylinders and the overall firing rate of the engine. Harmonics of other mechanical frequencies are often present as well. In addition to the engine sounds, for most vessels of any size, propeller cavitation is a significant source of sound (Kudryavtsev et al., 2003; Pollara et al., 2017). Cavitation bubbles are mainly generated when the propeller blades pass through the wake of the vessel in the upward part of their rotation. The periodicity in cavitation creates low frequency tones. The tones in the envelope of the high frequency noise are found at the propeller's rotation and blade pass rates and their harmonics. Many of the algorithm described above, such as DEMON algorithm, extract those tonal frequencies (Kudryavtsev et al., 2003).

Small vessels are much less well studied than large vessels (Pollara et al., 2017). These vessels typically do not have complex power plants or auxiliary systems. For this reason, it is often assumed that the propeller and engine are the only sources of sound from small vessels, and those characteristics have been used for the vessel classification (Pollara et al., 2017).

Given the shallow water environment, accurately segregating the tonal component from the broadband sound is very challenging. Instead, in this section, both broadband and tonal components are utilized for the detection and classification of the vessel sounds. This is assumed to serve as a "handy" classifier at single location.

In section 2.1, motorized vessel was considered as one of the sources of tonal noise, but such sound was mostly recorded when vessels moved away from the recorder. In this section, vessels passing in vicinity are considered as the detection targets.

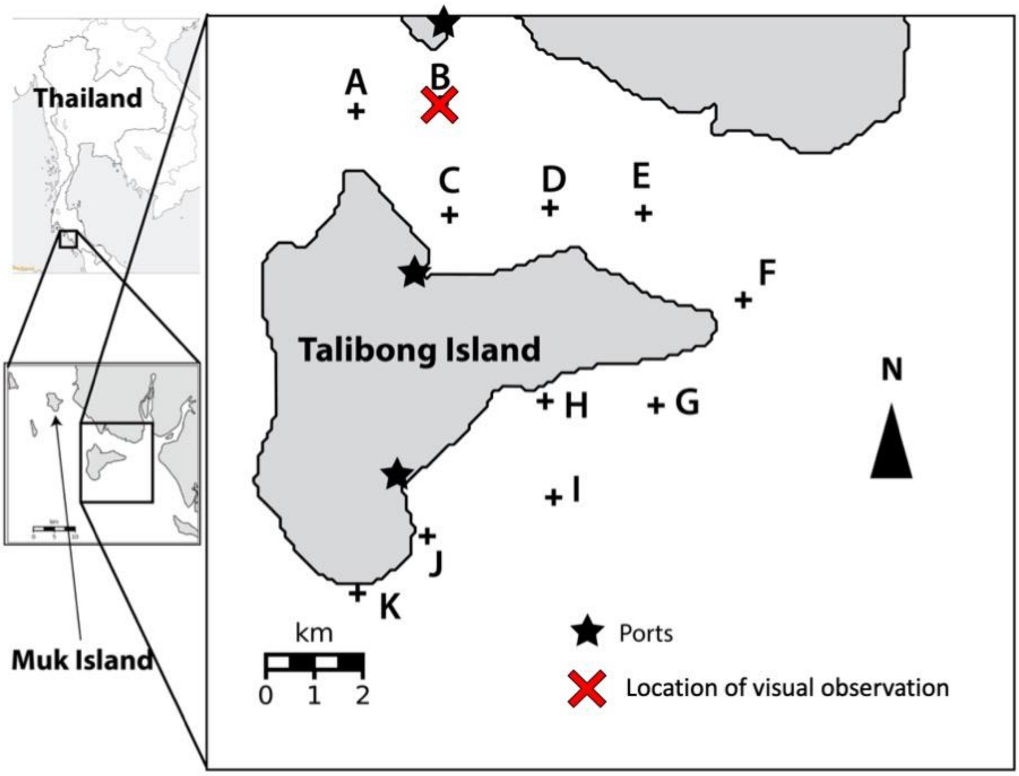

Fig. 2.7 Recording location of vessel sounds.

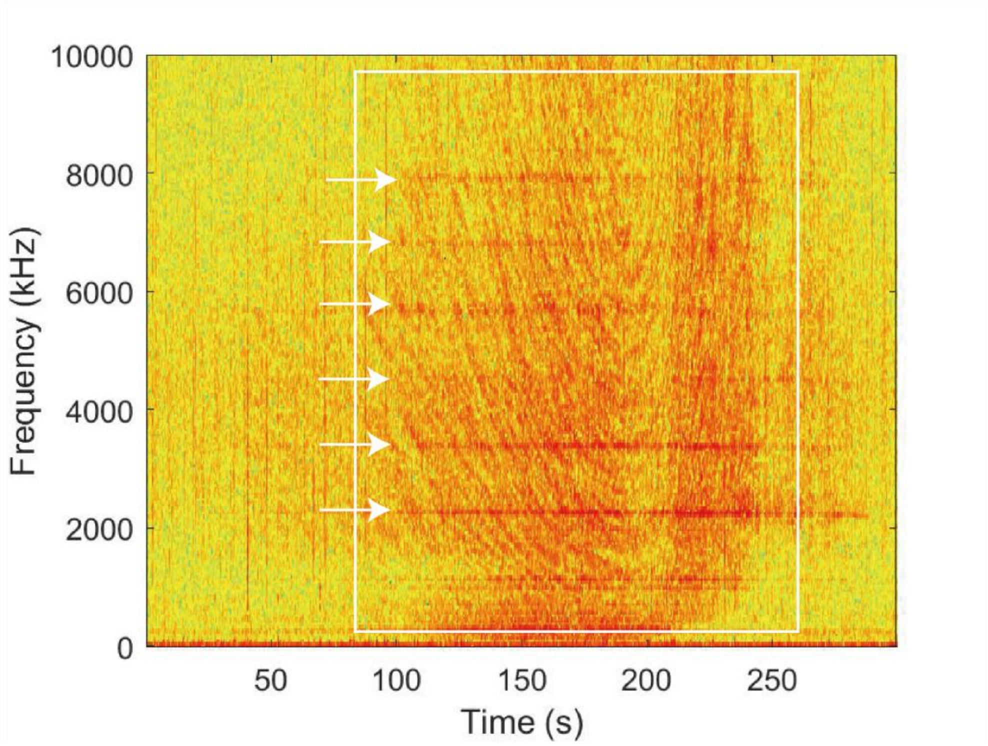

Fig. 2.8 Example of a spectrogram of vessel sound (speedboat). White box indicates the broadband component, and the white arrows indicate the harmonical tonal components.

Design of Automated Detection and Classification Algorithm

i. Broadband Sound Detection

Vessel sounds were detected by Shannon entropy threshold detector. As described above, vessel sounds targeted in this study is characterized as high-amplitude and broadband sound which is observed when the vessel passes vicinity of a recorder (Fig. 2.8). First, input audio stream was divided into 10-sec segments, and Short-Time Fourier Transform (STFT) was applied to tabulate spectrogram (1024 points, 50% overlap, hamming window). Then, Shannon entropy along frequency axis was calculated in each time bin, and those values were averaged within the 10-sec segment. Entropy along frequency axis tends to be high when high amplitude and broadband sound, which is typically the sounds generated by motorized vessels in shallow seas, are recorded in a segment. Time series of entropy value is then smoothed by moving average filter with a window length 6, which is equivalent to 60 sec. If the level of averaged entropy exceeded user-defined threshold, that 10-sec segment was considered as the vessel present segment. The threshold of the entropy was defined in each location and each season through the following procedure. Six hours file was randomly chosen and manually inspected, and the onset and offset time of vessel presence were annotated. Then, the Receiver Operating Characteristic (ROC) curve was plotted with different threshold value of entropy. The highest threshold of the entropy value which satisfied 1% false positive rate was adopted and used for the detection process at that location.

All detection results were first manually scrutinized, and false positives (non-vessel sounds) were removed. If detections exceeded a manual check capacity, a supervised classifier was used to remove the false positives. From the preliminary inspection of recorded audio stream, heavy rains and active fish chorus were confirmed, and they often detected as false positive since those sounds tended to have high entropy value as well. Thus, this broadband sound classifier had four output classes, which are vessel, fish, rain and other. Energy values in each 100 Hz frequency band were calculated as input features, and random forest classifier (Breiman, 2001) was trained. Ground-truth data was randomly selected from the detected segment which exceeded the entropy threshold, and classifier was trained by 70% of those and tested by the rest. The classifier was trained at each location, and after the classification step, the results were manually scrutinized. Thus, no false positives were used for further analysis. The manual check was carried out with the visual inspection of spectrogram and auditory check of the sound clips.

ii. Feature Extraction

For the detection result at location B, further analysis to classify vessel type was attempted (Fig. 2. 9). To create ground truth data, the passage event was determined by manual examination of the onset and offset time of vessel sound, and corresponding vessel type was annotated based on the record of visual observation. STFT was applied (FFT size 1024 points, 50% overlap, hamming window), averaged within 10-sec segment and used as input features of the classification. Since this spectrum was computed in each 10-sec segment level, a passage event can be divided into multiple segments if it was longer than 10 seconds. In addition to the frequency feature, duration of the event was adopted as a feature, given the speed of the vessels, i.e. the duration that a vessel stays in the recording range of recorders varied among vessel types. Duration was calculated by subtracting onset time from offset time, and represented in seconds. Although the detection process and feature extraction / classification process were computed in 10-sec segment level, consecutive segments were integrated into a single ‘event’, and the final classification decision is made in this event level. In the integration step, the gap between the detected segments were allowed up to 60 seconds, i.e. if two consecutive sequences of detected segments were separated more than 60 seconds, those sequences are considered as the different events. Unlike spectrum, duration is a single value throughout the event, i.e. all segments in a same event have same values.

iii. Classification and Validation

The classification and validation were performed with the ground truth data collected through the visual observation at location B. Random forest classifier (Breiman, 2001) was employed for the vessel type classification in segment level, and was trained by 70% of the ground truth data and validated by the rest of it. After the classification in segment level, the classification result in event level is decided based on the majority vote basis within the event. This process was separately carried out in 2019 and 2020, since the observation location was slightly different.

As the acoustic data was only collected at a single location and thus there is no variation, compatibility among locations were not tested, unlike section 2.1.

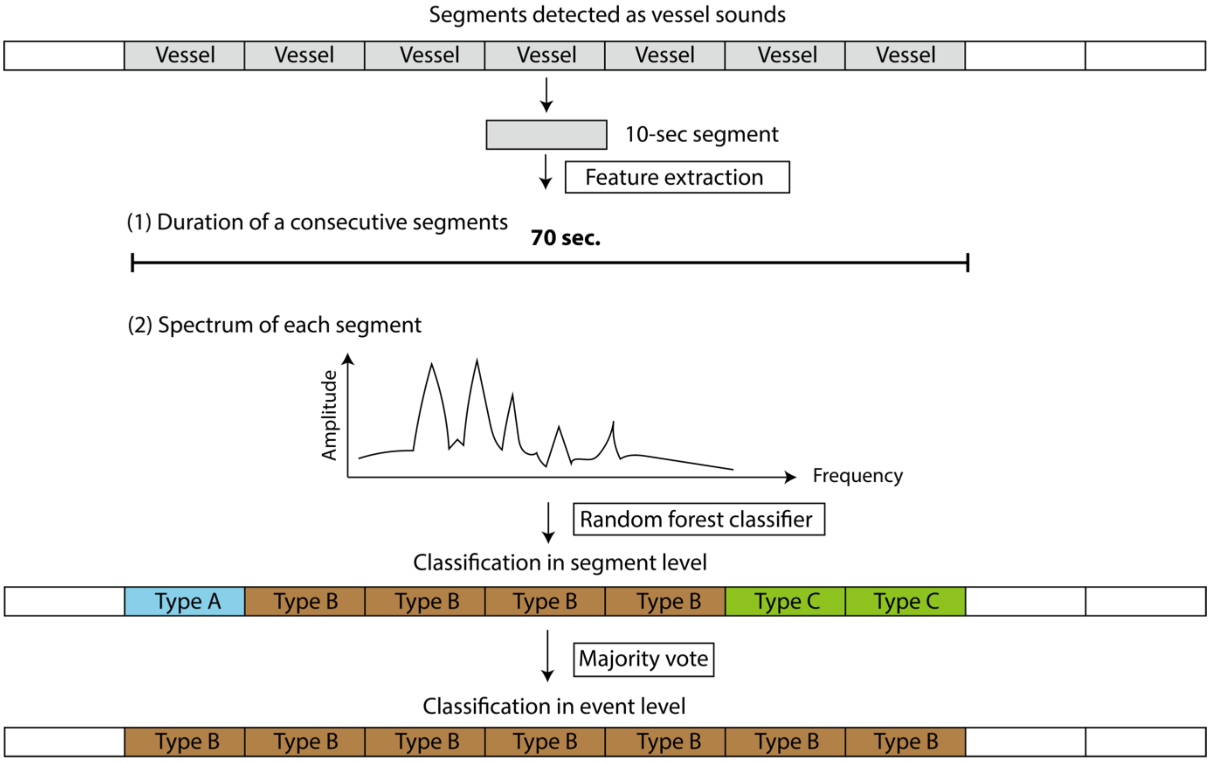

Fig. 2.9 The diagram of vessel sounds classification.

2.2.3 Results

Vessel sound detection

Threshold value of entropy detector was determined at each location based on ROC curve and the false positive rate (Fig. 2.10). Thus, posterior evaluation of this detector was not conducted. Classification performance of broadband sounds were reliable (Accuracy: 86.0%, Recall: 88.5%, Precision: 83.5%, Fig. 2.11, 2.12).

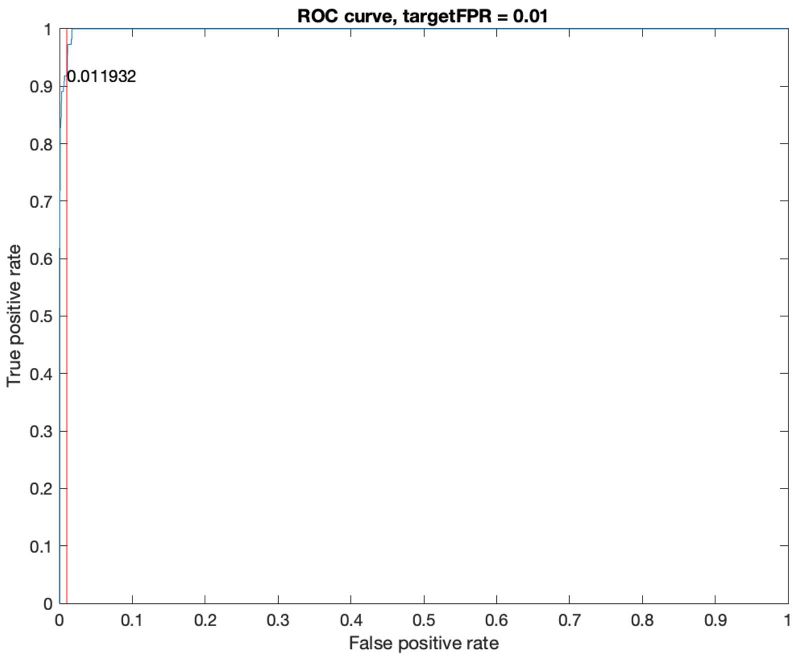

Fig. 2.10 Example of ROC curve of vessel sound detection. Entropy value (0.012 in this figure) was determined to satisfy the target false positive rate (1%).

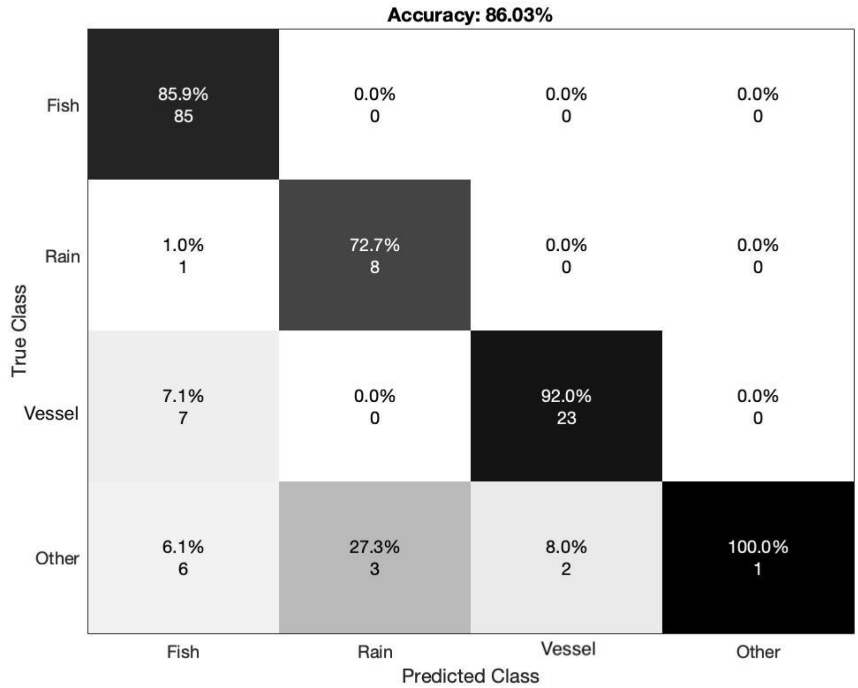

Fig. 2. 11 Example of the confusion matrix of broadband sound classification.

