Using data mining and spatial analysis for mapping the economic value and resources of indigenous communal sea in Indonesia: Kei Islands

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Abstract. One of the most effective ways to control the rate of illegal exploitation and illegal fishing in order to maintain the sustainability of marine resources in Kei Islands, Indonesia, is by using the custom way of life and local wisdom approach. The indigenous communal right of the sea is one of the traditional rights that is still strongly used to manage the exploitation of certain parts of the seas in the region. The purpose of the study is to map the economic value, the rate of fish exploitation and the type of fish species in the indigenous communal seas. The aim is a better understanding of marine resources in 22 indigenous communal seas, providing a significant input for local government that can be used in further policies to maintain the sustainability of marine resources in Kei Islands. Given the large number of the dataset used, with over 3000 samples, based on a one-year survey from June 2017 to June 2018, the integration of data mining and spatial analysis is useful for a better understanding of our findings. The result of the study provides significant input for the local government, which can consider the application of marine protected areas (MPA) to preserve the marine resources, and creating programs to increase the welfare of coastal communities.
Key Words: coastal communities, Kei Islands, MPA.

Introduction. Kei Islands is an archipelagic region with a higher degree of dependency to the sea compared to other regions in Indonesia. Thus, the need for sustainable marine resources is inevitable. In practice, illegal fishing and illegal conduct in fishing activities still occur (Parsons et al 2014). Current conditions and fishing behavior may endanger the sustainability of marine resources in the region, considering the declining trend of fish availability (Teniwut 2016). In addition, more than half of coastal communities in the region rely on the sea and its resources to support their daily needs. The money generated from the coastal area in the Kei Islands amounts to 17766 USD monthly (Picaulima et al 2017), which is very low, considering some socio-economic indicators, such as the high number of children in each household related to the expenses for food and education.

The current socio-economic condition in the region has forced many local fishermen to increase their efforts in utilizing marine resources for enhancing the generated income. This resulted in illegal fishing activities and the overexploitation of marine resources in the region. Other fishery activities such as aquaculture also contribute to another source for revenue. If local fishermen risk entirely turning from fishing to aquaculture, the unpredicted outcome might jeopardize their food security (Lopes et al 2018). In addition, latent problems arise in marine culture in the region, such as asymmetric information on seaweed supply chain, price and demand; the seaweed farming activities are increasing more than other aquaculture activities (Teniwut et al 2017a; Teniwut et al 2017b; Teniwut & Teniwut 2018). Therefore, this delicate condition has to be dealt with properly. On one side there is the economic pressure, while on the other side is the sustainability of marine resources. Nevertheless, as Stead (2005) pointed out, addressing the socio-economic conditions in every policy can preserve the sustainability and increase the welfare of the fishermen. Therefore, using all available options and approaches is a necessity to gain marine sustainability. In the current case, the socio-cultural approach has been addressed.

In contradiction with most developed countries in the world, some regions in Africa and Asia still hold local traditions and ways of life in strong belief and respect. However, there are places where even this respect is absent (Kristiansen & Sulistiawati 2016). In Kei Islands, "adat" is the term referring to the traditional way of life that is passed through the generations and regulates coastal communities in the region, including the rights for certain parts of the sea, known as "ulayat", meaning "right of the sea". The indigenous communal rights on certain parts of the sea have certain procedures for utilizing, managing and prohibiting the exploitation of resources in each communal sea. In Kei Islands, there are 22 parts of indigenous communal seas plus 1 public domain, as an agreement by all "raskap" ("raskap" is the territory of each kingdom, based on customary rights). There are 22 "raskap" heads. "Rat" is a native term for the "king" that holds the rights to prohibit and manage the land and sea in the area they rule. Each "raskap" employs a different procedure to allow their region to be utilized by communities from other "raskap". In general, there some paid sums known as "uang nasi" are involved. When there is no "uang nasi", those who enter the territory to use its resources will be expelled from the region, but it is free to enter for non-profitable purposes, likes transportation. Thus, managing the way local fishermen conduct their fishing activities based on a socio-cultural approach can ease the potential conflicts between them and the villages, and can also decrease the resistance against the sustainability of marine resources in the region, as there are also indigenous ways for preserving marine resources.

One way to satisfy each party regarding fishing management is by collecting data from local fishermen (Stead et al 2006) and managing the conflict (Bruckmeier et al 2005; Garza-Gil et al 2015). Fishermen need to balance social, economic and ecological aspects to preserve the sustainability of marine resources. Knowledge and information obtained can provide a better understanding to create a sustainability policy. Barrowclift et al (2017) had pointed out the importance of information regarding catch, trade, markets and socio-economy for future conservation of fisheries. The study of Silvano & Valbo-Jørgensen (2008) showed that knowledge about fish species, ecology, and habits can improve the management of fisheries. The idea of preserving marine resources in Kei Islands is widely acknowledged by the local fishermen in the region. A study of Hamid et al (2017) found that, in general, most of the local fishermen acknowledge the importance of sea resources conservation, and, at the same time, most of them agree that certain sea areas in Kei Islands have to be preserved for the future.

