Aquaculture Pond Mapping in Sungai Udang, Penang, Using Google Earth Engine

Pemetaan Kolam Akuakultur di Sungai Udang, Pulau Pinang, menggunakan Engin Bumi Google

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ABSTRACT *Aquaculture has a vital function in ecology, environment, and economy. Without adequate monitoring and management, aquaculture might have negative environmental repercussions. In terms of managing and design the industry's long-term operations, it is necessary to map the distribution of aquaculture ponds. Aquaculture ponds can now be detected and mapped using remote sensing. A large-scale mapping can be performed fast due to the recent advancements in cloud computing and big data. In this study, 10 m Sentinel 2 images were used to classify aquaculture in Sungai Udang, Pulau Pinang. This study aims to compare three machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF) and Classification and Regression Tree (CART) that available in the Google Earth Engine (GEE) cloud computing platform in mapping aquaculture ponds. From 2016 to 2020, the SVM, CART, and RF generated 97.35%, 93.86%, and 93.48% overall accuracy, respectively. In general, SVM was the most accurate among the three machine learning classifier algorithms in classifying the three classes (aquaculture, vegetation, and urban). The area of the aquaculture pond derived from Google Earth Pro is nearly identical to the classified image's region. This study shows that GEE is useful in mapping aquaculture ponds on a small scale using a cloud-based and free platform. The result of this study can be used by a variety of organisations to manage and monitor aquaculture pond fish production and environment degradation.*

Keywords: Google Earth Engine, Aquaculture Mapping, Remote Sensing, Sungai Udang, Penang.

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ABSTRAK *Akuakultur memainkan peranan penting dalam aspek ekologi, alam sekitar dan ekonomi. Tanpa pemantauan dan pengurusan yang baik, akuakultur berkemungkinan untuk menyebabkan dampak negatif kepada alam sekitar. Dalam aspek mengurus dan merancang operasi jangka panjang industri ini, pemetaan kolam akuakultur amat diperlukan. Kolam akuakultur kini dapat dikesan dan dipetakan dengan menggunakan kaedah penderiaan jauh. Kini, pemetaan berskala besar dapat dilaksanakan dengan pantas kerana kemajuan terkini dalam pengkomputeran awan dan data besar. Dalam kajian ini, gambar 10m Sentinel 2 digunakan untuk mengklasifikasikan akuakultur di Sungai Udang, Pulau Pinang. Kajian ini bertujuan untuk membandingkan tiga mesin pengelasan pembelajaran seperti Support Vector Machine (SVM), Random Forest (RF) dan Classification and Regression Tree (CART) yang terdapat pada platform pengkomputeran awan, Google Earth Engine (GEE) dalam pemetaan kolam akuakultur. Dari 2016 hingga 2020, SVM, CART, dan RF masing-masing menghasilkan ketepatan keseluruhan sebanyak 97.35%, 93.86%, dan 93.48%. Antara tiga algoritma pengelasan pembelajaran mesin ini, SVM algoritma pengelasan pembelajaran mesin paling tepat dalam mengklasifikasikan tiga kelas (akuakultur, tumbuh-tumbuhan, dan bandar). Kawasan kolam akuakultur yang diperoleh dari Google Earth Pro adalah hampir sama dengan kawasan gambar yang dikelaskan. Kajian ini menunjukkan GEE dapat digunakan untuk memetakan kolam akuakultur dalam skala kecil melalui platform bebas berasaskan awan. Hasil kajian ini boleh digunakan oleh pelbagai organisasi untuk mengurus dan memantau pengeluaran ikan kolam akuakultur dan kemerosotan alam sekitar*

Kata kunci: Google Earth Engine, Pemetaan Akuakultur, Penginderaan jauh, Sungai Udang, Pulau Pinang.

1. Introduction

From 2001-2018, global aquaculture production of farmed water animals increases on average at 5.3 % per annual (FAO, 2020). A growth of world fish supplies up till 187 million tons with aquaculture like world production of capture based on projection data from the World Bank in year 2030 (The World Bank, 2013). This demonstrates that aquaculture is quickly growing. In the field of inland fisheries, aquaculture, and capture fisheries, Malaysian Fisheries produced 1.85 million ton fisheries production with a projected gain of RM 14.5 billion (DOF, 2020). Latest analyses by the Department of Fisheries Malaysia revealed that, agricultural gross national (GDP) in Malaysia is presently about 12.5% with the approximate commercial worth of RM 7.5 billion (DOF, 2020). Agriculture makes up around 92% of Malaysian level of self-sufficiency, with more than 18 000 farmers locally. The aquaculture sector in Malaysia has generated an estimated 391,000 million ton, which is cost about RM 3.1 billion (Azra et al., 2021).