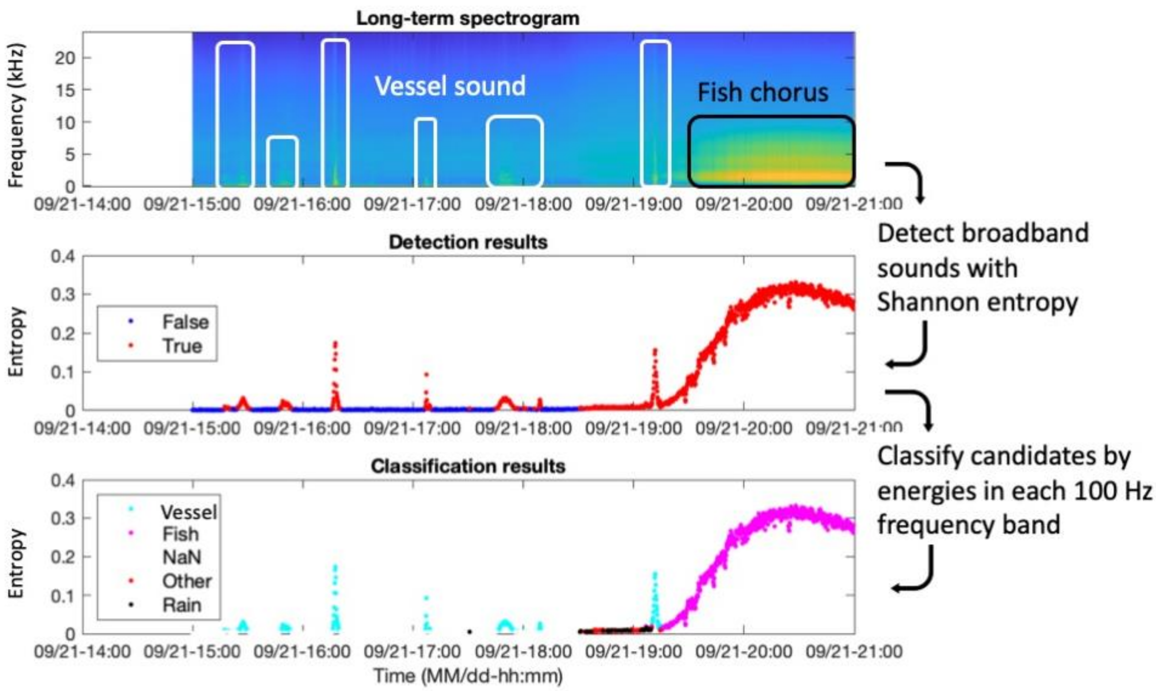

Fig. 2.12 Example of broadband sound detection and classification. Top: Long-term spectrogram of a six-hour recording file. Vessel sound and Fish chorus are shown with white and black box, respectively. Middle: detection result of entropy detector. Each dot represents the 10-sec segment. The segment in which the entropy value exceeded the threshold is shown in red, and those which did not is shown in blue. Bottom: classification result of detected broadband sound. The color of each dot represents the output class. NaN means the segment which did not exceed the entropy threshold.

Vessel type classification

As a result of visual observation at location B, long tail boat, small long tail boat, speedboat, trawler, and tugboat (with cargo) were recognized, although there was a variation between two seasons (Fig 2.13). Among those vessel classes, classification was carried out with the classes which had enough sample size. As a result of performance evaluation within the ground truth data, it scored 90.00% accuracy (93.8% precision, 88.9% recall) in 2019 (rainy season), and 90.32% accuracy (90.7% precision, 89.8% recall) in 2020 (dry season) (Fig 2.14). Since the sample size, namely the number of observed vessels, in 2019 was limited compared to it in 2020, the classification result is interpreted as a referential result.

2.2.4 Discussion

This section developed the "handy" detection and classification method of vessel sound in shallow coastal waters. In addition to the frequency characteristics, duration was extracted as another feature to distinguish vessel types. Although the compatibility of the developed classifier was not tested between different locations and thus only available at a specific location in a local coastal sea, it would still provide valuable information for an appropriate coastal management, as there are no other ways to continuously monitor vessel traffic in a local area where many of vessels did not equip Automatic Identification System (AIS, discussed more in Chapter 4).

Performance of broadband sound classification was fairly reliable, although relatively simple feature, i.e. energy values in each 100 Hz band, was adopted as an input feature. This could stem from the clear difference of frequency features. While vessel sound is the broadband sound which has the largest energy in the low frequency band and the tonal component (Reis et al., 2019), the energy distribution of fish sound tends to be limited to the low frequency band, and rain sound is more akin to white noise, that is, the energy is equally distributed from low to high frequency band. Although the manual scrutiny would still be required to confirm that no false positive is included, it significantly reduced the time and effort of such manual labor.

Fig. 2.13 Vessel types visually observed at the monitoring location (Photo courtesy: Kotaro Tanaka). a: Long tail boat, b: Long tail boat (small), c: Speedboat, d: Trawler, e: Tugboat (with

cargo). Note that visual observation of passing vessels were conducted intermittently, and thus not necessarily all the vessels passing this area were covered.

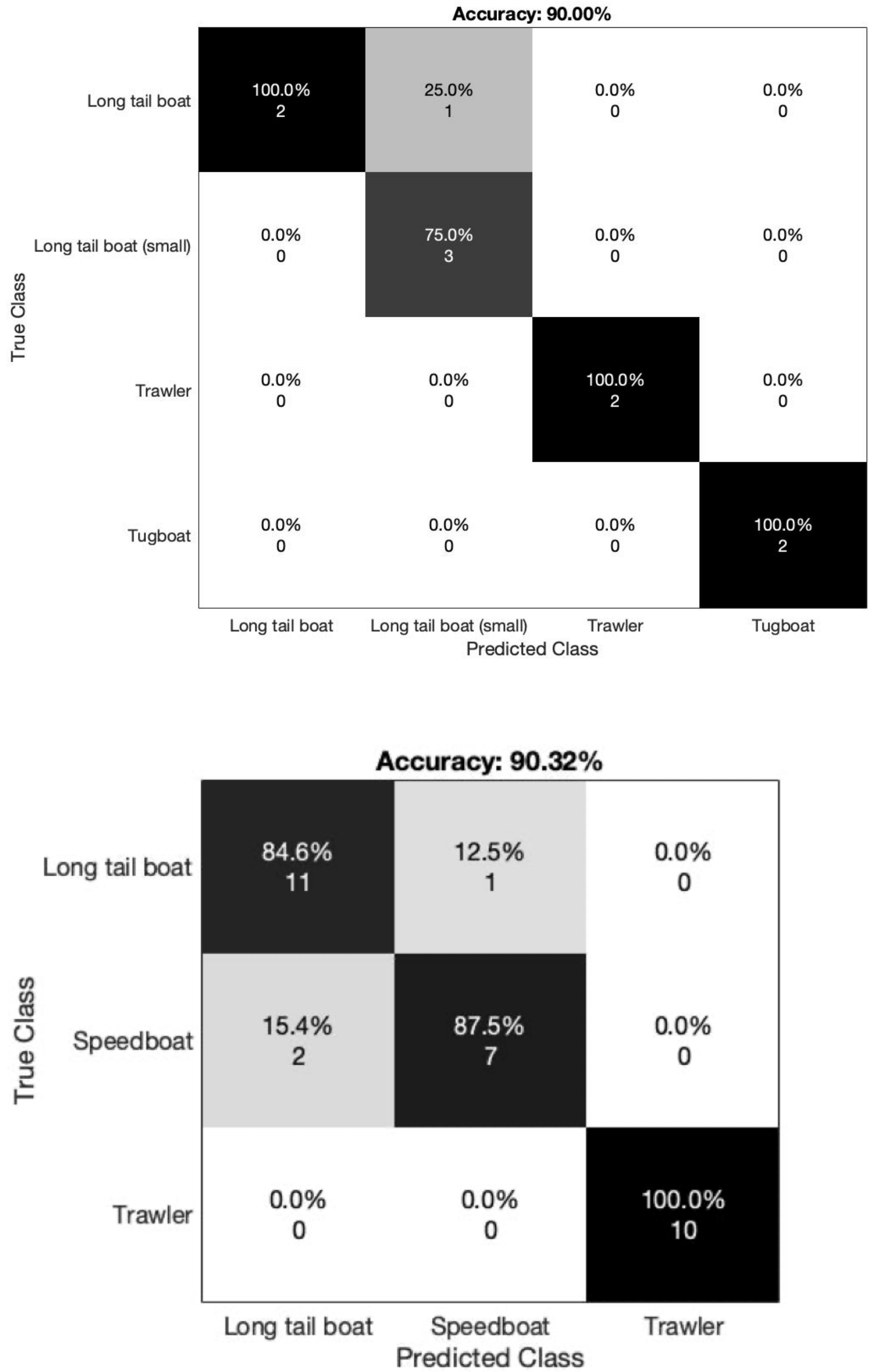

Fig. 2.14 Confusion matrix of vessel type classification in the rainy season 2019 (above) and the dry season 2020 (below).

Many of vessel classification algorithm which has been developed so far chiefly used frequency characteristics as input features, since it embeds the individual information of vessels, e.g. engine, hull and propeller (Pollara et al., 2017; Railey et al., 2020; Reis et al., 2019). However, as repeatedly described above, accurately and consistently extracting those features out of noisy acoustic environment in shallow sea is difficult. In this context, this section demonstrated the information about sound duration supports distinguishing vessel types, given its large variation between different types. Variation in their speed leads the difference of durations that vessels stay in the observation range of the recorder, although it also depends on the sound source level of each type and the distance between a recorder and a vessel.

As a limitation, not all types of passing vessel were covered in the field observation. There is a possibility that unknown type of vessel is classified into one of the classes, since the classifier was trained based on the vessels which was recognized during the visual observation. Moreover, the vessel type that the passage was fairly rare was not included in target classes. Accumulation of data, i.e. vessel type and corresponding sound would be expected. Furthermore, compatibility of classifiers among recording locations will need to be tested to realize a universal classifier, although it would be challenging as the characteristics of sound propagation and background sound often vary in shallow waters.

In addition to vessel type, monitoring vessel speed would be beneficial for the risk assessment and the surveillance. As the continuous spectrum of propeller cavitation noise is influenced by the propeller shaft rotation speed or the propeller blade rate frequency, vessel speed could be estimated from the spectrum, besides ship design and oceanographic conditions (McKenna et al., 2013; Railey et al., 2020). As another future perspective, real-time acoustic monitoring could be beneficial to avoid physical collision, as proposed in an alert system for manatee (Niezrecki et al., 2003; Yan et al., 2005).

Generally, many of technical development and continuous monitoring using underwater acoustic information have been concentrated in large ships and major ports given their impact to social-economical-ecological system and availability of relevant data such as AIS (Matzner et al., 2010; Pollara et al., 2017). However, those effort should also be applied to small vessels and local area, since considerable amount of waters where adequate coastal management should be enacted, e.g. ecological or biologically significant areas and important marine mammal areas (IMMA), are located in local area (di Sciara et al., 2016; Hoyt and Sciara, 2021). Further research is expected to enhance the efficacy of acoustic monitoring for vessels towards the harmonized management in local coastal seas, not only in industrialized area.

2.3 Conclusion

Detection and classification of target sounds is the first key step in PAM to conduct reliable long-term and continuous observation. However, this is considerably challenging and crucial in coastal shallow waters, where undesirable noise from anthropological, biological and geological sources are abundant. In this chapter, I aimed to develop the automated framework to extract the sound of dugong and vessel from noisy underwater sounds in coastal area.

Section 2.1 demonstrated an effective method to discriminate tonal noise from dugong calls by employing a supervised SVM. From the results, I would recommend using both contour information and MFCC as input features and collecting around 1000 training data samples, if possible, to train the classifier for each recorded location. Although the seasonal compatibility of the classifiers needs to be tested, this method can contribute to facilitating long-term and wide-range passive monitoring of the habitat use of dugong.

Section 2.2 developed the automated detection and classification method of the underwater sound produced by motorized vessels using random forest classifier. Although multiple algorithm has been proposed, most of them assumed the sound in deep waters, which has less impact from ambient noise. As a technical novelty, I employed the information of duration in addition to spectral information as input feature to enhance the classification performance. It must be noted that, given the complex characteristics of reflection and reverberation and those could largely vary in shallow waters, classifiers should be trained at each location.

The extracted sounds are subsequently analyzed in the following chapters. Although the re-training process and fine-tuning will be required, the concept of the developed algorithm could be available in other habitats. The developed method would contribute to assessing the habitat use of passing vessels and vocalizing marine mammals (producing audible tonal sounds) in coastal waters.

Chapter 3 Spatio-temporal variation of vocalizing dugongs

3.1 Introduction

Examination of the spatial and temporal distribution of animal habitat use is essential when considering priorities of effort allocation for their conservation, which is one of the key inputs in coastal management. Thus far, acquisition of spatial information on dugong habitat use, for example, distribution, home range, migratory path, population size and densities, has been performed by conducting visual observations from aircraft (Hines et al., 2020, 2005; Marsh et al., 2004; Pollock et al., 2006; Ponnampalam et al., 2015), by collecting sighting information through interviews (Briscoe et al., 2014; Hashim et al., 2017; Rajamani and Marsh, 2010), and by tethering very high frequency transmitters or satellite tags to wild individuals (Iongh et al., 1998; Marsh and Rathbun, 1990; Sheppard et al., 2007, 2006; Zeh et al., 2015). These surveys are undoubtedly important to explore dugong habitat use and to estimate their spatio-temporal importance; however, an information gap remains. For example, data obtained by visual observation and by collection of sighting information do not provide animals' information at night. Further, attachment devices are not permitted in some countries, and if permitted, sample sizes considered for analysis via utilization of devices are often small.

As explained in Chapter 1, since 2003, the habitat use of dugongs has been studied with PAM in the coastal area around Talibong Island, Trang, Thailand (Fig. 3.1). Trang has a tropical monsoon climate. The year is divided into a short dry season, from January to February, and a long-wet season from March to December, with the heaviest rain in September (Thai Meteorological Department). There is the largest seagrass bed in Thailand designated as the first Ramsar site in the country (Khogkhao et al., 2017), which makes this area a suitable habitat to dugongs. Although the existence of vocal hotspot has been suggested, the extent of vocal hotspots in the Thai population of dugongs has only been investigated by conducting towed acoustic surveys during the daytime or fixed recordings at a maximum of only two locations in their habitat (Tanaka et al., 2017). Furthermore, the monitoring period of such fixed recordings was less than one month. Although the seasonality of the dugongs' vocal behavior has been examined (Matsuo et al., 2013), but that study was limited to a single location in their habitat. Therefore, there are many gaps that exist in terms of understanding the local population's temporal and spatial coverage. Filling such information gaps will help to understand the spatial and temporal habitat use of dugongs.

In this chapter, I aimed to explore the areas where and when dugongs actively vocalize by conducting continuous acoustic observations at 11 locations in their habitat in two distinctive seasons. This study not only extended the number of monitoring sites, but also aimed to demonstrate the effectiveness of an automated classification method developed in Chapter 2 for recognizing dugong calls and tonal noise.