The combination of initial support for marine conservation with existing local wisdom in Kei Islands are the advantages of preserving marine resources in each indigenous communal sea. In this study, we used integrated data mining with spatial analysis to provide a better view on the current condition of each indigenous communal sea. The use of data mining in fisheries has been widely and rapidly increasing in the last decade: Oliveira et al (2017) on artisanal fleet in Portuguese; Cabreira et al (2009); Robotham et al (2010); Demertzis & Iliadis (2016) on fish species identification; Ogunlana et al (2015) on fish classification; and Joo et al (2011) on fishing set positions, among others. Spatial analysis has been widely and commonly used for mapping fisheries, especially in small island regions. Gill et al (2017) used it for mapping small-scale fishery activities in Barbados; Teniwut et al (2019) for selecting seaweed information; Le Cornu et al (2018) for determining relations between small-scale fisheries and climate change adaptation in Pacific islands. The combination of data mining and spatial analysis in fisheries, especially in small islands and small scale fisheries, is still lacking. Thus, the purpose of the study is to map the economic valuations and fish species, cluster the most exploited regions and forecast the future condition of some fish species in the region with the application of data mining and spatial analysis.

Material and Method

Study locations. The study was performed in the Kei Islands, in the southeastern part of Maluku Province, Indonesia (Figure 1). The study area is included in the coral triangle (CT) regions that contain high biodiversity and are part of a region that contributes to the food security of the country. The study area of 1438 km^2 is located at 5°45′0″S, 132°43′48″E. The study covers two administrative regions, Tual City and Southeast Maluku District, consisting of the three largest islands, Kei Besar Island, Kei Island, and Dullah Island, with 88 small islands combined. The study area is located in between two fishery management areas known as WPP 715 and WPP 718.

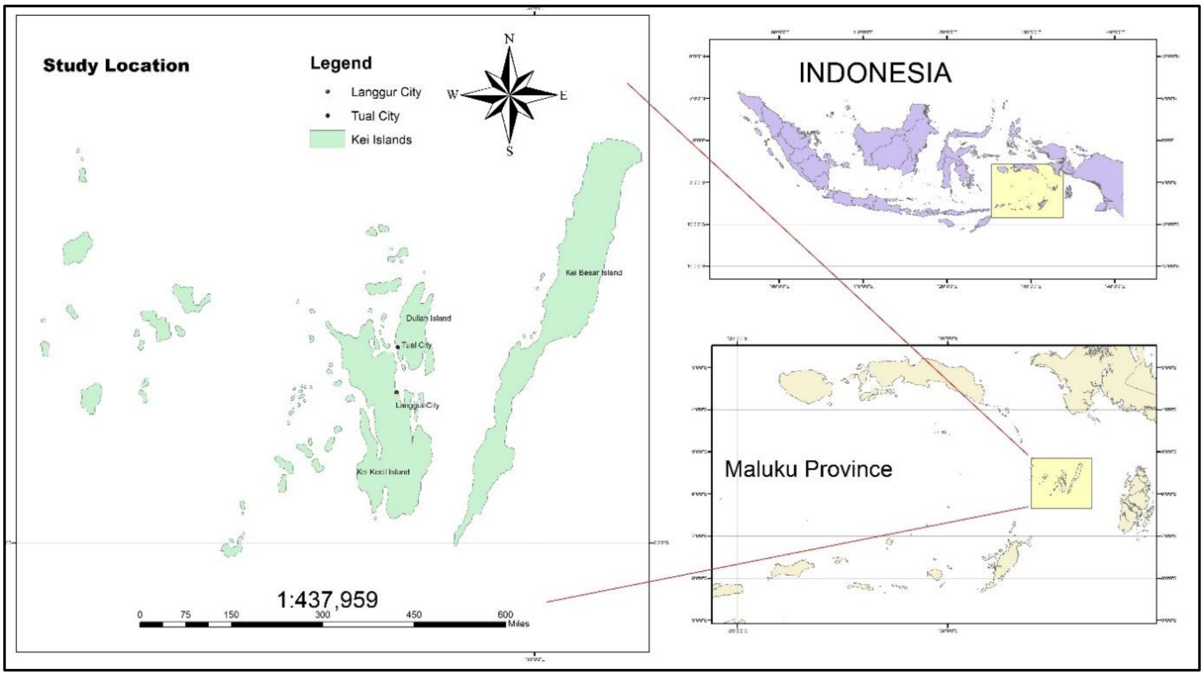

Figure 1. Study location.

Methodology. For data collection, we used field surveys using questionnaires and in-depth interviews with fishermen and fish sellers in the region. Data collection started with interviews and questionnaire filling at two local markets in Kei Islands, one in Tual City and the other in Southeast Maluku District, which are the center of fishery commodity transactions. Data collection took place from June 2017 to June 2018, being collected every first and third week in every month. By doing this, the collection the information needed was carried out, and the purchasing power of the customers in the region could be measured, in terms of fish products. Data regarding fish species, fishing grounds and sellers in the region was also collected. 3036 datasets were obtained. The data were cross-checked with fish sellers, fishermen in landing spots and fishermen from each village. The analysis method in this study consisted in two main analysis tools. The first was data mining and the second was spatial analysis. Prior to these, a descriptive analysis was conducted to enrich the discussion of the findings.

Data mining. Data mining has been widely used in every field of study, including in fishery and marine sciences. In this study we used two data mining techniques. The first is classification clustering with K-means and predictions with deep learning technique. The initial process of data mining followed the steps as proposed by Han et al (2012), starting with data cleaning and data integration to remove noise and inconsistent data and to combine multiple data sources. The next step was data selection, followed by data transformation. After this, data mining was run, arriving to results (Figure 2).