Fish is the only major food item and is still mostly harvested from the wild rather than from farms. Historically, marine catch constitutes over 80% of the world's supply of fish. In recent times, however, catch fisheries could not keep up with the increasing requests, and numerous marine fisheries have already been overfished. The rate of fish consumption increased higher than supply from marine capture fisheries. The demand on the harvesters has risen, which leads to increasing pressure on many commercial fisheries and overfishing. Almost half of the known ocean fishing is fully exploited. Aquaculture fisheries can be more beneficial compared to captured fisheries. In terms of food security, worldwide figures show that aquaculture will make up for the deteriorating supply of seafood from captured fisheries and provide animal protein to increasing human population (Natale et al., 2013). Nonetheless, the rapid global expansion of the aquaculture sector has resulted in changes to huge regions of critical coastal and inland ecosystems, as well as a loss of products and services provided by natural resources (Pattanaik & Prasad, 2011). Besides that, bad environmental law and absence of correct planning and administration policies on level of international and national strategy (Smith et al., 2010) resulted to unsanctioned and disorganized growth of aquaculture and trigger the important current rate of environmental deterioration (Ottinger et al., 2016). The further expansion of world aquaculture creation will however offer a direct challenge to the management's ability to endure and human development of our planet. This is a global problem and is especially true of rural coastal populations in evolving nations (Beveridge et al., 2013; Hossain et al., 2013), because agriculture offers good nutrition and is a primary source of income for the poor (Ahmed & Lorica, 2002). The aquaculture sector pollutes freshwater bodies or rivers and water significantly in the surrounding waters. Wastewater produced during aquaculture is generally released unfiltered (Ottinger et al., 2016) producing pharmacological (He et al., 2016) and heavy metal storage (Liang et al., 2016), acceleration of eutrophication (Herbeck et al., 2013) and ensuring the accumulation of hazardous algal blooms (Keesing et al., 2011; Lee et al., 2011; Wang et al., 2008; Stiller et al., 2019).

Global statistical databases on aquaculture should be carefully assessed since there are evidence that certain data reported by Member States of the FAO are of doubtful standard. There are many causes for this, including over reporting of output levels by some nations (Pauly & Froese, 2012), underestimation for aquaculture volumes because the production volumes of huge quantities by small scale farmers in Asia and different areas whose production and trade information are incomplete, entering national and regional markets (Allison, 2011). Global aquaculture inventory and monitoring is a challenge and takes effort, time, and substantial expenditures (Marini et al., 2013). Considering that aquaculture has spread significantly throughout the world, it is imperative that production volume and value data on a worldwide scale be compiled, as well as the identification and aquaculture spatial distribution assessment on a national and international level. Such information is beneficial in analyzing the growing strain on ecosystems and the resulting environmental repercussions of this pressure (Ottinger et al., 2016). Additionally, improved aquaculture management via the use of remote sensing and geographic information systems (GIS) have been pushed (FAO, 2016). For the most part, until recently, the most prevalent method of obtaining data on aquaculture has depended on reviewing previously collected statistics data. However, there is lack of study regarding aquaculture pond mapping in Malaysia as there is no or limited research nor study have been done especially using Google Earth Engine. To the best of our knowledge, several studies have been done in Malaysia using Google Earth Engine for oil palm mapping (Shaharum et al., 2020), so this will be the first study on aquaculture pond mapping in Malaysia using Google Earth Engine.

The Google Earth Engine (GEE) which is a cloud computing platform is particularly tailored to satellite image processing and allows anyone to access and use image data to both the public and commercial sectors (Gorelick et al., 2017). GEE is accessible to everyone, simple to build algorithms and can batch image data rapidly, reducing geographic data analytics cost and complexity, in comparison with conventional image processing tools. This platform allows openly sharing and validating algorithms and results (Xia et al., 2020). It is critical to create an aquaculture pond map for the purpose monitor and plan the preserved operation of aquaculture. As a result, to evaluate the performance of machine learning classifiers such as Random Forest (RF), Support Vector Machine (SVM) and Classification and Regression Tree (CART) for inland fishpond mapping, we will use Classification and Regression Tree (CART), Random Forest (RF) and Support Vector Machine (SVM) for inland fishpond mapping. Penang's aquaculture fisheries experienced a remarkable average annual growth rate of 8.2% in production and 23% in value between 1995 and 2015. Penang's food fish production had the second highest wholesale value in the country, with aquaculture accounting for over 54% of the state's food fish production (58,736 metric tonnes valued at RM1,090.6mil). After Sabah, the state is now the second largest producer of aquaculture goods in the country, and the fish farming business has the potential to become a key driving force in the state's economic development. By using satellite imagery, we have identified Sungai Udang consists the most number of inland aquaculture ponds compare to other areas in Penang (Vaghefi, 2017). Sungai Udang is a fishing village located at Nibong Tebal, Penang at the end of Sungai Kerian towards the straits of Malacca. Number of ponds identified in Google Earth image for the year 2020 are 591. The total area of ponds 2.88km^2 and the shape of ponds are mostly rectangular and square, there are also some irregular shape ponds found. Therefore, this study aims to compare the SVM, RF and CART machine learning classifier algorithms that available within GEE for generating a better aquaculture ponds mapping across Sungai Udang, Penang.