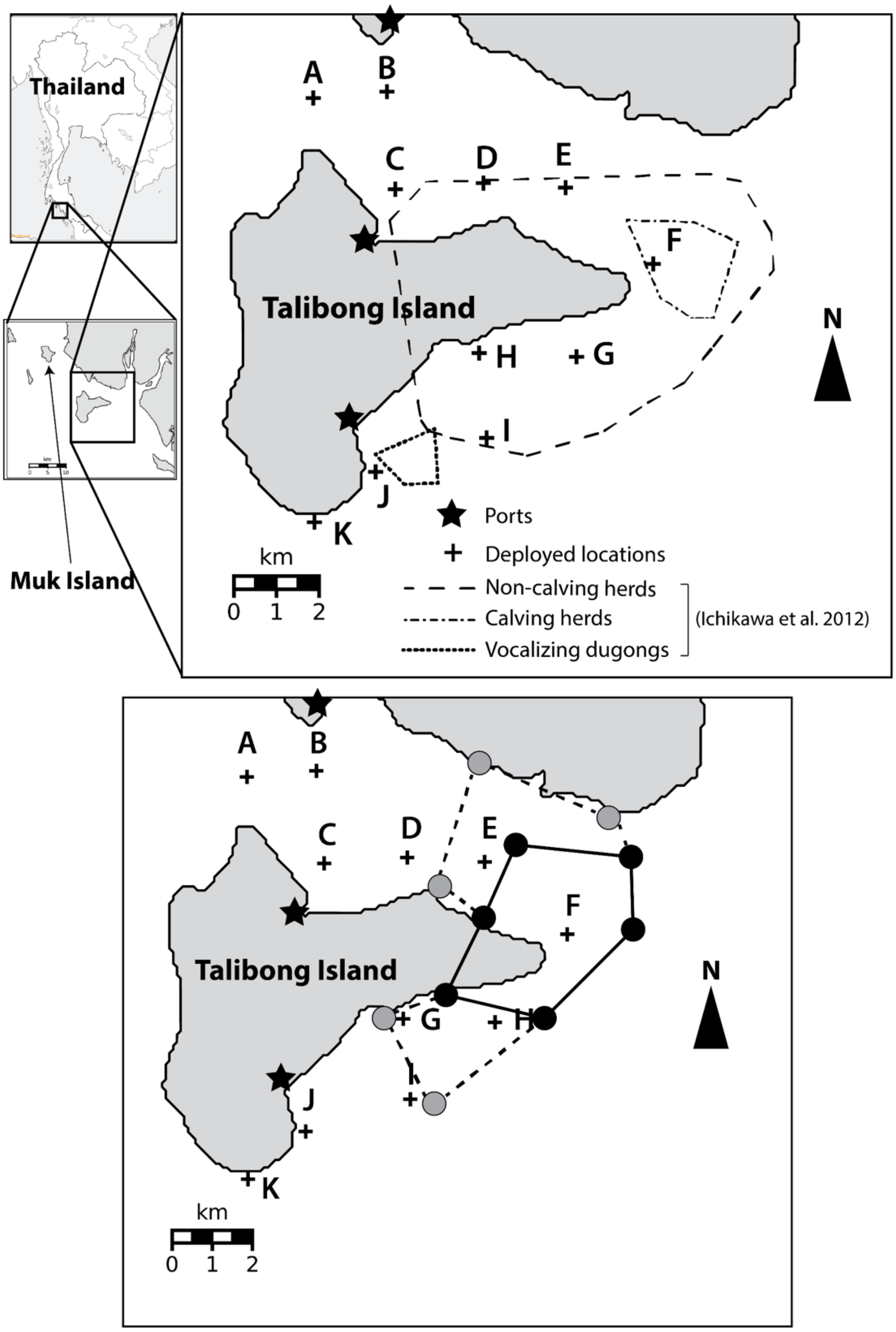

Fig. 3.1 Study site, Talibong Island, Trang, Thailand. (above) Crosses represent the deployed locations of underwater recorders. Different types of dashed lines indicate the distribution range (75% minimum convex polygon) of non-calving herds, calving herds, and vocalizing herds, which were obtained via performance of visual and acoustic surveys by Ichikawa et al., (2012). Deployed locations were slightly different between rain and dry seasons (up to 345 m difference), but information on only one location was plotted for visibility. (below) the extent of Community-based dugong protected area. Area surrounded by black circles and solid lines represents "Main zone" and area surrounded by grey circles and dashed line does "Secondary zone", which have different level of restrictions (Marine National Park Operation Center 3 Trang 2018). Stars represent the locations of ports.

3.2 Materials and Methods

3.2.1 Field Survey

The field surveys were conducted around Talibong Island, Thailand (7.2151°N, 99.4012° E, Fig. 3.1), in September 2019 and from February to March 2020, corresponding to the rainy and dry seasons, respectively. Five to seven SoundTrap HFs (Ocean Instruments, New Zealand) were deployed, roughly covering the east coastline of the Talibong Islands, to record underwater sounds (Table 3.1, Fig. 3.1). The number of deployed SoundTraps varied among observation periods (Fig. 3.2). The west coast of the island was excluded from the observations as it is mostly covered by coral reefs with no seagrass beds, where few sightings of dugongs have been reported (Ichikawa et al., 2012, 2009, K. Kittiwattanawong pers. comm.). Underwater sounds were recorded continuously with a sampling frequency of 48 kHz with 16-bit resolution (preamplifier gain was on and sensitivity was 173 dB). SoundTraps were anchored by rope to the seafloor using two or three sandbags and suspended in the water column at a depth of 1 m to 1.5 m above the seafloor, and maintained in an upright position using a surface buoy and a middle buoy (Fig. 3.3). The distance between each recorder was at least 2 km, and the depth varied among the locations (Table 3.1). After 7 to 10 days of deployment, the recorders were retrieved to download the data, to charge the batteries, and to remove any attached organisms (e.g. algae) from the hydrophones. Thereafter, they were re-deployed at different locations, while a few locations, which were considered to be important locations for dugongs, were permanently monitored (Fig. 3.2). Locations that were permanently monitored were not consistent across the two seasons, as the survey in 2020 was based on the preliminary results of a survey conducted the year before, and thus some locations were considered to demonstrate more active dugong vocalizations than those observed at other locations. Specifically, during the rainy season, recorders were deployed at locations F and J throughout the survey, while locations C, H, and J were permanent observatories in the dry season. One period spanned approximately 7 to 10 days due to the period of tidal rhythm, that is, to capture at least one spring tide and one neap tide. Actual deployment coordinates in each location were largely consistent across the seasons, although at some locations, I had to deploy the recorders further from the intended locations to avoid entanglement with fishing gear that was set nearby. The largest distance between deployment locations across the two seasons was 345 m at location B.

3.2.2 Data Analysis

Dugong calls were automatically detected from the recorded sound streams using customized software that was developed in a previous study using MATLAB (Ichikawa et al., 2006). Although the detailed detection algorithm is omitted here, briefly, it is a bandpass energy detector to extract successive tonal components from the sound stream after denoising and emphasizing processes (Ichikawa et al., 2006). Both chirps and trills were targeted by the automated detector. In the presence of tonal noise that lies in a similar frequency band, the detector can yield numerous false detections as described in Chapter 2. To address this, a classification method developed in Chapter 2 was applied. All detection results were first manually scrutinized by the the author, and false positives were removed. If detections exceeded a manual check capacity, for example, 1000 detections in a three hours file, the developed classifier was used to remove the false positives.

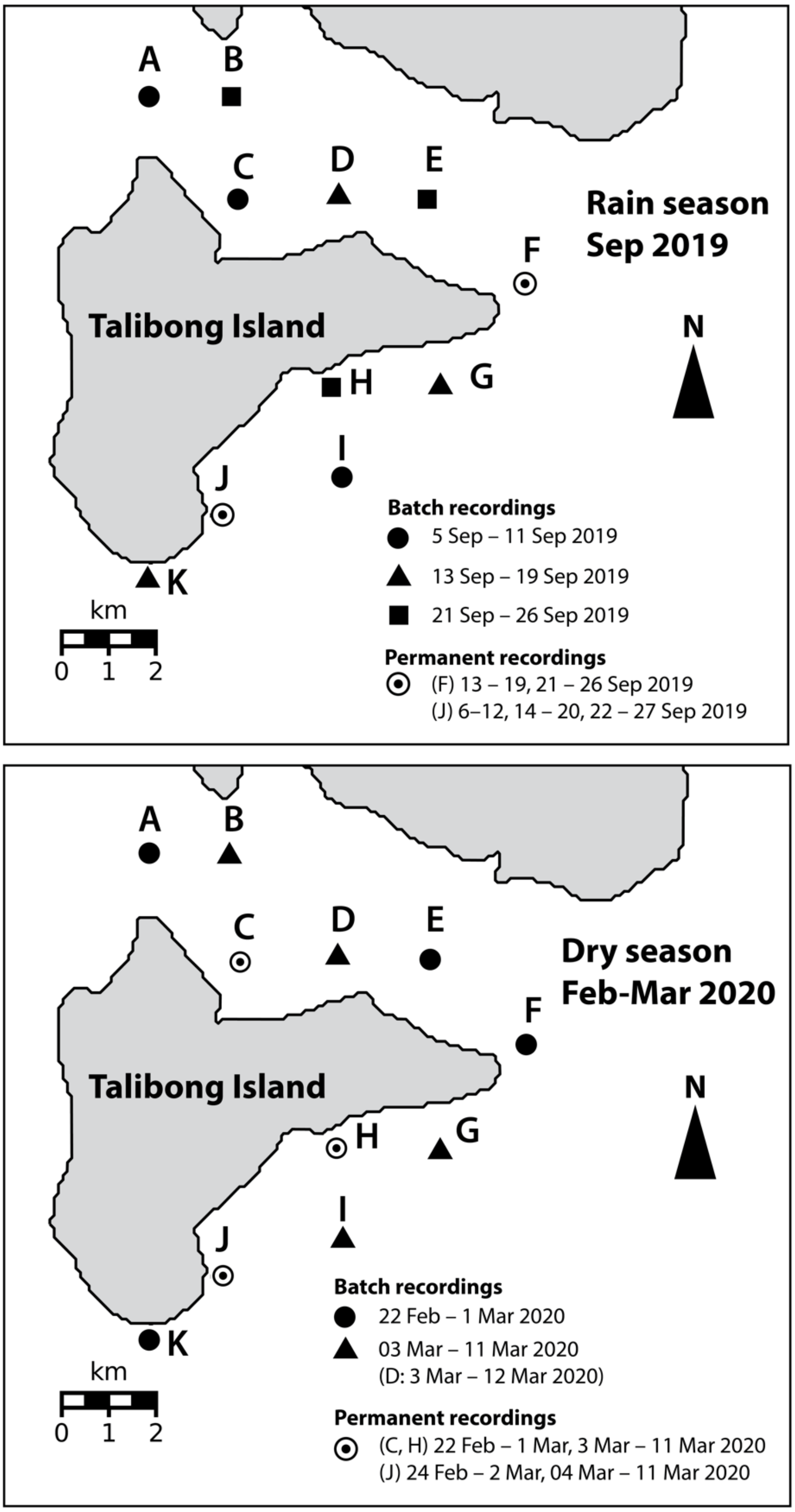

Fig. 3.2 The deployed periods of each location. Different markers represent different periods. Deployed locations were changed once every 7 to 10 days to retrieve and download data, to charge batteries, and to remove attached algae. The double circle indicates the permanent monitoring station where the recorders were deployed throughout the survey. Except for the permanent monitoring station, deployed locations were randomly chosen in each seasonal period (Batch recordings). In 2019, the recorder was deployed at location F in 5-11 Sep, but data could not be downloaded because of a system error.

Table 3.1 The coordinates and the water depth of each recording location. Water depth was measured at the deployment. For the permanent monitoring stations (Location F and J in 2019 and Location C, G and J in 2020), average water depths of each deployment are shown.

	2019	
Location	Coordinates	Water depth at the deployment (m)
A	N7° 17.512' E99° 23.282'	7.5
B	N7° 17.508' E99° 24.358'	10.7
C	N7° 16.426' E99° 24.363'	1.7
D	N7° 16.420' E99° 25.470'	3.7
E	N7° 16.434' E99° 26.535'	6.8
F	N7° 15.394' E99° 27.415'	3.6
G	N7° 14.308' E99° 25.419'	1.6
H	N7° 14.297' E99° 26.517'	1.7
I	N7° 13.222' E99° 25.413'	3.3
J	N7° 12.799' E99° 24.196'	4.4
K	N7° 12.156' E99° 23.279'	8.8

	2020	
Location	Coordinates	Water depth at the deployment (m)
A	N7° 17.539' E99° 23.266'	8.3
B	N7° 17.620' E99° 24.201'	4.8
C	N7° 16.384' E99° 24.306'	2.2
D	N7° 16.462' E99° 25.424'	2.3
E	N7° 16.404' E99° 26.466'	7.5
F	N7° 15.438' E99° 27.578'	5.6
G	N7° 14.309' E99° 25.370'	2.0
H	N7° 14.262' E99° 26.605'	2.2
I	N7° 13.235' E99° 25.465'	3.3
J	N7° 12.806' E99° 24.058'	4.5
K	N7° 12.166' E99° 23.281'	8.1

Fig. 3.3 Mooring system of autonomous recorder (Photo Courtesy: Kotaro Tanaka). SoundTrap (marked with white circle) was anchored to two or three sandbags by rope, and maintained upright in the waters by middle and surface buoy. GPS coordinate was obtained right after the deployment.

The classifier was trained at each location, and after the classification step, the results were manually scrutinized. Thus, no false positives were used for further analysis. The manual check was carried out by the first author, with the visual inspection of spectrogram and auditory check of the sound clips (Tanaka et al., 2017). A decision was made based on the comparison with the accumulated acoustic data of dugong calls recorded in the same area before (Fig. 3.4). The detection range of the automated detector were assumed to be approximately 250 m (Ichikawa et al., 2012), considering that the root-mean-square source levels of the dugong call ranged from 134 dB to 138 dB, and that sound propagation followed a spherical spreading model (Ichikawa et al., 2012). Therefore, the calls recorded at each site were determined as independent as the distances between the sites were far greater than the detection range.

To assess the automated detector, 15-min audio clips that included at least one dugong call were randomly selected from six locations as representatives and the dugong calls were detected as the ground truth via manual listening by the author of this thesis, and recalls and False-positive rates of the detector were calculated (Table 3.2).

I defined 'rate of detected calls' as the number of detected calls per hour (number of detected calls divided by observation duration), because the same index has been used in previous studies to investigate the activity of dugongs' vocal behavior (Ichikawa et al., 2006; Tanaka et al., 2017). The rate of detected calls was compared among the locations using a Kruskal–Wallis test to examine the spatial variation of the dugongs' vocal activity. The rate of detected calls was also compared between the rainy and dry seasons using a Mann-Whitney U test to determine the seasonality of their vocal behavior. To investigate the variation of temporal pattern, at the locations where many vocalizations were detected, the rate of detected calls was compared between day and night by a Mann-Whitney U test.

3.3 Results

3.3.1 Spatial Variation

A total of 4,652 hours of acoustic observation data were obtained (1,933 hours and 2,719 hours in the rainy season and the dry season, respectively). The periods before and after the deployment were not included in that total because the loud noise from our research vessel and divers were recorded and no dugong sounds were recorded. From those observations, 37,677 calls were detected (21,340 and 16,337 calls in the rainy season and the dry season, respectively, Table 3.3). The rate of detected calls differed significantly among locations in both seasons ($P < 0.001$ in each season, Fig. 3.5). In the rainy season, the mean rate of detected calls (± SD) in the locations C, H, and J were 15.6 ± 32.7, 13.5 ± 37.3, and 40.5 ± 71.1 number/h, respectively, while the mean rate of detected calls of all other locations was 0.3 ± 0.9 number/h. In the dry season, location B, C, H, and J exhibited the highest rate of detected calls, at 9.7 ± 33.2, 12.8 ± 35.8, 7.4 ± 26.4, and 15.9 ± 46.8 number/h, respectively (Table 3.3). The mean rate of detected calls of all other locations in the dry season was 0.8 ± 3.1 number/h. Overall, the mean rate of detected calls was higher in the rainy season than the dry season ($P < 0.001$). Among the few locations where many calls were recorded, locations C and J had significantly higher rate of detected calls in the rainy season than that in the dry season ($P < 0.001$), while at location J, there was no significant difference in the rate of detected calls between the rainy and dry season ($P = 0.35$).

3.3.2 Temporal Variation

Among the locations where many vocalizations were detected, i.e. location B (only in dry season), C, H and J, temporal pattern in the rate of detected calls varied (Fig 3.6). In rainy season, more vocalization was observed in nighttime (18:00 – 6:00) than daytime (6:00 – 18:00) at location H ($p < 0.05$, Mann–Whitney U test), while there was no significant difference between day and night at location C and J ($0.1 < p$, Mann–Whitney U test).

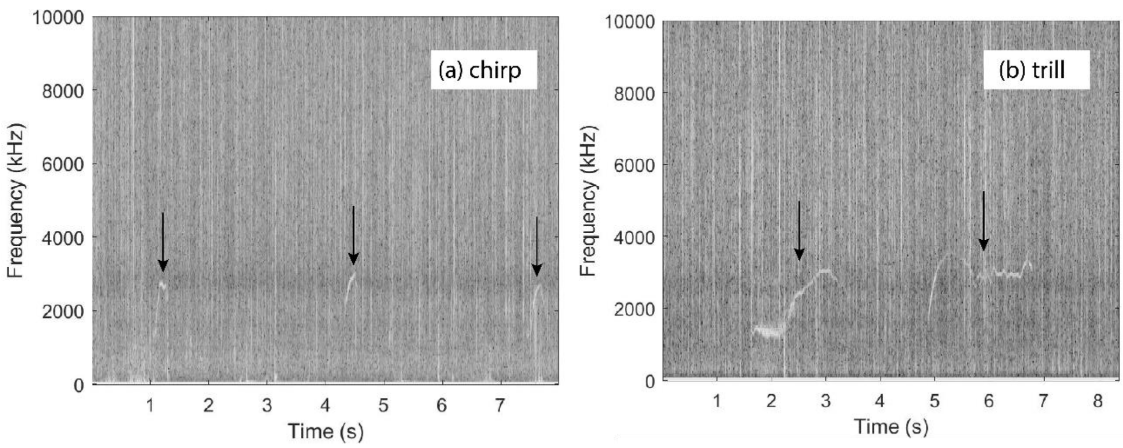

Fig. 3.4 Examples of spectrogram of the signals which were manually classified as dugong calls, a: chips and b: trills (Sampling rate is 192 kHz, Hamming window, FFT window size is 4096, 50% overlap). The black arrows in the spectrograms indicate where the signals are shown.