K-means clustering is used to classify the time, species and fishing grounds where fishing is most profitable. It is important to determine what species, period (month) and fishing ground have the most value in order to maintain its existence and manage the exploitation to preserve the marine resources in the region. Technically, k-means is based on the definition of k centroids, one for each cluster by minimizing the norm, as shown in the equation below. $\overline{M}_i$ are the mean points of all $M_j \in S_i$. V is the objective function, k is the cluster number, M_j is the data point, and S_i is the cluster case i.

$$V = \sum_{i=1}^{k} \sum_{M_j \epsilon S_i} (M_j - \overline{M}_i)^2$$

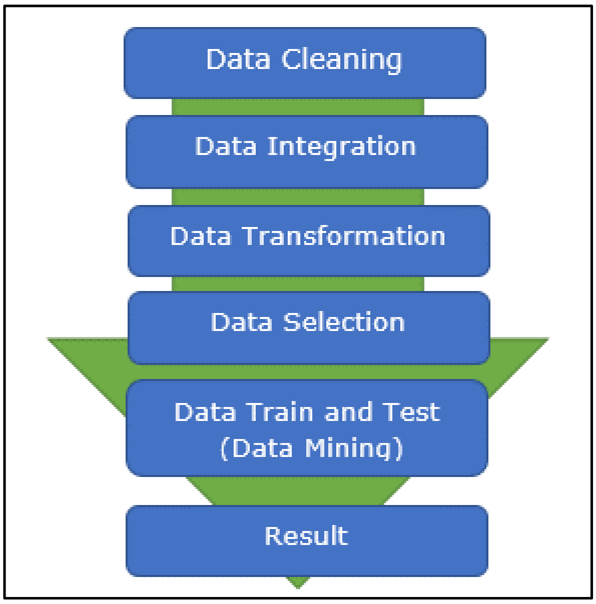

Figure 2. Data mining phases.

For predictive purposes, deep learning (DL) was used. DL models are able to learn useful representations of raw data and exhibit high performance on complex data (Bengio 2009). One of the many modern DL techniques is H2O. It has some advantages for predictive multiple layers from the ability of automatic, per-neuron, adaptive learning rate for fast convergence, optional speciation of learning rate, annealing, and momentum options. It is also able to prevent the model to be overfitting (Candel et al 2016) (Figure 3). The input is treated as a label with the same values, automatically identified as nonlinear. The choices for the activation function *f* are *tanh*. Function were rescaled and shifted to logistic functions, where the rectifier is the special case of maxout, in which the output of one channel is always 0. Maxout is a generalization of the Rectified Linear activation. Various *f* functions are defined below.

Tanh formula*:*

$f(\propto) = \frac{e^{\propto} - e^{-\propto}}{e^{\propto} + e^{-\propto}}$; range: $f(.) \in [-1,1]$

Rectified linear formula:

$f(\propto) = \max(0, \propto)$; range: $f(.) \in R_+$

Maxout formula:

$f(\propto 1, \propto 2 = \max(\propto 1, \propto 2)$; range: $f(.) \in R$

Where: x_i represents the firing neuron input values and w_i represents the weights; $\propto$ denotes weights combination $\propto = \sum_i w_i x_i + b$ (Candel et al 2016).

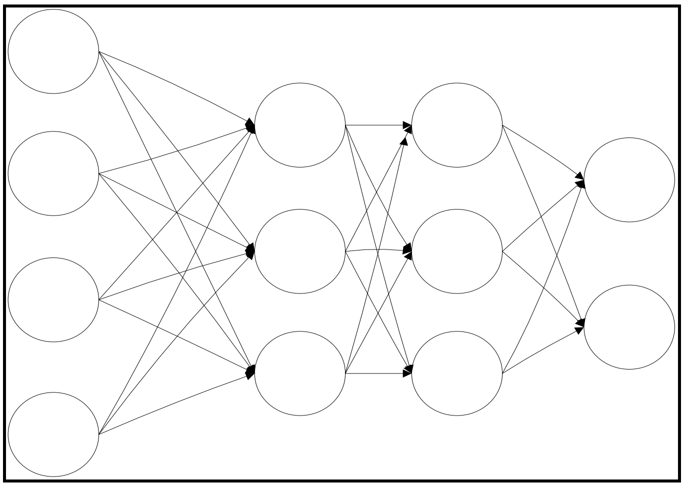

Figure 3. Basic deep learning neural network hierarchy.

In Figure 4, the categories of “raskap rights” distribution across lands and seas in the Kei Islands area are presented. There are 22 areas of indigenous communal seas and 1 public area, where every community can access and utilize the resources.