In dry season, at location C, H and J, more vocalization was observed in nighttime than daytime ($p < 0.01$, Mann–Whitney U test). Oppositely, at location B, more vocalization was observed in daytime than nighttime ($p < 0.01$, Mann-Whitney U test).

Table 3.2 15-min recordings at six stations which included at least one call was randomly selected and the detector performance (recall and false positive) were examined in both wet and dry seasons. Note that all detections were manually scrutinized and false positives were removed.

Locations	2019 Recall (Detected calls / recorded calls)	False positive rate (False detections / signals detected as calls)	Start and end time of the audio clip
A	100% (1 / 1)	83% (5 / 6)	Sep 06 10:09:27 – 10:14:27
C	100% (5 / 5)	00% (0 / 5)	Sep 10 07:38:52 – 07:53:52
E	41% (7 / 17)	36% (4 / 11)	Sep 22 07:29:14 – 07:29:14
F	57% (4 / 7)	0% (0 / 4)	Sep 25 01:25:32 – 01:40:32
G	95% (38 / 40)	15% (13 / 51)	Sep 26 09:10:36 – 09:25:36
J	100% (13 / 13)	84% (68 / 81)	Sep 19 18:23:33 – 18:38:33

Locations	2020 Recall (Detected calls / recorded calls)	False positive rate (False detections / signals detected as calls)	Start and end time of the audio clip
A	100% (7 / 7)	50% (7 / 14)	Feb 23 08:00:42 – 08:15:42
C	86% (6 / 7)	70% (14 / 20)	Feb 29 16:12:08 – 16:27:08
E	100% (2 / 2)	0% (0 / 2)	Feb 25 16:58:53 – 17:13:53
F	100% (3 / 3)	57% (4 / 7)	Feb 24 01:23:07 – 01:38:07
G	100% (9 / 9)	94% (130 / 139)	Feb 27 12:13:32 – 12:28:32
J	58% (11 / 19)	0% (0 / 11)	Feb 29 21:09:17 – 21:14:17

Table 3.3 Observation durations, number of detected calls and the rate of detected calls at each monitoring location.

Location	2019 Observation durations (h)	Number of detected calls	Rate of detected calls (number / h)	Standard deviation
A	144	23	0.2	0.4
B	120	18	0.2	0.4
C	145	2268	15.6	32.7
D	143	21	0.1	0.4
E	120	13	0.1	0.3
F	270	53	0.2	0.5
G	150	24	0.2	0.6
H	126	1698	13.5	37.3
I	145	176	1.2	4.7
J	420	17029	40.5	71.1
K	150	17	0.1	0.3
total	1933	21340		

Location	2020 Observation durations (h)	Number of detected calls	Rate of detected calls (number / h)	Standard deviation
A	192	37	0.2	0.5
B	204	1988	9.7	33.2
C	396	5065	12.8	35.3
D	222	39	0.2	0.4
E	192	72	0.4	1.5
F	192	56	0.3	1.9
G	204	41	0.2	0.5
H	396	2947	7.4	26.4
I	198	396	2.0	9.2
J	326	5181	15.9	46.8
K	197	515	2.6	7.7
total	2719	16337		

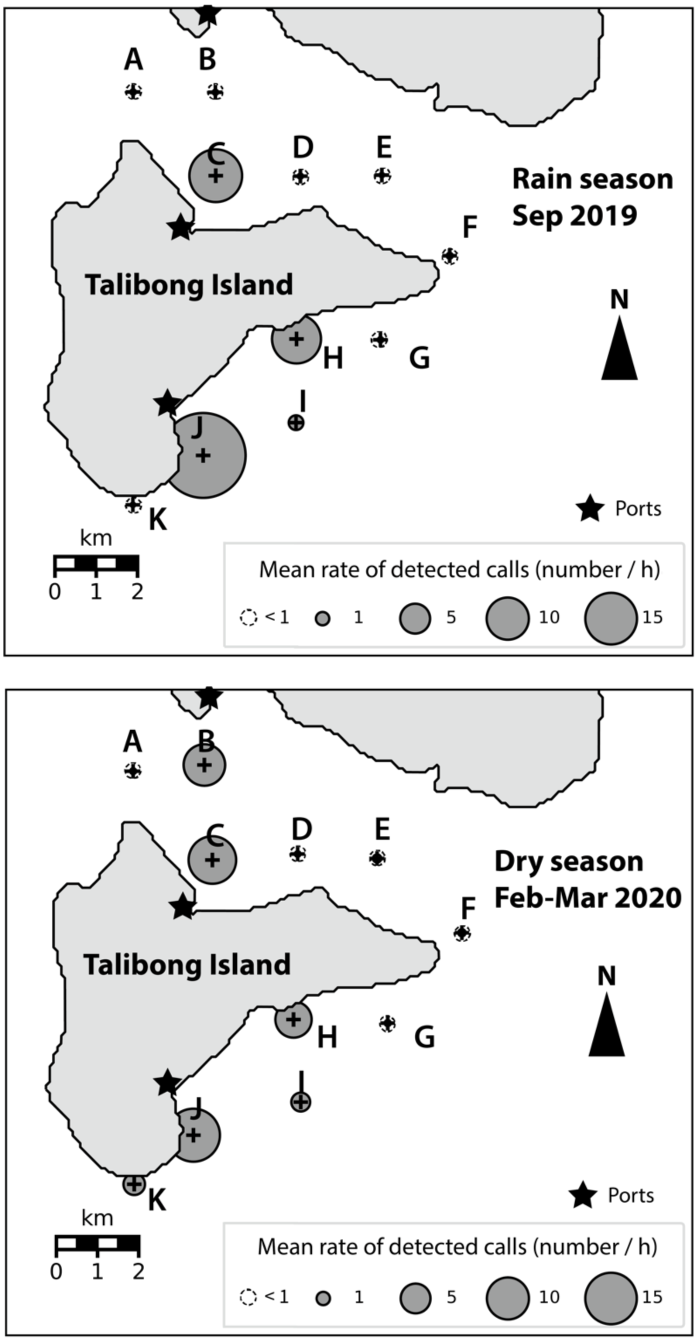

Fig. 3.5 Detection results of dugong calls along the coastline of Talibong Island. Crosses show the deployed locations of the recorders, and the size of the circles represent the mean rate of detected calls (number/h). Stars show the locations of ports.

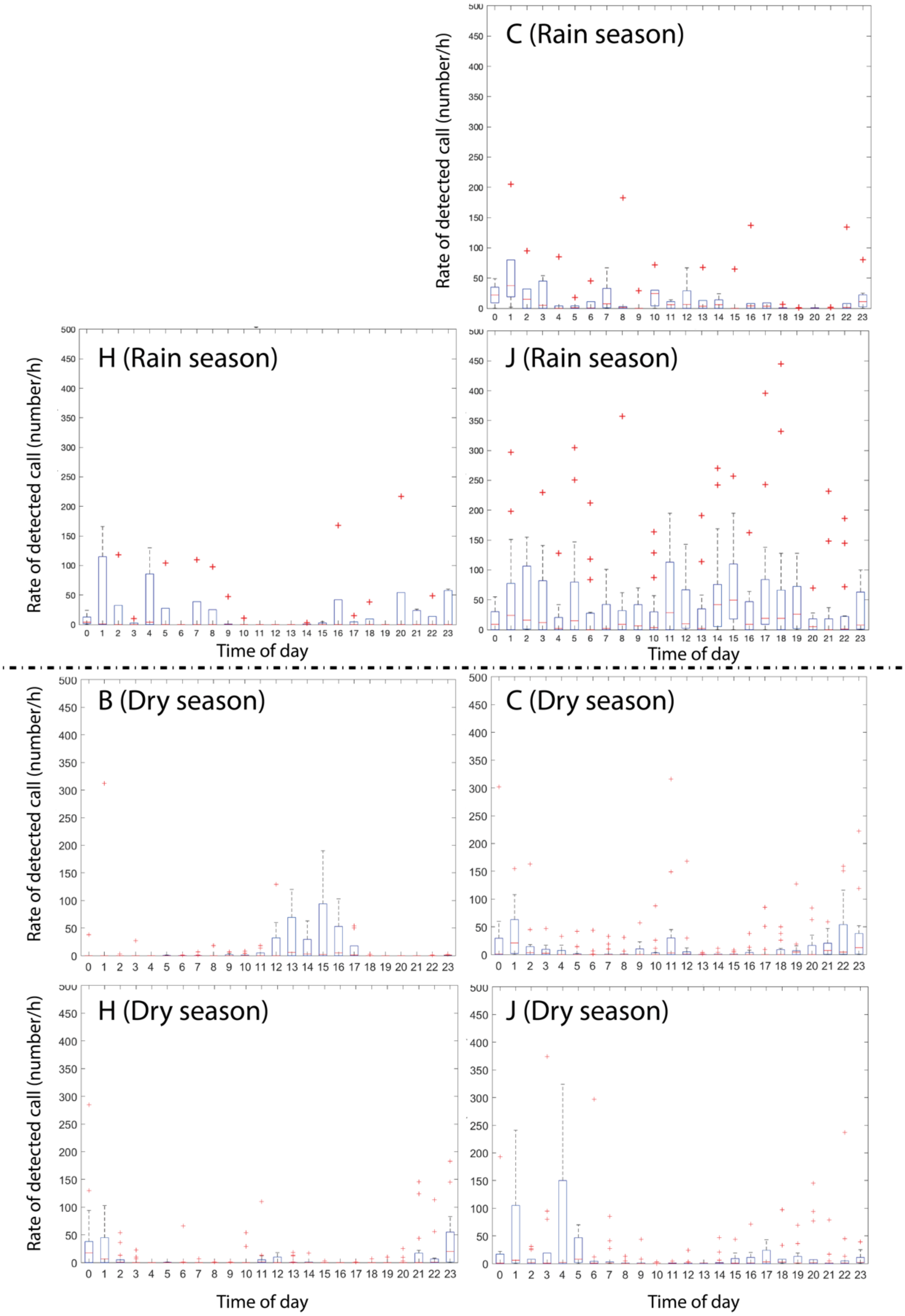

Fig. 3.6 Temporal variation of the rate of detected call at location B (only dry season), C, H and J, where more active vocalization was observed than the other locations (Table 3.3, Fig. 3.5). The horizontal axis represents time of day, and the vertical axis represents the rate of detected call (number / h). Red crosses indicate outliers.

3.4 Discussion

This chapter demonstrated the variation of the spatio-temporal acoustic presence of dugongs in coastal areas around Talibong Island through continuous monitoring of underwater sound. The results can assist in prioritizing locations and time toward harmonized coastal management, although combining other layers derived from different methodologies should be conducted. In this chapter, ecological interpretation of their acoustical habitat use and the implication to the conservation strategy will be mainly discussed. Examining relationship between spatio-temporal variation and environmental/anthropological factors would be beneficial to estimate their acoustical habitat use, and thus it will be discussed in Chapter 5. The implication to the coastal management measure will be chiefly discussed in chapter 6, taking several aspects investigated in this thesis into account.

3.4.1 Spatial Variation

The spatial variation of vocalizing dugongs around Talibong Island was investigated in both rainy and dry season in 2019/2020. Dugongs vocalized in several locations other than the known vocal hotspot (Fig. 3.1 and 3.5). However, these additional locations were scattered. It is likely that dugongs exhibit a preference for certain specific locations for their vocal activity at least within the monitoring range of this study. It should be noted that the number of vocalizing individuals was not examined here. Certain locations that demonstrated the presence of many calls, for example, locations B, C, and J, were either at the periphery or outside the distribution range of dugongs which were found by visual observation (Ichikawa et al., 2012, 2009) (Fig. 3.1 and 3.5). The spatial variation of the vocalizing dugongs was relatively consistent in both the rainy and dry seasons, except for the observation that calls in location B were at a much higher rate during the dry season only.

There are several potential reasons for reporting different areas of active dugong vocal behavior compared to those reported in previous studies. First, this study included certain periods and locations that were not covered by previous studies. Thus far, all towed acoustic surveys have been conducted in the daytime and have not covered all the monitoring locations included in this study. For example, locations C and H were located outside the transect lines defined by studies conducted by Ichikawa et al. (2009, 2012). Further, in previous studies, fixed underwater recorders were only deployed around the vocal hotspot, which corresponded to the single location J in this study (Ichikawa et al., 2006; Matsuo et al., 2013; Tanaka et al., 2017). I might have observed behaviors in dugong habitats that had been overlooked in previous research. Second, considering that location B was covered in the previous studies, but no vocalization was detected (Ichikawa et al., 2012, 2009), the behavior pattern of the local population in this area might have changed. The acoustic presence and behavior of certain baleen whales have shown differences between years, or even within the same seasons (Henderson et al., 2018; Risch et al., 2013). This could be attributed to interannual changes in environmental conditions, such as temperature, food resource availability, and oceanographic current. This may also be the case for dugongs. In addition to other conditions, the distribution of seagrass, the exclusive food resource of dugongs, was reported to change interannually with changes in environmental factors (Tesei et al., 2020; Traganos and Reinartz, 2018). The study population of dugongs might have shown changes in their behavioral patterns to adapt to this environmental shift, compared to their behaviors when the previous survey was conducted.

Finally, different groups of dugongs may have migrated from another area into the monitoring range. In recent years, less dugongs have been sighted around Muk Island, which is located approximately 10 km northwest of Talibong Island, potentially due to an increase in marine traffic from tourism (K. Kittiwattanawong, pers. comm.). I suggest that such a group may have moved to Talibong Island, settled there, and communicated among themselves via vocal cues.

At location F, in both seasons, few calls were detected consistently, although a previous study identified a clumped distribution of calving herds (Ichikawa et al., 2012). It has been suggested that mother and calf pairs of dugongs may not use vocalizations to maintain their cohesion, while vocal signals often facilitate group cohesion in Amazonian manatees (Sousa-Lima et al., 2002) and Florida manatees (O'Shea and Poché, 2006), which are other members of the order Sirenia. This study validates this hypothesis through long-term continuous monitoring using multiple fixed recorders in two distinctive seasons, augmenting the existing evidence from towed surveys conducted during the daytime only. The observed seasonality in the rates of detected calls in this study may have reflected the mating status of the dugongs in this population. Hishimoto et al. (2005) reported that captive male dugongs in Toba Aquarium, Japan, produce more and longer calls when they show active movement, including certain sexual activities, such as exposing the penis and rubbing the body or penis against objects. Thus, an increased rate of call production, especially calls of long durations, is hypothesised to be related to mating behavior. Multiple studies have suggested that dugong mating activity exhibits seasonality, even though there is a variation between populations (Adulyanukosol et al., 2007; Anderson, 1997; Preen, 1989). Mating behavior has been observed between February and March around Talibong Island (Adulyanukosol et al., 2007); further, in more recent years, mating behavior has also been observed around location J during the rainy season (K. Kittiwattanawong, pers. comm.). The active vocalizations observed during the rainy season might be related to such mating activity exhibited by dugongs aggregated around location J. As the reproduction and recruitment is one of the key life-history stages for population maintenance, the area used for animal's mating behavior should be understood to consider spatial priority in a management planning.

3.4.2 Temporal Variation

Regarding the temporal variation of dugongs' acoustic presence, the timing of their active usage varied among locations. For example, at the location in the south of the island they actively vocalized in the nighttime, but another location in the north they frequently vocalized during daytime, or their vocalization was evenly observed throughout the day at other locations (Fig. 3.6). The temporal pattern of their vocalization was similar between seasons, except location J (Fig. 3.6). The relationships between this temporal pattern and environmental/anthropological factors will be examined in Chapter 5.

Although this study did not distinguish vocalizing individuals, this temporal variation might be explained by the heterogeneity in behavioral pattern of individual or individuals. Given the vocalizing individual was not identified in this study, the frequent vocalization in the daytime at location B could not be distinguished either different individual(s) vocalize at each location or same individual(s) moved between two or more locations and vocalized. From the survey using satellite Platform Transform Terminal and/or GPS tracking, it was reported that dugongs in Australian waters showed movement heterogeneity over large spatial scales

(Sheppard et al., 2006). Radio and satellite tracking in Indonesia also reported that the movement pattern and the size of their home range greatly varied among four tethered individuals (Iongh et al., 1998). Such individual variation is plausible given their possible fission-fusion society (Marsh et al., 2011a). In this sense, conducting tracking survey to examine the movement and habitat use in individual level and combining it with the results of this chapter would lead to interpret the variation in the temporal pattern of their acoustic habitat use. If the differences in temporal pattern derives from their individual heterogeneity, each individual in this area may have fixed behavioral pattern. Exploring whether this fixed time schedule is also the case for other key behavior, e.g. foraging and resting, would be beneficial to create a management plan including their conservation.

3.4.3 Implication to the coastal management

The findings in this chapter contribute to the consideration of the MSP by highlighting the spatial and temporal importance of dugongs' vocal behavior in their local habitat. Location J, which is known as a vocal hotspot, is fairly close to the fishing port of the local fishery village. Furthermore, locations B, C, and J are not included in the extent of the community-based dugong protected area, which was set by local organization in 2017 (Marine National Park Operation Center 3 Trang 2018, Fig. 3.1 and 3.5). It may be necessary to consider these locations when evaluating the effectiveness of a management measure.