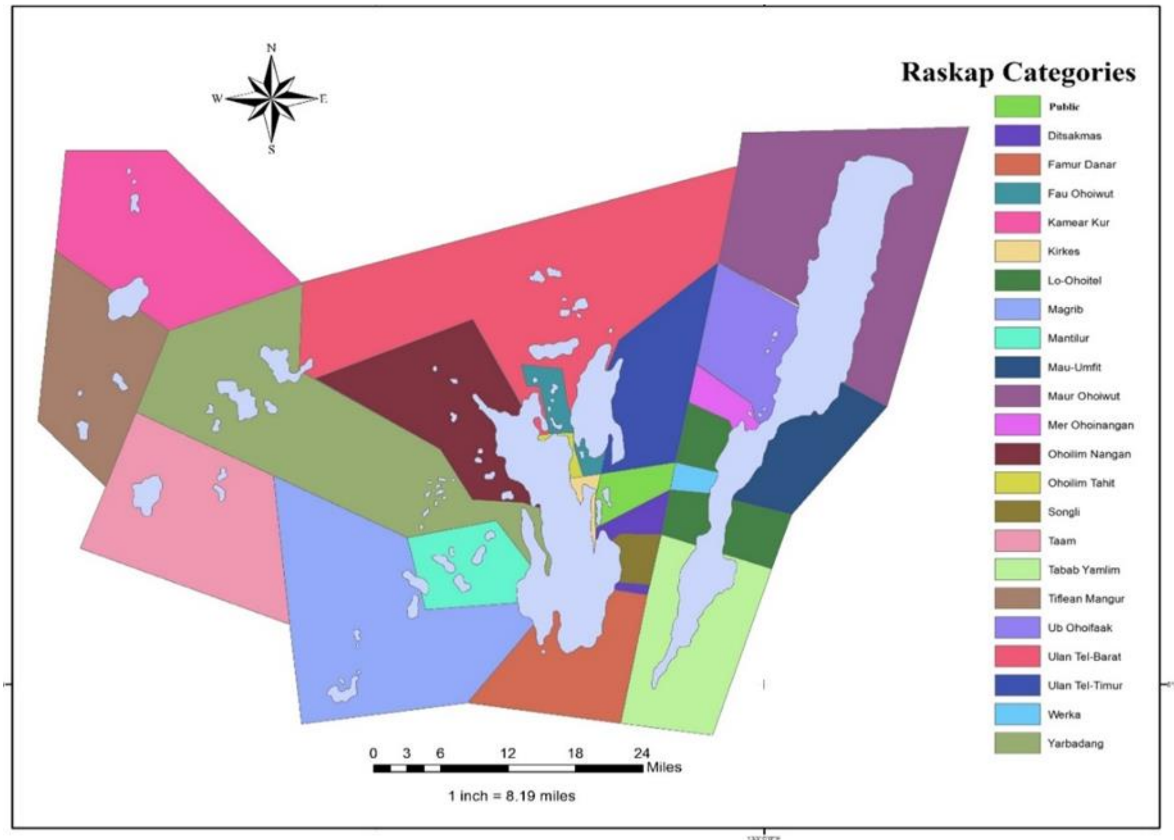

Figure 4. “Raskap” distribution in Kei Islands.

Spatial analysis. The spatial analysis has been carried out using the Geographic Information System (GIS), with ArcGIS software. The obtained data was processed with data mining, further being analysis in ArcGIS 10.4, as presented in Table 1. The data processing framework is summarized in Figure 5.

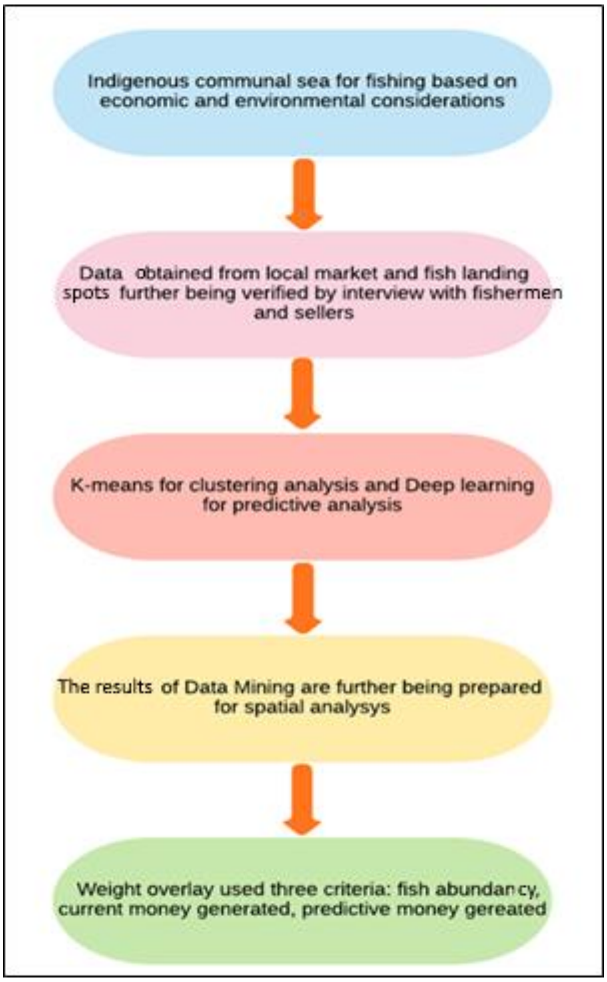

Figure 5. Analysis framework of the study.

Table 1

Spatial data

No	*Data*	*Method/Source*
1	Topography map	The local government of Southeast Maluku District and Tual City
2	Indigenous communal sea map	Rahail (1995), verified with field surveys and interviews
3	Money generated from each indigenous communal sea	Field surveys and interviews
4	Species from each indigenous communal sea	Field surveys and interviews
5	Clustering data of each indigenous communal sea	Field surveys and data mining
6	Predictive money generated from indigenous communal sea	Field surveys and data mining

Results and Discussion. Income generated from fishing activities in Southeast Maluku District showed that over half of it came from five fish species: *Stolephorus baganensis*, *Caesio xanthonota*, *Euthynnus affinis*, *Decapterus macrosoma*, and *Lethrinus lentjan*. These fish contribute to the income of fishermen with over 41715 USD per year. In Tual City, there were three fish species that contributed to half of the money generated from fishing activities: *Auxis rochei*, *Stolephorus baganensis* and *Caesio xanthonota*, generating about 43942 USD.

Based on the data obtained in the span of a year, for both Southeast Maluku District and Tual City, the highest income generated from fishing activity was from July to September, which was included the dry southeast monsoon (Figure 6). In addition, money generated from the fishing activity was higher in Tual City than in Southeast Maluku District, with about 81087 USD per year and 66883 USD per year, respectively.

Clustering analysis. The result of K-means analysis in Southeast Maluku District has indicated two clusters with an average distance of 3.578 between cluster 0 and cluster 1. Cluster 0 is a group of datasets with the following characters: the average fish selling data is 29.02%, with an average income 17% lower than the data in cluster 1. Cluster 1 is a group of datasets with 83% higher income characteristics than the dataset in cluster 0, with an average fish selling 129.48% higher than the datasets in cluster 0.

For Tual City, there were also two clusters with an average cluster distance of 3.224. Cluster 0 presented a number of fish selling 8.75% lower than datasets in cluster 1, with an average earning 22.25% lower than in cluster 1. Cluster 1 represented the datasets with a number of fish selling that was 57.47% higher than in the datasets in cluster 0 and the earnings were also 146.22% higher than in cluster 0 (Table 2).

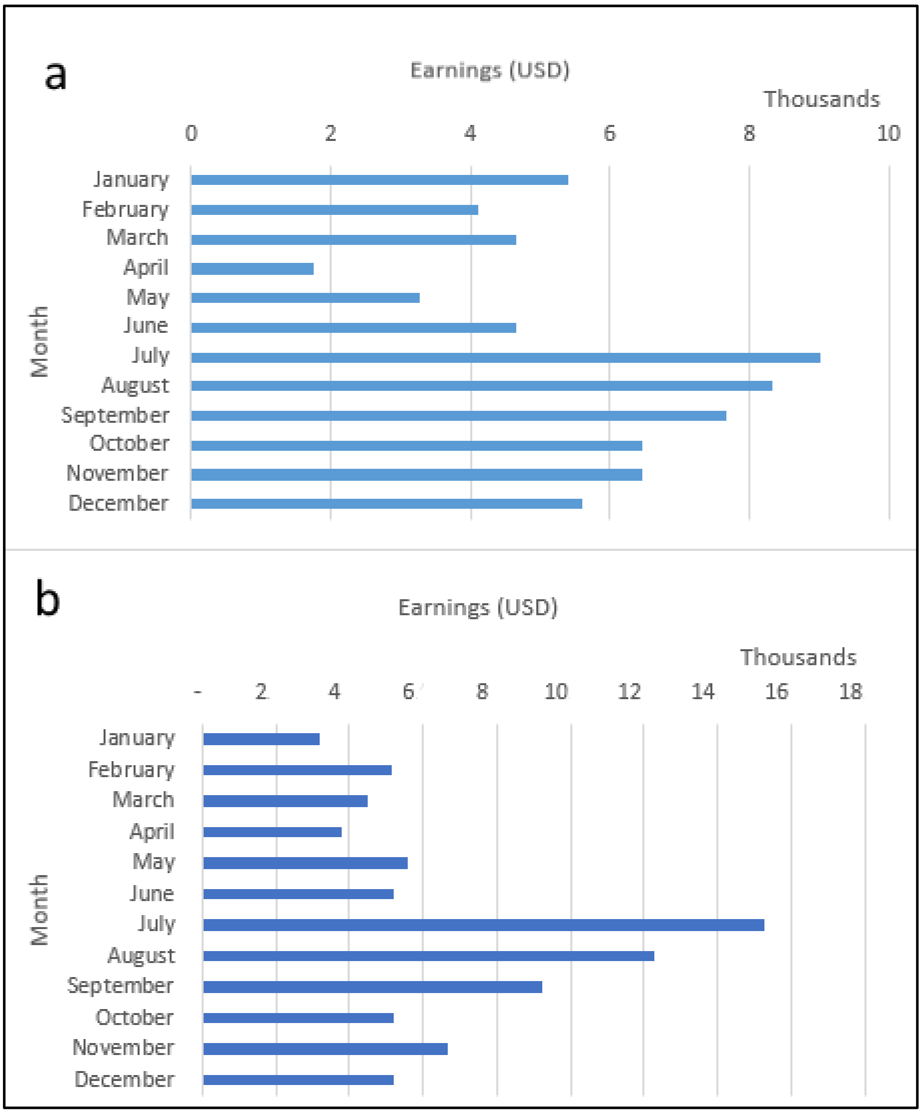

Figure 6. Earning generated from fishing per month: (a) Southeast Maluku District; (b) Tual City.