Furthermore, the temporal factors could also be considered in implementing management measures. The MSP for marine megafauna primarily considers the spatial aspects of coastal management (Augé et al., 2018). Although the long-term plasticity of MSP has been proposed considering the dynamics of coastal socio-ecological systems and the effect of climate change (Gilbert et al., 2015; Gissi et al., 2019), fine-scale temporal dynamics have not been previously proposed to the best of our knowledge. Based on our findings about the temporal variations in dugongs' habitat use, incorporating short-term temporal variations into MSP might harmonize species conservation and human livelihood activities. This aspect should be examined further, particularly in coastal areas.

More detailed discussion on the implication to the coastal management will be described in chapter 6.

3.5 Conclusion

This chapter revealed the spatial and temporal variation of vocalizing dugongs using multiple recorders around Talibong Island in two distinctive seasons. Given that their vocalization is assumed to be associated with key life events, namely social behavior and reproduction, the outcome of this study may provide information for the effective management for the conservation of local population of dugongs, such as avoiding an accidental catch by fishing gear and disturbances by vessel traffic. In terms of spatial variation, their vocalizations were concentrated in a few locations in both dry and rainy seasons. Some of the locations where many calls were detected were outside of existing community-based conservation area. Paying attention to those location would reduce further potential threats to dugong. Despite this spatial consistency, temporal pattern varied among locations, i.e. active vocalization was observed during nighttime at some locations, but at another location, it was frequently observed during daytime. In local scale, concentrating conservation priority to those time at each location may enhance the effectiveness of preserving local population. However, imposing complicated regulation may potentially cause negative backlash from local residents. Furthermore, to examine such temporal variation in other habitat, long-term and wide-range acoustic monitoring would be required. Enacting spatial conservation measure should be primarily effective and thus such survey effort would be prioritized, based on the consistency of spatial variation in their acoustic habitat use. Potential explanations of those spatio-temporal variations were listed from the behavioral viewpoint, but further study will be required to narrow down the reason. In Chapter 5, the output of this chapter will be integrated with environmental factors (e.g. tidal current and seagrass bed) and anthropological factor (i.e. vessel traffic) to generalize the findings, foreseeing to apply it into different season and other habitats.

Chapter 4 Spatio-temporal variation of vessel traffic

4.1 Introduction

Several methodologies have been carried out to monitor the vessel traffic in a certain area. Manned surface patrols are the most common method for monitoring and enforcement in coastal MPAs (Davis et al., 2004), but they are cost-prohibitive and resource demanding (Read et al., 2019). Automatic Identification System (AIS) is an automatic tracking system intended to enhance the safety of life at sea (IMO 2002), the efficiency of navigation and the protection of the marine environment under the IMO's 1974 International Convention for the Safety of Life at Sea (SOLAS). AIS identifies the position of vessels, their course and speed, and thus it is also used to assess the threats of noise pollution and vessel strike to marine megafauna, and thus to support marine spatial planning (Le Tixerant et al., 2018; Metcalfe et al., 2018). IMO requires AIS use by all vessels >500 gross tons, for any vessel >300 gross tons that is engaged on international voyages and for all passenger vessels irrespective of size (IMO 2002). However, those criteria often do not meet vessels running in local areas, which mostly consists of smaller and non-international vessels for fisheries and transportation. Vessel monitoring systems (VMS) have also been utilized for monitoring, control and surveillance to successfully deter noncompliance events and have been used to analyze fishing activity in MPAs (Lambert et al., 2012). However, similar to AIS, VMS is limited by fleet coverage (Kline et al., 2020). Satellite imagery provides a means of identifying vessels unequipped with VMS or AIS, or vessels that have shut off their transponders to avoid detection (Cabral et al., 2018; Kline et al., 2020). However, this imagery is limited by a satellite's scope of coverage, image resolution, and various atmospheric and lens effects (Kline et al., 2020).

To overcome this problem, PAM offers a cost-effective method for a continuous observation in order to identify the spatio-temporal occurrence of motorized vessel traffic (Kline et al., 2020; Reis et al., 2019). As described in Chapter 2, multiple detection and classification methods of vessel sound have been proposed so far. However, the spatio-temporal scale of PAM in marine protected areas is limited to the monitoring at a few location or scarce compared to their spatial coverage (Wilson et al., 2022). Particularly in the coastal area, where small vessels are commonly maneuvered (Smott et al., 2018; Wilson et al., 2022), fine-scale monitoring by multiple recorders is expected to provide a baseline information for the assessment of their potential impact and subsequent consideration of management measure.

In terms of dugongs, potential threats from vessels, i.e. noise pollution and vessel strike could be greater than other marine mammals, because of their co-existence as described in Chapter 1. Death of dugongs from collisions with boats have been reported in Asia, Africa and Australia (Marsh et al., 2011b; Marsh and United Nations Environment Programme, 2002), and the high-speed recreational vessels are recognized as the high risk source (Hodgson and Marsh, 2007). Along the urban coast of Queensland, Australia, vessel strike mortality of dugongs is becoming increasingly common (Limpus et al., 2003) and dugongs are particularly vulnerable to boats travelling at high speed (Hodgson, 2004). Increases in mortality and injury due to vessel strikes could have serious impacts on the small and patchy populations of dugongs found in many countries (Marsh et al., 2011b). The investigation about noise pollution to dugongs' behavior is still underway to accumulate the assessments. Potential behavioral changes in response to vessel traffic were reported, e.g. reducing feeding time budget (Hodgson and Marsh, 2007) and the change of call characteristics (Ando-Mizobata et al., 2014). In addition to those influence, masking of their vocalization cannot be ignored given the fact that the sound pressure level of boat sound is much higher than that of dugong's call (Ando-Mizobata et al., 2014). In Talibong Island, Thailand, three death cases by vessel strike had been reported as of 2006 (Adulyanukosol and Poovachiranon, 2006), and the potential impact of vessel sound to dugongs' call characteristics was also inferred (Ando-Mizobata et al., 2014). Recognizing those potential threats, the quantitative knowledge about vessel traffic plays the fundamental role for the subsequent impact assessment and mitigation measure consideration.

However, vessel traffic in dugong's habitat has not been extensively and continuously assessed so far. One of the reasons of this would be the difficulty to monitor dynamic vessel traffic in local dugong habitat, because the vessels passing many of dugongs' habitats are either small or non-international for fisheries or transportation, and thus they are not required to equip AIS or VMS. This is also the case in Talibong Island, AIS vessels are considerably few compared to large port, e.g. Bangkok and Phuket (MarineTraffic). The vessel traffic and fishing activities have been mapped to assess the bycatch risks in several habitats so far, but there were basically derived from snapshot aerial survey (Briscoe et al., 2014; Hines et al., 2020; Ponnampalam et al., 2015). While the applicability of PAM to the continuous monitoring of vessel traffic is described above, its potential has not been well applied to the habitat of dugongs. Given those circumstances, the potential of PAM to monitor vessel traffic should be more exploited in dugong habitat. This method would be beneficial from the cost-effectiveness aspect, since it could observe the dugongs call at the same time.

The objective of this chapter is, with the automated detector developed in Chapter 2, to visualize the spatio-temporal distribution of vessel traffic around Talibong Island using underwater acoustic information. Furthermore, at one of the monitoring locations, the temporal pattern of each vessel type was examined with the classifier developed in Chapter 2 as well, although this would serve as a reference information because of its limited sample size. This classification procedure is expected to identify the potential high-risk time period that speedboat actively passes, in terms of assessing the noise masking to dugongs' vocal communication and vessel strike.

4.2 Materials and Methods

Acoustic data was collected in the same field survey in September 2019 and February-March 2020, which was described in Chapter 3. Therefore, the monitoring locations and periods were identical with that survey (Fig. 3.2, Table 3.1).

Vessel sounds were detected from the recorded underwater sound with the automated detector developed in Section 2.2. Entropy threshold was determined at each location. If detections exceeded a manual check capacity, the developed classifier for broadband sounds was applied to remove the false positives. The classifier was trained at each location, and after the classification step, the results were manually scrutinized. Thus, no false positives were used for further analysis.

I defined 'rate of detected vessel passage' as the duration of detected vessel sounds per hour in minutes (total duration of detected vessels divided by observation duration) as the index to represent the heaviness of vessel traffic. Those values were calculated at each location in each season. Note that the number of passing vessels were not counted here. The rate of detected vessel passage was compared among the locations using a Kruskal–Wallis test to examine the spatial variation of the activeness of vessel traffic. The rate of detected vessel passage was also compared between the rainy and dry seasons using a Mann-Whitney U test to determine the seasonality. To investigate the variation in their temporal pattern, at the locations where heavy vessel traffic were detected, the rate of detected vessel passage was compared between day and night by a Mann-Whitney U test.

At location B, the classifier developed in Chapter 3 was subsequently applied to the segments which was identified by the vessel entropy detector. It must be noted that this classifier was only applied to the vessel sound detected at location B, where the training data was obtained. The classification results in 10 seconds segment level were then put together into the result in event level by the majority vote basis within the event, as described in Section 2.2. After this classification stage, temporal variation of each classified vessel type was examined. Since the sample size was limited in 2019 (rainy season), this classification process was only carried out in 2020 (dry season).

In addition to the vessel classification, rough estimation of sound source level per vessel type was calculated with the received sound pressure level and the distance to the target vessel. Distance from the observer to a vessel was measured by laser distance meter (KLR-600A, KenkoTokina Corporation, Japan). The sound source level was calculated for several vessels and timings for each type, and averaged over them. Those values are only used for reference value since (1) the distance between research vessel and target vessel was not always very accurately measured, (2) received sound level is considerably affected by reflection at sea surface and sea floor in shallow waters, and thus the accurate measurement is quite challenging.

4.3 Results

4.3.1 Spatial variation

In total, 6233 mins of passing were acoustically detected (1968 mins and 4265 mins in the rainy season and the dry season, respectively, Table 4.1). Rate of detected vessel passage was also significantly different among locations in both seasons ($p < 0.01$, Kruskal-Wallis test, Fig. 4.1). In the rainy season, the mean rate of detected vessel passage (±SD) in the locations A, B, F, J was 3.0 ± 6.4, 5.7 ± 9.6, 2.6 ± 6.3 and 1.2 ± 2.5 min/h, respectively, while the mean rate of detected vessel passage of all other locations was 0.4 ± 2.0 min/h (Table 4.1, Fig. 4.1). In the dry season, the mean rate of detected vessel passage (±SD) in the locations A, B, F, J was 3.7 ±5.4, 8.7 ± 9.7, 1.7 ± 3.2 and 1.8 ± 2.7 min/h, respectively, while the mean rate of detected vessel passage of all other locations was 0.5 ± 1.6 min/h (Table 4.1, Fig 4.1). Overall, the mean rate of detected vessel passage was significantly higher in the dry season than the rainy season ($p < 0.05$, Mann-Whitney U test). In both seasons, the highest mean rate of vessel passage was observed at location B. The spatial patterns were not considerably differed between rainy and dry seasons.

4.3.2 Temporal variation

Temporal patterns of vessel passage were generally common in all locations (Fig. 4.2). At location A, B, F and J, which had heavy vessel traffic, the rate of detected vessel passage was higher in daytime (6:00 – 18:00) than nighttime (18:00 – 6:00) in both seasons ($p < 0.01$ for all locations, Mann-Whitney U test).

4.3.3 Vessel type classification

At location B in dry season, long tail boat, speedboat and trawler were frequently observed, and their passing times were 1017 min (45%), 107 min (5%) and 1121 min (50 %), respectively (Fig. 4.3). The passage of speedboat, which is faster than other vessel types, is concentrated in daytime (09:00 – 15:00) (Fig. 4.4).

Roughly estimated sound source level of long tail boat, long tail boat (small), speedboat, trawler and tugboat (with cargo) are 154 dB (re 1µPa, RMS level, hereafter the same), 138 dB, 165 dB, 179 dB and 166 dB, respectively.

4.4 Discussion

Spatio-temporal pattern of vessel traffic was highly consistent in the study site, i.e. heavy traffic was mostly observed in the daytime, and either in the channel between the mainland and the island, or at a location nearby a port (Fig. 4.1). It is fairly reasonable that the spatial variation associates on the characteristics of human livelihood, i.e. heavy traffic was observed at the locations near sea route and port (Fig. 4.1). For instance, according to the local people, the channel between the mainland and the island is part of a sea route between west and east of the Island (K. Tanaka unpublished data), and thus relatively heavier traffic was observed at the locations in this channel (Fig. 4.1). The heaviest traffic at location B in both seasons could be derived from that fact, as well as the fact that it is in the transportation route between the mainland and the island. High rate of vessel passage at the location J is assumed to be because it is close to a fishing port (Fig. 4.1). The consistency in the temporal variation of vessel traffic (Fig. 4.2) is also plausible since the marine traffic in this area mostly consisted of transportation and fisheries (K. Tanaka unpublished data), which are typically carried out in relatively fixed time schedule. Considering bathymetric feature of the surrounding area of the island, the skippers might avoid their vessels from stranded on shallow flat in the nighttime because of the poor visibility. The reason why heavier traffic was detected in the dry season than the rain season would be the high demand of the transportation for the tourists (Table 4.1).

From the classification results, while most of the vessel types pass around location B in the daytime, the timing of the passage of speedboat particularly clumped in 09:00 – 15:00. From the rough estimation, the sound source level of speedboats and trawlers were higher than that of long-tail boat. Furthermore, speedboat travels much faster than long-tail boat since it is mostly used for the transportation or tourism (K. Tanaka unpublished data). Given those facts, this time period at location B should be paid attention for the potential negative impact to dugongs, e.g. the physical collision or noise pollution to their vocal communication. The details about such relationships between dugongs' habitat use and ecological/anthropological factors, and the management measure implied from such information, will be discussed in Chapter 5 and 6.

Although the quantitative comparison of vessel types among monitoring locations were not conducted in this study, from the empirical observation in the field, location B encountered heavy passage of larger vessels such as trawler or speedboat, since that location in the middle of the sea route (K. Tanaka unpublished data). On the contrary, at location J, long-tail boat for small scale fisheries were frequently observed while no speedboats and trawlers were spotted during the field survey (K. Tanaka unpublished data). Thus, particularly at location B, the potential disturbance risk of noise masking and collision from speedboat could be higher than that at location J. Given the high risk deriving from speedboat, in the time period that speedboat actively passes at location B, namely 09:00-15:00, a speed restriction could be imposed to mitigate the potential disturbance. Hodgson (2004) reported that, in Australia, dugong's behavioral response to the vessels differ depending on the vessels' speed, i.e. they swam away from slow approaching vessels (15 km/h), while they did not respond to fast responding vessels (50 km/h). This result could provide a guideline of vessels' traveling speed in the study site as well. Reduction of travel speed could contribute to not only decreasing the collision risk to marine mammals but also greenhouse gas emissions and underwater noise (Leaper, 2019), although this was reported in larger vessels and broader spatial scale. Paying attention to the surroundings could also be recommended to local skippers.

Table 4.1 Duration and mean rate of detected vessel traffic at each monitoring location.