Table 2

Clustering analysis

No	*Clusters*	*Indicator*	*Value (Southeast Maluku District)*	*Value (Tual City)*
1	Cluster 0	Total fish sold	-29.02%	-8.75%
		Earnings by sold fish	-17.46%	-22.25%
2	Cluster 1	Total fish sold	129.48%	57.47%
		Earnings by sold fish	83.27%	146.22%

Table 3

Performance of the predictive model

No	Predictive method	RMSE (Southeast Maluku District)	RMSE (Tual City)
1	Generalized Linear Model	273540.6	271658.3
2	Deep Learning	114155.0	229171.6
3	Random Forest	169168.5	362545.9
4	Support Vector Machine	427730.5	685685.7

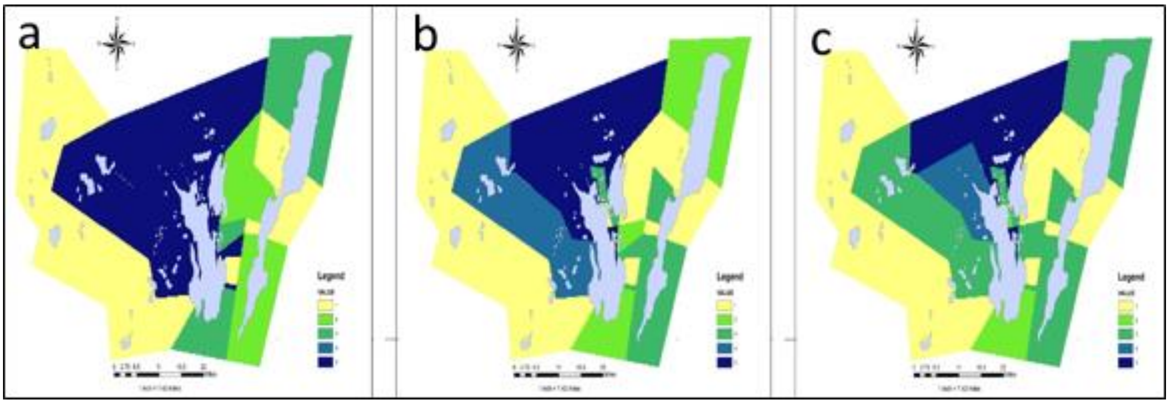

Figure 7. Spatial analysis criteria for each indigenous communal sea in Southeast Maluku District: (a) catch per year; (b) prediction of income generated; (c) current income generated.

Predictive analysis. The performance of various predictive tools for data mining based on the Root Mean Squared Error (RMSE) can be seen in Table 3. Deep Learning came up with the best performance, with the lowest value of RMSE. Therefore, predictive results from Deep Learning were used for further analysis for both Southeast Maluku District and Tual City. The earnings predictive model for Southeast Maluku District, based on fish species showed, in general, for the same fleet, the purchasing power and demand have negative influence on earnings generated from fishing activities of 8.05%, approximately 2229 USD. For Tual City, the predictive factors have a positive impact on earnings generated from fishing of 0.06%, or approximately 196 USD per year.

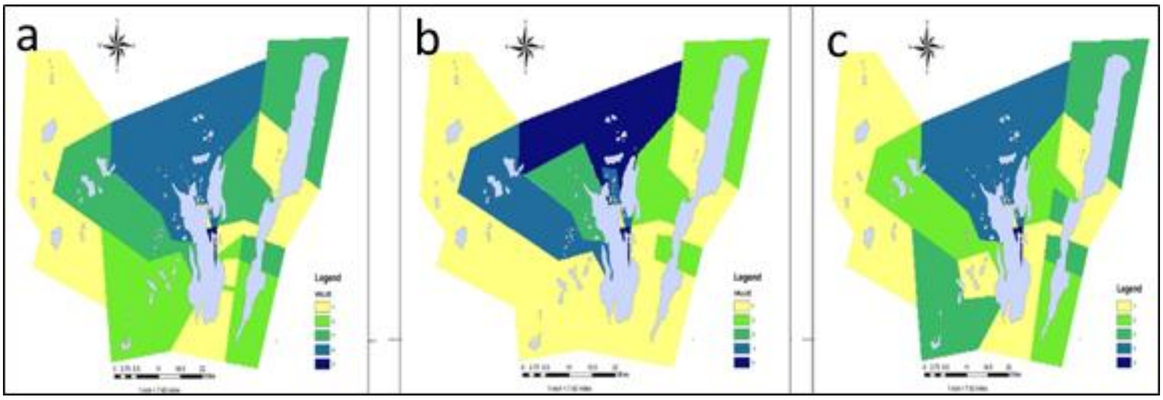

Figure 8. Spatial analysis criteria for each indigenous communal sea in Tual City; (a) catch per year; (b) prediction of generated income; (c) current generated income.

Spatial analysis. Results from data mining were used in the spatial analysis. In the clustering analysis, the data resulted from cluster 1 was processed. For the predictive results, the deep learning results with the best performance were compared to other predictive tools. Three categories were used in spatial analysis: current earnings generated, catch per year to measure the degree of fishing activity in each indigenous communal sea, and predicted earnings generated from fishing activities (Figures 7 and 8). These categories were analyzed by weight overlay. 1 to 5 categories were used, where 5 is the highest and 1 the lowest value of each criteria. As for the weight of each criteria, two scenario were constructed: the economic value and marine resources potential of each indigenous communal sea. The weight of the current generated earnings was 25% for both economic value and marine resources potential. The second criteria for economic value was the catch per year, in order to measure the degree of fishing activities in each indigenous communal sea. It was 35% for the economic value and 50% for the marine resources potential. The third criteria, predictive earning generated from fishing activities, was 40% for economic value and 25% for marine resources potential. These weights were determined based on inputs from practitioners and academicians (Figures 9 and 10).

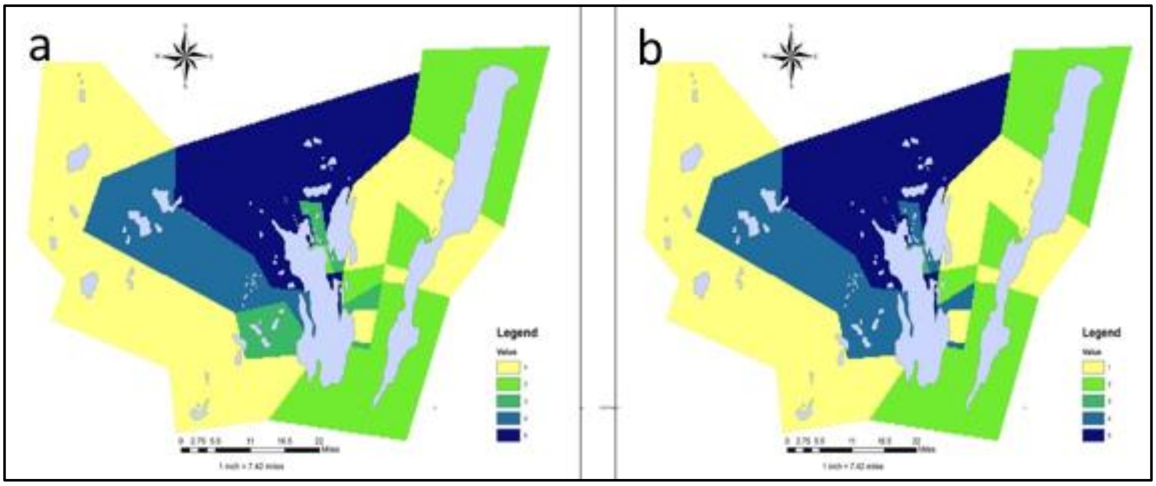

Figure 9. The result of weight overlay for each indigenous communal sea in Southeast Maluku District: (a) marine resources potential; (b) economic value.

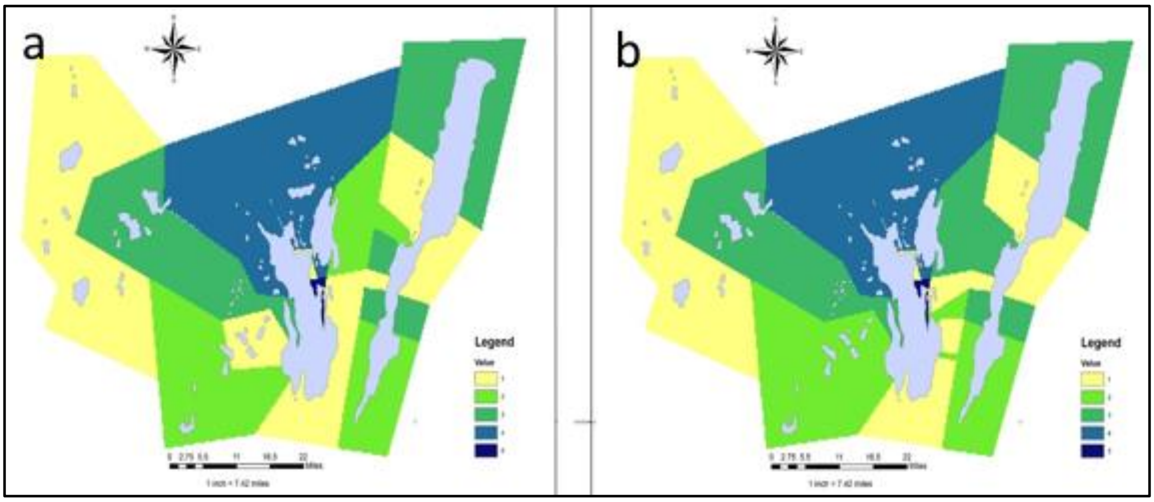

Figure 10. The weight overlay of each indigenous communal sea in Tual City: (a) marine resources potential; (b) economic value.