2019	Location	Duration of detected vessel passage (min)	Mean rate of detected vessel passage (min/h) ± SD
	A	432	3.0 ± 6.4
	B	686	5.7 ± 9.6
	C	93	0.6 ± 3.0
	D	149	1.0 ± 3.5
	E	29	0.3 ± 1.1
	F	334	2.6 ± 6.3
	G	0	0
	H	5	0.04 ± 0.1
	I	72	0.5 ± 1.2
	J	154	1.2 ± 2.5
	K	14	0.1 ± 0.4
	Total	1968	

2020	Location	Duration of detected vessel passage (min)	Mean rate of detected vessel passage (min/h) ± SD
	A	710	3.7 ± 5.4
	B	1778	8.7 ± 9.7
	C	139	0.3 ± 1.0
	D	326	1.5 ± 2.9
	E	239	1.2 ± 2.6
	F	320	1.7 ± 3.2
	G	20	0.1 ± 0.3
	H	5.2	0.01 ± 0.08
	I	95.8	0.5 ± 1.2
	J	578	1.8 ± 2.7
	K	54	0.3 ± 1.2
	Total	4265	

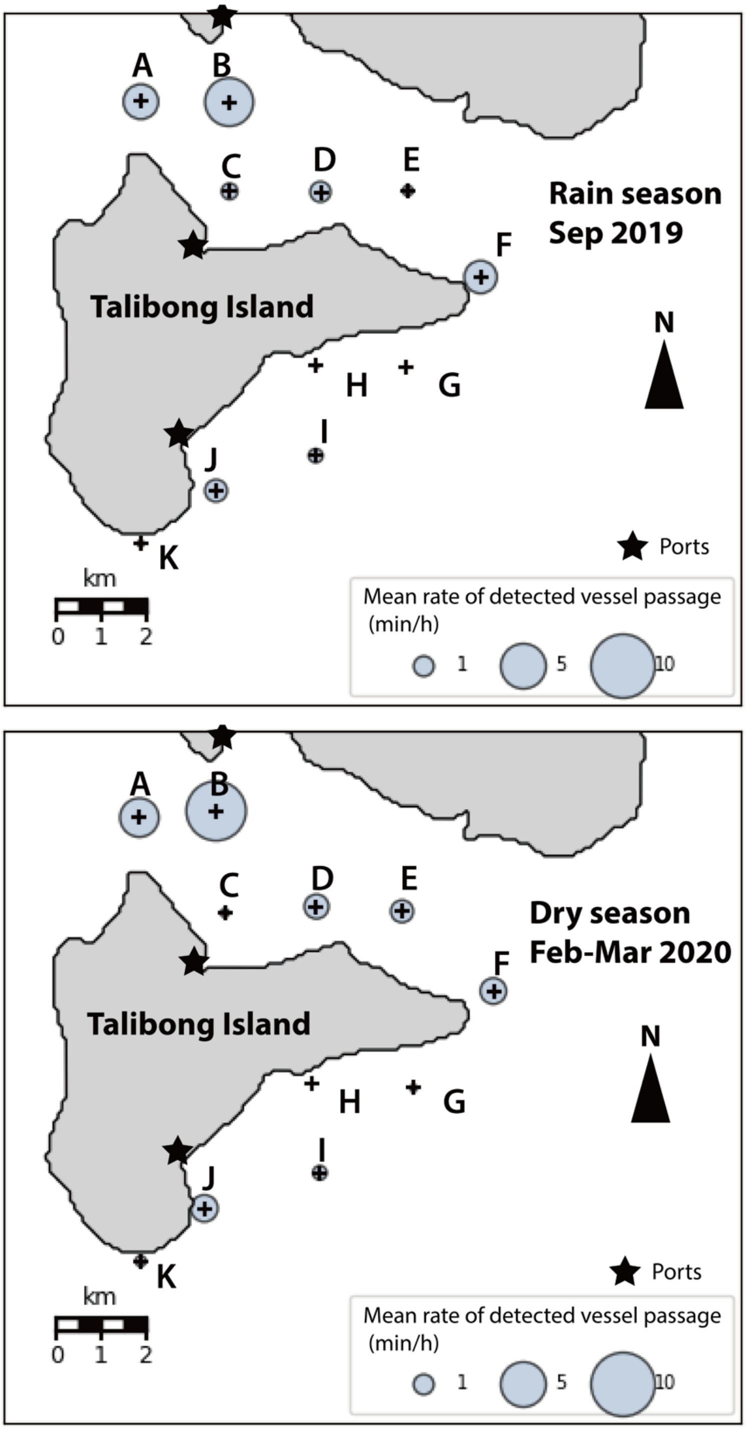

Fig 4.1 Detection results of vessel passage along the coastline of Talibong Island. Crosses show the deployed locations of the recorders, and the size of the circles represent the mean rate of detected vessel passage (min/h). Stars show the locations of ports.

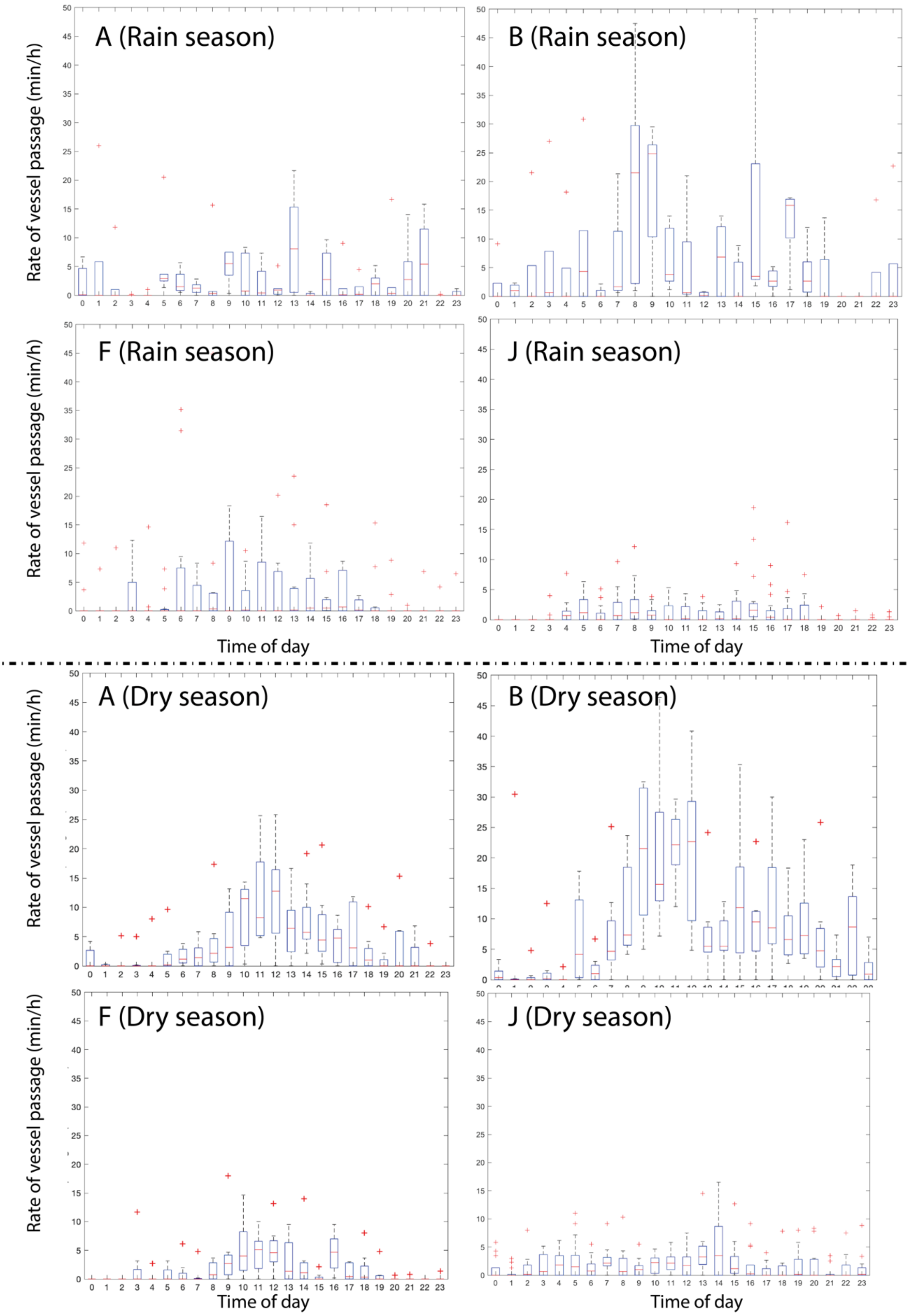

Fig 4.2 Temporal variation of the rate of detected vessel passage at location A, B, F and J, where heavier passage was observed than the other locations (Table 4.1, Fig 4.1). The horizontal axis represents time of day, and the vertical axis represents the rate of detected vessel passage (min / h). Red crosses indicate outliers.

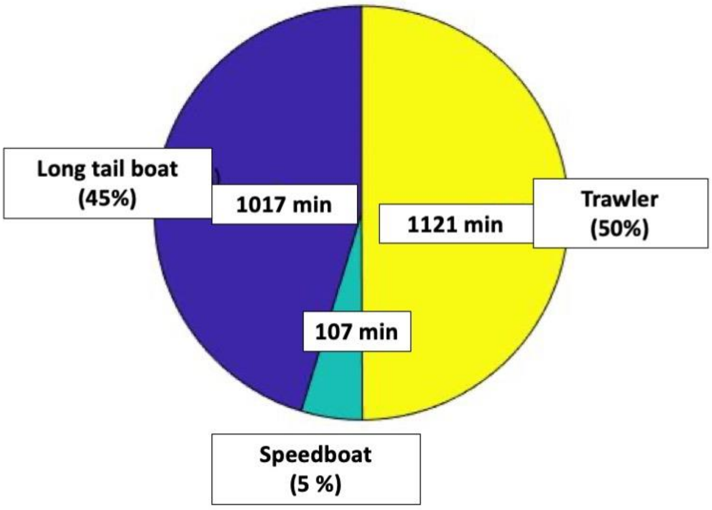

Fig. 4.3 Durations and proportions of each classified vessel type at location B in 2020.

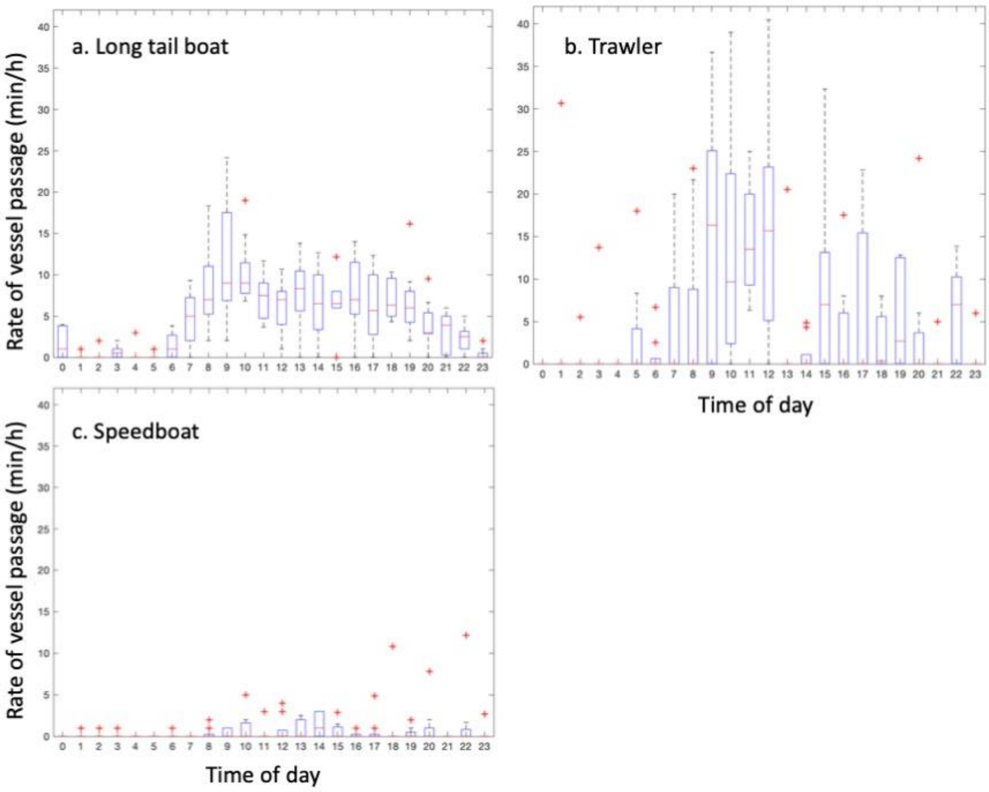

Fig. 4.4 Temporal variation of the rate of detected vessel passage in each classified type at location B. The horizontal axis represents time of day, and the vertical axis represents the rate of detected vessel passage (min / h). Red crosses indicate outliers.

Ando-Mizobata (2014) conducted interview survey to local fishermen and tourism officers at five coastal villages including Talibong Island, in order to investigate the monthly and daily patterns of boat activities around dugong habitat. The findings of this study include (1) most local fisherman and tourism officers use long-tail boat with engine (2) boats with 6–10 m in length were mainly used (3) they mostly work in the daytime (0500h –1800h), especially in the morning (0500h–1000h) (4) tourism vessels are active in the dry season (November to May). Those results are consistent with the findings of this chapter.

It would be important to keep in mind that there are two groups of stakeholders regarding the vessel traffic; islander and non-islander. Based on the results in this chapter and previous interview survey (Ando-Mizobata 2014), many parts of potentially high-risk vessels, i.e. trawlers or speedboats, are likely to come from outside of Talibong Island. As described in Chapter 1, islanders generally have high motivation to dugong conservation partially because the eco-tourism associates to their own livelihood. There is also a community-based unwritten rule to turn off the engine and use long pole to move the vessels around Batu-putae mountain where dugongs constantly use (K. Tanaka unpublished data). How to deal with the consciousness gap between islander and non-islander and how to approach those non-islanders would be challenging but a crucial matter, in order to realize harmonized local coastal management.

One of the limitations lies in the classification process of vessel type, as also described in Chapter 2. During the visual observation at location B, not all vessel types were confirmed since some vessel types are rare than others and field observation was not conducted in nighttime and bad weather condition. Although machine learning technique steadily progresses, conducting accumulating training data plays key role to enhance the classification performance. Continuous monitoring is expected in this context as well. Furthermore, while motorized vessel passage can be acoustically detected, several other anthropogenic activities cannot be detected by PAM, such as deployment of fishing gear.

As a future perspective, risk-analysis of vessel strike with the speed estimation by the passive acoustics could be beneficial. A risk-analysis ideally constitutes two steps: (1) modeling the probability of a collision based on encounter rate theory and (2) modeling the probability that the collision is fatal (Schoeman et al., 2020). This thesis partially attempted to address step 1, but more information will be required as PAM only can detect vocalizing individuals. Estimation of the probability of lethal injury for marine mammals given a vessel strike as a function of vessel-related factors (e.g. speed, draft, size) has been conducted to consider risk reduction measure, but most of them used AIS as an information source (Conn and Silber, 2013; Crum et al., 2019; Martin et al., 2016). However, as repeatedly raised in this chapter, many of vessels passing in local coastal area do not equip AIS. Thus Chapter 2 proposed the method to classify vessel type from their radiated sound, and also raised the possibility of speed estimation, referring to the previous studies. Such acoustic-derived information could potentially be integrated into a risk-analysis of vessel strike in local coastal area, in order to apply quantitative evidence to the decision-making. This potential should be investigated in future.

In addition to the physical strike, noise pollution such as masking effect and hearing loss (temporal threshold shift and permanent threshold shift) should be paid attention. Although those threats will also be discussed in Chapter 5, on the vessel side, simulating radiated sound (e.g. "ship noise footprint") could provide a baseline information to quantify its impact to the ecosystem (Andre et al., 2016). Detailed investigation of chronic and cumulative noise effects will require consistent and fine-scale studies of ambient noise trends in marine habitats. However, again, those studies in local coastal area is either rare or limited to the areas where AIS-equipped vessel is the majority (Merchant et al., 2014). Further effort to obtain ambient noise situation in local coastal area will be expected.

As pointed above, collecting baseline information about vessel traffic in local coastal area is one of the keys to accomplish harmonized management in those area. Although PAM could propose an effective tool to perform such assessment particularly for non-AIS vessels, it is also true that it requires investments to equipment (underwater recorder) and human resource (analysis skill of signal processing), which are not always available in local community. In this sense, capacity building and technology transfer will be expected to spread the benefit of PAM.

4.5 Conclusion

This chapter visualized, as a baseline input for a risk assessment and successful coastal management, the vessel traffic around Talibong Island in spatial and temporal manner, by observing the emitted sounds. I identified times and locations where active passage was observed, i.e. daytime in the north and southeast of the island, where is either near the ports or in the middle of the sea route. Furthermore, the classification result of vessel types at one location suggest potential high-risk vessel is concentrated around noon. Overlapping with the habitat use of dugongs would provide an information to spot the potential risk and the priority of conservation of local population while limiting the restriction of local maritime activity. This chapter also implied the efficacy of passive acoustic monitoring for vessels in local coastal area, where not many vessels equip AIS to examine their spatio-temporal occurrence. Not only for dugong conservation, the framework provided here could be integrated with other biological, ecological and socioeconomical layer, and would contribute to coordinated managements and decisions to minimize user-user and user-environment conflict in local coastal seas.

Chapter 5 Relationship between dugongs' acoustic habitat use and environmental/anthropological factors

5.1 Introduction

Given the complexity of socio-ecosystem in coastal area, there are multiple environmental and anthropological factors that could impact the habitat use of marine megafauna directly or indirectly in coastal area. Quantifying the relationships with those factors and animals' habitat use enhances generic understanding of species, the accuracy of future prediction or estimation in other habitat, and thus provide baseline information to consider management measure (Sheppard et al., 2010, 2009). Species distribution models (SDMs) which take environmental and anthropological factors in to consideration are increasingly used in conservation planning and wildlife management, including for cetaceans (Hammond et al., 2013), especially in developing MSP and designing MPAs (Sahri et al., 2021) and identifying time and areas of potential conflict between human activities and marine organisms (Guisan et al., 2013). Guisan et al. (2013) identified how SDMs contribute to decision making, i.e. identifying a problem, defining possible alternative actions, assessing the trade-offs between benefits and costs of actions and assessing and dealing with uncertainty. Not only the distribution, the effect of those external factors to habitat use of animals, such as foraging (Sheppard et al., 2010), nursery (Bangley et al., 2018; Dwyer et al., 2020b) and socializing (Tanaka et al., 2017), would elaborate the prioritizing process in coastal management since those behaviors are key social events and thus should be well-preserved for population maintenance (Teixeira et al., 2019). In this context, PAM for social calls, or bioacoustics approach, is expected to be a powerful tool, as it can provide spatiotemporal information on the key life events of species, particularly those associated with reproduction and recruitment, alarm and defense, and social behavior (Teixeira et al., 2019). Combining outputs produced by PAM of social calls and habitat modeling would support deepening the generic understanding of animal's habitat use.

Conventionally, MPA and MSP has mostly been discussed as a spatially static measure. Dwyer et al. 2020 suggested that, based on the temporally dynamic habitat use of delphinid species, static spatial exclusions (e.g. static boundary line on a map) would not be an optimal management option. Particularly in coastal area, where the environmental (tidal and diel cycle, influx of river water) and anthropological (maritime transportation, fisheries and tourism) factors dynamically and continuously change in several time scale, such dynamism should be well considered. Furthermore, given the fine-scale spatial and temporal shift of those factors in coastal area, examination of the relationship between animals' habitat use and external factors should also be examined in high spatio-temporal resolution.

The habitat use of dugong had been examined so far, as well as its relationship with the environmental and anthropological factors. Sheppard et al. (2006) showed a dugong individual's short-term home range was approximately 0.6–12.4 km^2. Within their daily home ranges, 72% of their time was spent within three meters of the surface (Louise Chilvers et al., 2004). Both tidal and diel cycles influence dugong movement; they tend to be closer to shore at high tide than low tide and at night than during the day (Sheppard et al., 2009). As a result of the tracking survey in a coral lagoonal ecosystem, dugongs spent most of their tracking time within the lagoons, although a few individuals used the fore reef shelf outside the barrier reef in the open ocean (Cleguer et al., 2020). Derville et al. (2022) modeled ecoregional and temporal dynamics of dugong habitat use in a complex coral reef lagoon ecosystem, and demonstrated that shallow waters were preferentially used by dugongs at night/dusk during high tide. Since dugongs are strictly marine and forage over shallow, intertidal seagrass meadows, tidal periodicity restricts dugong accessing those feeding ground (Sheppard et al., 2010, 2009, Amamoto et al. 2009). It was suggested that dugongs prefer forage in microhabitat that allow escape from potential predators (Wirsing et al., 2007a, 2007b). Tsutsumi et al. (2006) monitored dugong's feeding by a passive acoustic approach, and reported that the feeding sounds were mostly detected during nighttime, which might be because of the avoidance of the human activity during daytime.

However, more information on the habitat use of dugongs and its relationship with physical factors is required, particularly with increasing the spatio-temporal scale in coastal area. In additional to the environmental factors, anthropological factors, e.g. vessel traffic should be taken into consideration.

Given that the spatio-temporal pattern of dugongs' acoustic habitat use is distinctively different from those of their distribution obtained by visual survey, as suggested in the previous study (Ichikawa et al., 2012) and this study (see Chapter 3), their acoustic habitat use should be separately modeled from the distribution. Tanaka et al. (2017) examined the relationships between dugongs' vocal behavior and environmental factors at two neighboring locations, and reported that those factors that correlated with changes in detected vocalization rate differed between the two locations. This result suggested that dugongs' habitat use varies at fine spatial scales. Since the monitoring location in the previous study was limited to two locations in local habitat, spatial and temporal scale of the monitoring need to be expanded in order to provide beneficial information toward the management of their habitat. Furthermore, Tanaka et al. (2017) did not consider the anthropological factors, although they should also be paid attention as one of the crucial elements in coastal socio-ecosystem. Filling those knowledge gaps would enhance the reliability and plausibility of the baseline information of their habitat use, not only in their local habitat but also other habitat.

The objective of this chapter is to explore the relationship between dugongs' acoustic habitat use and environmental/anthropological factors. Spatio-temporal pattern of dugongs' vocal behavior and vessel traffic, which was obtained in Chapter 3 and 4 respectively, will be used for this analysis as well as the features of tidal current and seagrass bed. The information from this chapter would be beneficial to enhance the generic understanding of their ecology and to manage their habitats to ensure animal's protection as well as to guide policies mitigating potential threats from anthropological factors.

5.2 Materials and Methods

In many cases, to generate probabilistic predictions and habitat models for target species, single statistical model such as Maxent (https://biodiversityinformatics. amnh.org/open_source/maxent) is applied taking occurrence (which could be presence data) as a response variable and environmental/anthropological factors as explanatory variables. However, the locational variation of observation points (i.e. ground-truth data) in this study is much less than that of typical habitat modeling. Instead, statistical models were applied to each location to estimate the temporal pattern of dugongs' vocal behavior and its relationship with environmental/anthropological factors. Regarding the spatial pattern, clustering approach of geographical feature was conducted and then those clusters were compared to the spatial variation of dugongs' vocal behavior.

I applied generalized additive model (GAM) to examine the correlation between the temporal pattern of dugongs' acoustic presence and the environmental factors in this area, as well as the correlation with vessel traffic (Zuur et al., 2009).

Rate of detected calls (calculated in Chapter 3) was used as a response variable of this model. In GAM, Tweedie distribution was chosen because the response variable was not assumed to follow normal distribution, and overdispersion was observed (Dunn and Smyth, 2005; Wood et al., 2016). I used 'mgcv' package in R for model analysis. As explanatory variables, time, moon age, water level and rate of vessel passage were adopted. Interaction terms of those variables were not assumed in this study. Time of the day was considered as a cyclic value. Moon age was included to represent the tidal change, i.e. the shift between neap tide and spring tide. Moon age was calculated by 'pylunar' package in python, based on the coordinate of study site and date/time, adopting same value for all recording locations. The baseline water level in the study site was obtained from a tide table published by the Hydrographic Department of the Royal Thai Navy. Actual water level for each location was calculated by adding the baseline water level to the difference between the actual depths when recorders were deployed and the corresponding depths of the baseline. Rate of vessel passage (calculated in Chapter 4) was used to represent the heaviness of vessel traffic at each location. GAM models were separately created only at the locations where many dugong calls were observed. An overall model including geographical characteristics as one of the explanatory variables was not created because the number of monitoring locations was too limited to ensure the variation of those characteristics. Instead, the relationship between the spatial pattern of dugongs' acoustic presence and geographical characteristics were examined by comparing spatial variation of rate of detected calls and the fine-scale ecoregion, which is described later. Additionally, the models were separately created in rainy and dry season, rather than adding another explanatory variable such as 'season', since the deployed locations were not identical between two seasons (Table 5.1). The significances of the variables' effect were also investigated by comparing Akaike Information Criterion (AIC) values among multiple models which are created by several combination of explanatory variables.

Fine-scale ecoregion was categorized to represent the geographic characteristics of each location, which is comprised of euclidean distance to the closest shore, the distance to the closest seagrass bed and mean water level (Table 5.1). If a recording location is within the seagrass patch, the distance to the closest seagrass bed was presented as zero. Those distance values were calculated on QGIS (QGIS.org, 2022), with coastline data (Global Administrative Areas 2022) and seagrass bed data (K. Kittiwattanawong pers. comm.). The recording locations were grouped into several clusters by k-means clusters based on those three variables. Those clusters were calculated in each season separately. The optimum number of clusters (i.e. the value of 'k') was determined by a majority vote of 30 indices provided by 'NbClust' package in R (Charrad et al., 2014), and manual inspection of the scatter plot of the variables. This clustering approach was used to characterize ecoregions in Derville et al. (2022), and the ecoregional and temporal dynamics of dugong habitat use was reported as a result, although the spatial scale was much larger (~200 km) and comprising valuables were different from this study.

5.3 Results

The correlation between the temporal pattern of the rate of detected calls, and the environmental and anthropogenic factors largely varied among locations (Table 5.2, Fig. 5.1). In rainy season, the rate of detected call significantly correlated with time, moon phase and vessel passage rate at location C, with time at location H, and with water level and moon phase at location J. In dry season, the correlation between the rate of detected calls and the water level was significant at location H and J while the moon age significantly correlated at location B, C, H. Regarding the hour, although it significantly affected in all locations, the temporal pattern was different among locations as described above. A significant correlation between the vessel traffic and vocalization rate was observed at location C in both season and location H in dry season, although the vessel traffic at location C was relatively less.

As a result of the k-means clustering and search for ‘optimal’ number of clusters, the recording locations were divided into three fine-scale ecoregions in the rainy season, and two in the dry season, based on the geographical features (Table 5.1). The relationship between spatial pattern of dugong’s vocal presence and fine-scale ecoregion was not very obvious. For instance, in rainy season, location C, D, F, G, H and J are included in the same cluster, but few vocalizations were observed at location D, F and G, while many was observed at location C, H and J (Table 3.3, 5.1, Fig. 3.5). Such is the case in dry season. For example, there was huge variation in the rate of detected calls among the locations in cluster 2 (Table 3.3, 5.1, Fig. 3.5).

5.4 Discussion

There were significant correlations between the temporal variations in the acoustic presence of dugongs and environmental/anthropological factors, but they were not consistent among the monitoring locations. In terms of spatial variation, it was not fully explained by the geographic characteristics, e.g. distances to the shore and seagrass bed, by comparing the spatial pattern and the clustering results of fine-scale ecoregion (Table 3.3, 5.1, Fig. 3.5). This seems to be intuitively contrary from the previous study in New Caledonia (Derville et al., 2022), but it has to be noted that the spatial scale of that study was tens of kilometer, which is far larger than this study. Furthermore, dugongs’ habitat use was examined via satellite tracking in that study so that it does not necessarily correspond to the vocal behavior. In this sense, fine-scale habitat use of dugongs from acoustic viewpoint might be able to provide novel layer for local coastal management. Furthermore, the correlation with the vessel traffic was not consistently obvious from GAM results, in other words, acoustic presences were frequently observed even at locations where heavy vessel traffic was detected, such as location B and J (Table 5.2, Fig 3.5, 4.1). Those results suggest that the acoustic presence of dugongs is not universally explained by specific factors that this study considered, and thus fine-scale monitoring may be required, instead of interpolating or extrapolating from those factors.

Besides the spatial pattern, particularly at some locations where many vocalizations were observed, the temporal pattern of their vocal behavior varied among locations, as well as the correlation with the environmental and anthropological factors (Table 5.2, Fig 3.6, 5.1). In other words, significant correlations were observed, but those factors were different among locations in fine-scale. This difference was also reported in the previous study which compared two neighboring locations around 400 m apart from the other (Tanaka et al., 2017). This study demonstrated that the suggestion of Tanaka et al. (2017), i.e. dugongs use several locations in their home range for different purpose, might be consistent over their habitat.

In location B (dry season), only time had significant relationship with the rate of detected call, while the heaviest vessel traffic was observed at this location among the observation locations. Many vocalizations were recorded in the daytime, although heavy vessel traffic was also observed in this time period. Potential reasons of this behavior could be either or both (i) adaptation to the heavy vessel traffic (ii) benefit to use this location for vocal communication. Active vocalization during the daytime seems to be contradictory since many previous studies reported active vocal behavior in the nighttime (Ichikawa et al., 2006; Matsuo et al., 2013; Tanaka et al., 2017). Further continuous PAM study would be required to examine if this is a consistent habitat use pattern of local individual(s) in this area. The result that the vessel passage did not significantly relate to the rate of detected calls might be interpreted as supporting the adaptation hypothesis above, although further precise experiment of their behavioral change is required. However, it would be inappropriate, from this result, that the potential disturbance risks (e.g. noise masking of their vocal communication and vessel strike) is limited. Rather, if they “do not care vessel traffic”, those risks could be higher.

At location C, in both seasons, time and moon age showed significant relationship, and vessel passage did as well in dry season although not many vessels were detected (Table 4.1, Fig. 4.1.). Relationship with vessel traffic might not be uniform as no significant correlation with it was shown at location B. Their acoustic habitat use might be determined by multi-faceted factors, rather than single factor.

In dry season at location H, all four factors significantly correlated with the rate of detected calls, while only time did in rain season. Furthermore, average rate of detected calls is less in the rain season than the dry season (Table 3.3) Amongst four locations where many vocalizations were observed, only location H was located on the seagrass bed (Table 5.1). The seasonal variation of seagrass bed abundance might be reflected to their habitat use pattern.

In location J, water level significantly correlated to the rate of detected call in both season, while time (dry season) and moon age (rain season) did in one of the seasons respectively. Tanaka et al. 2017 examined the vocalization pattern at the same location in February 2015 (dry season), and reported (i) the rate of detected calls had distinctive 24-h periodicity, (ii) vocalization following sunrise (06:00-09:00) was limited (ii) current direction significantly related to the rate of detected calls. This diurnal pattern was consistent with the result of this study (Fig. 3.6), which was conducted in the same dry season. On the contrary, consistent vocalization day and night in the rain season might be attributed to their mating season, which is described in Chapter 4.

The reason behind how vocal hotspot was chosen was not clearly identified in this study, as the clear relationship between dugongs’ spatial variation of vocal behavior and geographical characters. Chavarría et al. (2015) reported the relationship between acoustic habitat, hearing and tonal vocalizations in the Antillean manatee (*Trichechus manatus manatus*). Dugongs might choose locations where their tonal vocalization is efficiently transmitted, although such acoustic habitat is also characterized by geographical features for some amount. Conducting frequency transmission experiment in the study site might bring an insight of the reason why vocal hotspots were chosen. The existence of vocal hotspot was suggested in Sibu-Tinggi Islands, Malaysia, but the geographical feature is considerably different from it around Talibong Island. Accumulating the information about vocal hotspot in other habitat might lead generic understanding about the reason behind, but if not, acoustic survey per habitat would be vital.

As a limitation, there would be some factors other than those considered in this chapter. Behavioral state, such as the existence of conspecifics in vicinity may influence their vocalization rate, in addition to the physical factors. Given dugongs show the callback response to the conspecific calls (Ichikawa et al., 2011), the vocalization rate might elevate when they communicate with other individual(s) nearby. Individual distinction was not carried out in this chapter, but it would enhance the understanding of their behavioral context behind the active vocalization.

Although the presented analysis included the vessel traffic as one of the explanatory variables in GAM, the response variable, i.e. rate of detected call, does not necessarily represent the behavioral states of dugongs. In other words, it is inappropriate to conclude that dugongs in this area was not affected by vessel traffic. Potential behavioral changes in response to vessel traffic have been reported in previous studies, for example, reduced feeding time budget (Hodgson and Marsh, 2007) and changes in call characteristics (Ando-Mizobata et al., 2014). Additionally, vocalization masking cannot be ignored, since the sound pressure level of boat sounds is much higher than that of dugong calls. The audiogram of dugong is not yet examined, while it was measured for West Indian Manatee (Trichechus manatus) (Gerstein et al., 1999). This information might potentially be crucial for the impact assessment and management strategy of vessel traffic, as Gerstein et al. (1999) suggested that, given the manatees' limited low frequency hearing sensitivity, it is likely that manatees have difficulty detecting and locating approaching boats from safe distances. If the same is applied to dugongs, the disturbance risk could be increased. Quantitative measurement of dugongs' hearing characteristics and subsequent behavioral response to vessel traffic such as Before-After Control-Impact studies is expected.

5.5 Conclusion

This chapter revealed that, the relationship between spatio-temporal pattern of dugongs' acoustic habitat use and environmental/anthropologic factors was not consistent within their habitat, although there were significant correlations at some of the locations. This implies the importance of the fine-scale monitoring, as the estimation (interpolation and extrapolation) of their acoustic habitat use might not be always adequate. In future, impact of human activity should be quantitatively assessed hearing characteristics and behavioral responses, in order to design a scientifically validated restriction guideline.

Table 5.1 The detailed information of the deployment in both seasons. 'Water depth' means the water level measured at the timing of deployment, and average depth was calculated over the observation periods. Cluster No. was determined by the k-means clustering considering average depth, distance to the shore and distance to the seagrass bed.

Location	2019 Coordinates	Observation periods	Durations (h)	Water depth (m)	Average depth (m)	Distance to shore (m)	Distance to seagrass bed (m)	Cluster No.
A	N7° 17.512' E99° 23.282'	5 Sep - 11 Sep 2019	144	7.5	8.0	1205	2562	1
B	N7° 17.508' E99° 24.358'	21 Sep - 26 Sep 2019	120	10.7	11.4	1504	1164	3
C	N7° 16.426' E99° 24.363'	5 Sep - 11 Sep 2019	145	1.7	2.6	1135	248	2
D	N7° 16.420' E99° 25.470'	13 Sep - 19 Sep 2019	143	3.7	3.0	775	375	2
E	N7° 16.434' E99° 26.535'	21 Sep - 26 Sep 2019	120	6.8	7.5	1544	591	3
F	N7° 15.394' E99° 27.415'	13 Sep - 19 Sep 2019, 21 Sep - 26 Sep 2019	270	3.6	3.1	762	85	2
G	N7° 14.308' E99° 25.419'	13 Sep - 19 Sep 2019	150	1.6	0.6	1079	0	2
H	N7° 14.297' E99° 26.517'	21 Sep - 26 Sep 2019	126	1.7	1.0	603	0	2
I	N7° 13.222' E99° 25.413'	5 Sep - 11 Sep 2019	145	3.3	2.7	2388	0	3
J	N7° 12.799' E99° 24.196'	6 Sep - 12 Sep 2019, 14 Sep - 20 Sep 2019, 22 Sep - 27 Sep 2019	420	4.4	4.1	1009	443	2
K	N7° 12.156' E99° 23.279'	13 Sep - 19 Sep 2019	150	8.8	7.6	435	2217	1
		total	1933					

Table 5.1 continued.