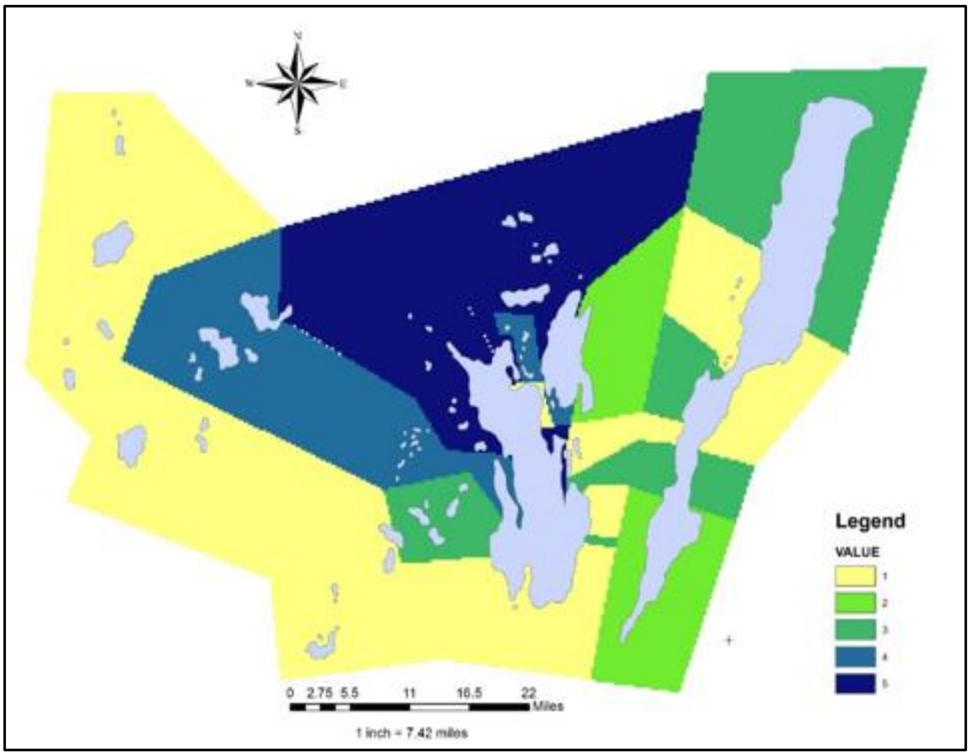

Figure 11. The most valuable indigenous communal seas in Kei Islands.

In Southeast Maluku District, the catch per year in most indigenous communal seas produces linear generated income, but there are some places where the income generated will decrease if the same pace on fishing activities is maintained, like in Raskap Maur Ohoiwut. For most parts, the communal seas will present an increase in income generated from marine resources. For Tual city, with the current pace of fishing activities, some areas will know a decrease in generated income, like Raskap Magrib, Yarbadang and Maur Ohoiwut, while in others the income will increase. The results of the two scenarios for Southeast Maluku District showed that the marine resources for most of the indigenous communal seas are in normal conditions, being no significant decrease in generated income from fishing activities in the area. There are, however, 2 exceptions for raskap, where the abundance of the fish have a negative relationship with the income generated, despite the high abundance of marine resources in the 2 regions. In Tual City, our findings also showed a similar situation, only three raskap having decreased income generated from marine resources. Four indigenous communal seas have the highest economic and marine resources in Kei Islands: Kirkes, Yarbadang, Oholim Nangan, Utan Tel-Barat. The seas with the highest potential were Ditsakmas, Lo-Ohoitel, Mer Ohoinangan, and Maur Ohoiwut (Figure 11). As for the rest of the raskap, the main reason in the regards of profitability was the long distance between the fishing grounds and local markets. The local fishermen tend to not conduct fishing activities in those communal seas, due to the distance, which is an obstacle for the traditional gears used, causing longer travel time, with a greater risk in terms of fish perishability.

Mapping each indigenous communal sea in Kei Islands is important to provide empirical information on the current condition of marine resources and their economic value in order to decrease the conflict potential among villages in the region. It also educates local fishermen regarding the best fishing grounds. These findings might help in avoiding illegal and unproductive fishing activities in the communal seas. Moreover, the best periods for fishing activities were established, from March to July. The monsoon contributes to the unstable rate of fishing activity of local fishermen in the region.

Most fishermen still concentrate in certain indigenous communal seas in the region. This is due to several reasons, one being customary knowledge passed from generation to generation based on ethnoclimatology (Dias et al 2018). Another reason is that, despite their eagerness to exploit marine resources available, the limited access and capabilities in capital impact the fishing gear owned, further resulting in the inability to conduct large scale fishing activities (Agapito et al 2019). Local fishermen in the region currently conduct their fishing activity traditionally and rarely use better technology, although, as Piovano et al (2012) pointed out, the socio-economic pressure might play a significant role the use of better technology by locals. The use of better technology can help not only to increase the economic aspects, but also to preserve the marine resources, because fishermen would know when to stop fishing to prevent overexploitation (Saville et al 2015). Despite that a higher catch mostly means the increase of income, there is an alarming condition for at least two raskap, Kirkes and Utan Tel-Barat. At the current pace of fishing activities, there is a great possibility for a decrease of marine resources in these two indigenous communal seas in the future. By mapping the indigenous communal seas, the current utilization and exploitation of the waters of Kei Islands can be known by local fishermen and help improve their income (Trouillet et al 2019). It can also provide information that might increase their support for marine conservation (Eriksson et al 2019).

Conclusions. To be able to sustain the marine resources in regions that are highly dependent on the sea for their source of economic welfare, producing useful information regarding water resources is one of the effective ways to persuade local fishermen to a certain form of sea conservation, like Marine Protected Areas (MPA). Our findings showed that the income generated from the sea in the Kei Islands tends to decrease yearly. Communal seas have met the criteria for marine conservation. By mapping the potential marine resources and economic value of each indigenous communal sea in Kei Islands, there are increasing chances for the local government to reach an understanding based on indigenous rules with local fishermen to prohibit overfishing, illegal fishing and over concentrated fishing in certain indigenous communal seas in Kei Islands as assurance to the future. The study concludes that the increase of fish catch does not always result in a high financial return in the region.

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