	2020							
Location	Coordinates	Observation periods	Observation durations (h)	Water depth (m)	Average depth (m)	Distance to shore (m)	Distance to seagrass bed (m)	Cluster No.
A	N7° 17.539' E99° 23.266'	22 Feb - 1 Mar 2020	192	8.3	7.6	1247	2562	1
B	N7° 17.620' E99° 24.201'	3 Mar - 11 Mar 2020	204	4.8	4.5	1199	1213	2
C	N7° 16.384' E99° 24.306'	22 Feb - 1 Mar 2020, 3 Mar - 11 Mar 2020	396	2.2	1.4	1214	311	2
D	N7° 16.462' E99° 25.424'	3 Mar - 12 Mar 2020	222	2.3	2.5	858	426	2
E	N7° 16.404' E99° 26.466'	22 Feb - 1 Mar 2020	192	7.5	5.9	1416	694	2
F	N7° 15.438' E99° 27.578'	22 Feb - 1 Mar 2020	192	5.6	3.8	1048	194	2
G	N7° 14.309' E99° 25.370'	3 Mar - 11 Mar 2020	204	2	2.1	965	0	2
H	N7° 14.262' E99° 26.605'	22 Feb - 1 Mar 2020, 3 Mar - 11 Mar 2020	396	2.2	1.2	541	0	2
I	N7° 13.235' E99° 25.465'	3 Mar - 11 Mar 2020	198	3.3	2.8	2398	0	2
J	N7° 12.806' E99° 24.058'	24 Feb - 2 Mar 2020, 4 Mar - 11 Mar 2020	326	4.5	3.6	751	430	2
K	N7° 12.166' E99° 23.281'	22 Feb - 1 Mar 2020	197	8.1	7.6	418	2200	1
		total	2719					

Table 5.2 The results of GAM. Significance codes indicate: "***" $p < 0.001$, "**" $0.001 < p < 0.01$, "*" $0.01 < p < 0.05$, "." $0.05 < P < 0.1$. "+" indicates those variables were selected in the best model based on the AIC value.

	2019 (Rain season)				
Location		Time	Water level	Moon age	Vessel
C	p-value	***		**	.
	AIC	+		+	+
H	p-value	*			
	AIC				
J	p-value		**	**	
	AIC		+	+	

	2020 (Dry season)				
Location		Time	Water level	Moon age	Vessel
B	p-value	***		***	
	AIC	+		+	
C	p-value	***		***	*
	AIC	+		+	+
H	p-value	***	***	***	***
	AIC	+	+	+	+
J	p-value	***	*		
	AIC	+	+		

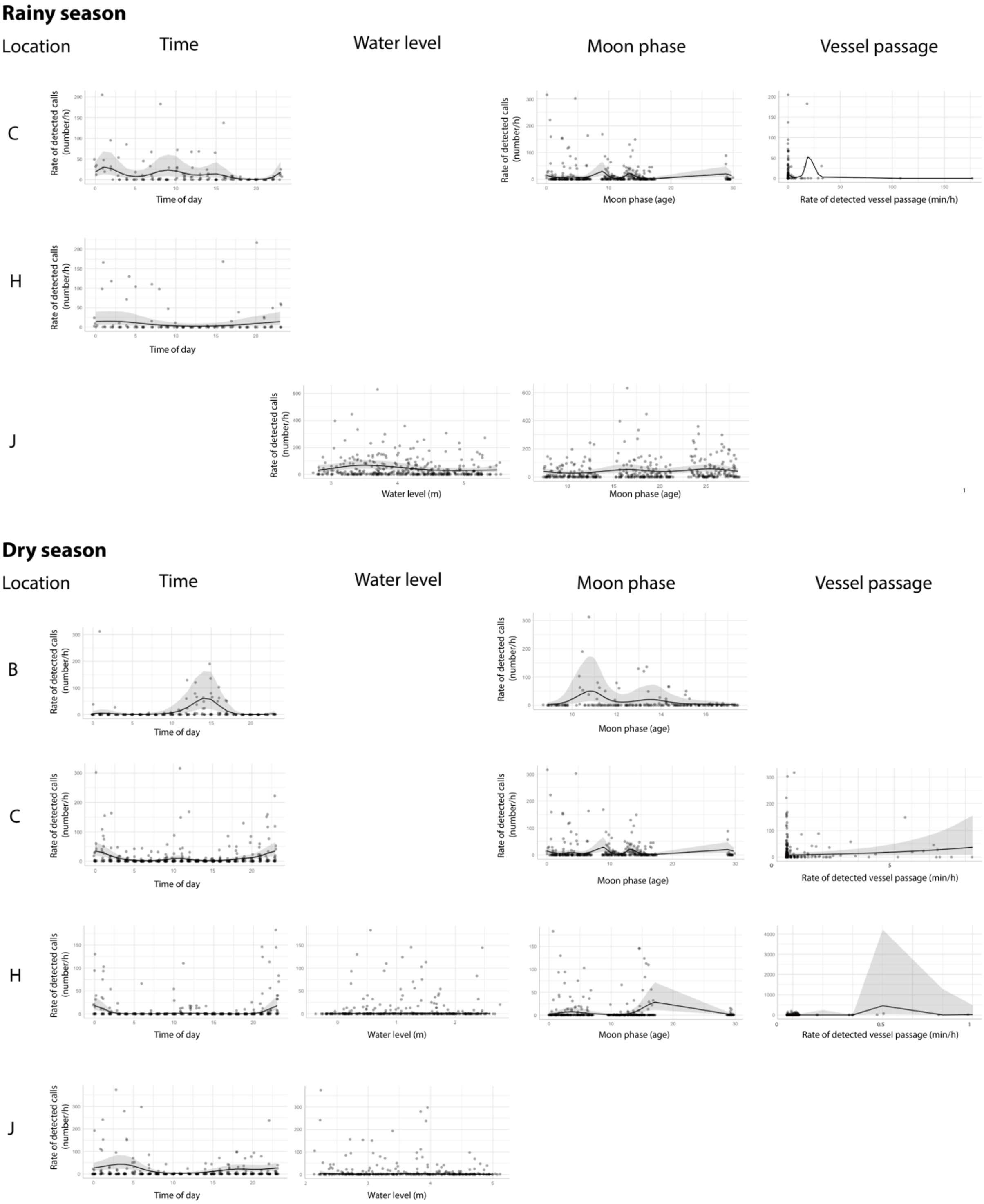

Fig. 5.1 Observed values (dots) and expected models (lines and shaded areas) of GAM for each variable. Shaded area indicates 95% confidence interval. Horizontal axis represents each variable, while vertical axis represents the rate of detected calls (number/h).

Chapter 6 General discussion

6.1 Summary of this study

In **Chapter 1**, a social context and current challenges toward harmonized coastal management, namely the necessity of collecting spatio-temporal socio-ecological information in fine scale were presented. In this context, I set the scope of this study, i.e. examining the habitat use of dugongs and vessel traffic with underwater acoustics in Talibong Island, Thailand. The knowledge gap arises from that many of the existing dugong MPA is designed based on the snapshot visual survey in relatively large scale and thus temporal plasticity and fine scale management has not been well considered. In the diverse concept of social informatics, this study attempts to demonstrate the effectiveness of applying ICT, namely underwater acoustic information, to propose a harmonized coexistence of human society and biosphere in a coastal area.

In **Chapter 2**, the analytical framework to automatically extract target sounds, i.e. dugong calls and vessel sound, was developed. This was necessary to handle large audio dataset collected by relatively long-term acoustic monitoring with multiple recorders. A technical challenge lies in the low sound-to-noise ratio in coastal shallow waters. To overcome this, supervised machine learning was employed. The developed classifier discriminates dugong calls and tonal noise which lies in the similar frequency band by combining contour and MFCC features. In terms of the vessel sound, entropy threshold detector was developed to detect broadband sound. To remove false positives, simple classifier was trained using energy value in different frequency bands. Furthermore, vessel types were classified with the frequency characteristics and duration of detected sounds, although it is still a preliminary result at one monitoring location. Those developed tools were utilized in the following chapters.

In **Chapter 3**, spatial and temporal variation of vocalizing dugongs were illustrated, based on the one-month continuous acoustic monitoring at 11 locations in two distinctive seasons. The spatial distribution of dugongs' acoustic presence was concentrated to a few locations and its pattern was mostly consistent in two seasons. On the other hand, the timing of their active usage varied among locations. Those variation might be due to the heterogeneity of their behavior. Based on this result, spatial management measure would be primarily expected to effectively preserve their social behavior via vocalization.

In **Chapter 4**, traffic of motorized vessels was examined in spatial and temporal manner. Unlike dugongs' habitat use, spatio-temporal occurrence of vessel traffic was relatively consistent in both seasons. Heavy traffic was observed in either sea route or near ports, and in daytime more than nighttime. This is assumed to reflect the time schedule of local livelihood, e.g. fisheries and transportation. In addition, based on the vessel type classification, the timing that speedboat passing at one location was concentrated around noon. Given this vessel type has relatively high disturbance risk (e.g. vessel strike and noise pollution), paying attention to this time period might be meaningful to mitigate the threat.

In **Chapter 5**, the correlation between dugongs' acoustic habitat use and environmental/anthropological factors was examined. In terms of temporal pattern, significant correlation was recognized, but those correlating factors varied among locations. At a few locations the spatial overlap of active vocalization and vessel passage was observed, but the correlation between them was not always significant. The relationship between spatial preference of dugongs' vocal behavior and geographical features (e.g. distance to shore, seagrass bed, average water level) was not obvious. Those results implied that interpolating and extrapolating the acoustic habitat use of dugongs with environmental and anthropological factors were not fully appropriate. Those findings raise the importance of fine-scale monitoring in their habitat.

Hereby in this **Chapter 6**, implication to local coastal management measure based on the findings of this study will be summarized. The potential recommendation to other dugong habitats will also be suggested subsequently, including the efficacy of passive acoustic monitoring in examining the habitat use of marine mammal and vessels in local coastal area. In addition, a potential importance to consider short-term temporal dynamics in marine spatial planning will be provoked. Limitation and the future perspective will be stated in the end.

6.2 Implication to coastal management

6.2.1 Implication to local management measure in the study site

This study illustrated the spatial and temporal overlap between dugongs' acoustic presence and vessel traffic, particularly at location B in the dry season and location J in both seasons (Fig. 3.5, 3.6, 4.1, 4.2), although significant correlation of them was not always distinctive (Table 5.2). At location B, around 12:00 – 17:00 the overlap of their usage was detected. At location J, temporal overlap was suggested around 6:00–18:00 (daytime) in the rain season and 18:00–6:00 (nighttime) in the dry season (Fig 3.6, 4.2). The results from GAM did not necessarily indicate that local residents do not have to pay attention to the influence of vessel traffic to dugongs. Rather, this imply that there are some remaining risks of physical collision with vessels and potential masking effect to their vocalization, because dugongs might not explicitly avoid the vessel traffic. More specifically, from the empirical observation in the field, location B encounters heavy passage of larger vessels such as trawler or speed boat, since that location is in the middle of the sea route as described above. On the contrary, at location J, long-tail boat for small scale fisheries were frequently observed while no speedboats and trawlers were spotted during the field survey (K. Tanaka unpublished data). The implications for local management from those evidence is that, vessel operators passing those locations and time, particularly location B in the afternoon, might be advised to pay attention to surroundings or lower their speed.

6.2.2 Implication to other dugong habitats

General implication for coastal management in dugongs' habitat, which is derived from the findings of this study is; (1) spatial management measure, e.g. designating a protected area, should be effective and primarily considered (2) temporally dynamic regulation in the habitat might be an option based on the temporal variation of dugongs' acoustic presence. Given the consistency of vocal hotspots, those areas should be prioritized in coastal management, in addition to the core area of their distribution identified by visual observation. In this sense, a survey to examine their acoustic presence, even though it is a snapshot towed acoustic survey, should be considered in a survey designing stage. Given the temporal variation, fine-scale continuous acoustic survey would be expected to inspect the prioritized time to optimize the local management measure. However, it naturally requires more times, costs and labors for the survey. Whether carrying out such fine-scale acoustic survey would be weighed against the urgency of population status.

6.2.3 Implication to coastal management

The MSP for marine megafauna primarily considers the spatial aspects of coastal management (Augé et al., 2018). Although the long-term plasticity of MSP has been proposed considering the dynamics of coastal socio-ecological systems and the effect of climate change (Gilbert et al., 2015; Gissi et al., 2019), fine-scale temporal dynamics have not been previously proposed to the best of our knowledge. Based on our findings on the temporal variations in habitat use by dugong, incorporating short-term temporal variations into MSP might harmonize species conservation and human livelihood activities. This aspect should be examined further, particularly in coastal areas.

This study also raised an efficacy of PAM to provide a layer of the habitat use of vocalizing animal and vessel traffic in a local coastal area. Efforts of scientific research have naturally been concentrated to coastal areas which is easily accessible from developed countries. This concentration is also reasonable since the disturbance risk to marine ecosystem is large in industrialized areas. Local coastal management in developing countries is also doubtlessly important, but the effort to collect information in such area is relatively less. One of many challenges lies in the limitation of available monitoring methods. As raised in Chapter 4, not many vessels passing in local coastal area equip AIS to collect information about their traffic. In this context, PAM has a potential to provide the baseline spatio-temporal information about motorized vessel traffic in addition to vocalizing marine megafauna. Given vessel traffic is one of the key layers in many areas to consider MSP, not limited to the habitat of vocalizing endangered species, this study's approach using PAM has a huge applicability. Adopting PAM as one of the tools, to collect baseline information of ecological-anthropological layer in local coastal area should be promoted in global scale.

6.3 Research limitation

This study has certain limitations. First, PAM cannot confirm animals' absence, particularly when social calls are targeted as this study did. Given that the vocalization rate of dugong varies even on a fine scale (Tanaka et al., 2017), associating acoustic presence with species presence/absence is not always suitable. For example, the distribution of the mother-calf pair, which should be conserved while maintaining the local population, was clumped around Location F in a previous study (Ichikawa et al., 2012); however, only a few vocalizations were detected at this location. Therefore, combining visual and acoustic surveys is important to provide spatial information on dugongs' habitat use. Similarly, while motorized vessel passage can be acoustically detected, several other anthropogenic activities cannot be detected by PAM, such as deployment of fishing gear. Moreover, this study did not thoroughly quantify the 'influence' of vessel traffic on dugong behavior. Potential behavioral changes in response to vessel traffic have been reported in previous studies, for example, reduced feeding time budget (Hodgson and Marsh, 2007) and changes in call characteristics (Ando-Mizobata et al., 2014). Additionally, vocalization masking cannot be ignored, since the sound pressure level of boat sounds is much higher than that of dugong calls. Thus, anthropogenic influences on hearing characteristics and behavioral responses should be quantitatively assessed to design a scientifically sound restriction guideline.

6.4 Future perspectives

To support the science-based decision making towards harmonized coastal management in dugong habitat, there are several ways forward to integrate with the output of this study. First, quantitative analysis of dugongs' behavioral response to vessel traffic could be more accumulated. Although GAM assumed in Chapter 5 adopt the rate of vessel passage as one of the explanatory variables, it did not directly examine its influence to dugongs' behavior. Adding such knowledge would be beneficial to carry out quantitative risk assessment, and consequently to create convincing guideline for local decision makers and stakeholders.

Second, combining multiple layers derived from several methodologies would be essential to achieve harmonized coastal management and planning, corresponding to the limitation raised above. Along with visual surveys and satellite tracking, interviews (Hashim et al., 2017; Rajamani and Marsh, 2010, 2010) should be conducted as they provide the practical information about fisheries, tourism and other human activities. Particularly, the spatio-temporal distribution of fishing gears (e.g. gill net), which has the highest proportion of incidental death, should be examined and integrated (Hashim et al., 2017; Hines et al., 2020). Additionally, habitat assessment (Budiarsa et al., 2021; Heng et al., 2022; Yamato et al., 2021) shows the suitability of key areas, such as feeding ground and rearing areas, and their temporal degradation patterns.

Finally, to support the decision making of local government and the public, economical point of view would play a critical role. This is because many conservation measures impose the restriction of human activities more or less. Cost-benefit analysis is important in a process of decision making, in parallel with the quantitative baseline information of ecological-anthropological situation in a certain area. Petcharat and Lee, (2020) measured the nonuse value of the dugong in Thailand, in order to elicit people's preference relating to dugong conservation. Potential costs derive from restrictions of fishing, vessel passage, and other activities. Benefits, on the other hand, would come from eco-tourism, cultural value and ecological service, although some of them are not straightforward to convert into monetary term. Estimating those cost and benefit in different scenarios of MSP would contribute to the policy consideration for coastal management.

6.5 Concluding remarks

While habitat use of dugong have been examined in multiple areas, there still is a knowledge gap because of the difficulty of continuous monitoring in fine scale. This study tackled this issue by utilizing passive acoustic approach, and at the same time illustrated the vessel traffic in their habitat. The outcome provides a unique layer in the consideration of coastal management strategy in dugongs' habitat. Furthermore, this study potentially shed a light on the importance to consider the temporal factors in MSP, and on the efficacy of PAM in local coastal area. Integration with other inputs from social, economic and ecological perspective would contribute to the harmonized and appropriate coastal management in dugongs' habitat.

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