2. Literature Review

The Food and Agriculture Organization (FAO) defines aquaculture as the cultivation of aquatic animals such as fish, crustaceans, molluscs, and aquatic photosynthetic organisms. Aquaculture industry involves either private or corporate ownership of the stock being grown, and it often includes the isolation of a species in a safe system (Beveridge et al., 2013; Naylor et al., 2000). The methods of farming are vastly different, but they always incorporate interventions to increase productivity, such as consistent storage, feeding, and predator deterrence (Campbell & Pauly, 2013; FAO, 2002). Aquaculture systems generate over 600 different animal species (Troell et al., 2014) such as, finfish (tilapia, salmon, carp, catfish, and trout), crustaceans (crabs, prawn, shrimp, and freshwater crayfish), and molluscs (clams, oysters, and mussels) (FAO, 2014). Aquaculture can be divided into several types of culture conditions that are used for the farming of aquatic creatures, according to the Food and Agriculture Organization (FAO, 2002), (1) Systems for brackish water aquaculture are often placed in estuaries, bays, lagoons, and fjords; (2) Mariculture (marine aquaculture) is defined as the growth of aquatic organisms in saltwater/seawater environments such as fjords, inshore and open waterways, and inland seas. (3) Freshwater aquaculture is the cultivation of aquatic creatures in freshwater bodies of water such as reservoirs, lakes, rivers, groundwater, and canals. However, for Sungai Udang, freshwater aquaculture is used for farming.

Water management is significant in aquaculture, since it excerpts the freshwater shortage and degradation of water quality through increasing waste (Verdegem & Bosma, 2009) and pollution (Cao et al., 2007; Peng et al., 2013). This has a negative effect on human health and the natural environment, especially in coastal regions which is low-lying that are ideal for fish farming and are therefore the most severely affected (Primavera, 2006). Aquaculture may help to provide food security and has other advantages in terms of economic and social, such as generating money, generating jobs and reducing related poverty (Paul & Vogl, 2011; Schumann et al., 2011; Slater et al., 2013; Smith et al., 2010). There is already proven evidence of the social, economic, and environmental significance of aquaculture as a major source of protein for a large number of countries, and it has the potential to substantially help alleviate global food insecurity. Aquaculture uses enormous quantities of water and substantially impacts water resource quantity and quality (Beveridge et al., 2013). With the development of the aquaculture sector, water contamination has emerged, and severe environmental consequences are caused. Bacterial and viral inflammation may lead to serious loss of productivity in the industry involved and may restrict growth of aquaculture. Aquaculture is a significant source of fertilizers, disinfectants, insecticides and other feed additives and is frequently applied to organisms including insects, waters, plant diseases in enormous amounts (Sabra & Mehana, 2015). Agricultural and wildlife biota, crop species may suffer toxicities, permanent damages, and loss if they come into contact with such pesticides (Holmstrom et al., 2003; Primavera, 2006). Additional contributions to the buildup of risk residues via adjacent habitat, heavy metals and other pollution from residential or industrial waste that has not been treated in aquaculture and across the whole food chain. Another environmental risk for aquaculture is the algal blooms in shallow waterways, since algal toxins impact the standard of cultivated species and may lead to a reduction or loss of whole harvests (Ottinger et al., 2016). Increasing consciousness of environmental effects of aquaculture, it is crucial to precisely evaluate and monitor this land use around the world. Understanding the connection between aquaculture development, environmental contamination, and the deterioration of natural resources may be gained through global information on the geographical extent, distribution, and variations of aquaculture.

Remote sensing is the study of utilizing reflected and emitted radiation to acquire information about a target that is a considerable distance away. Most of the time, sensor data is obtained through cameras, and the result is an image. The three types of platforms that offer remote sensing data are: airborne, land-based, and ground-based (Barbosa et al., 2015). Further, remote sensing sensor may be used for both passive and active data acquisition. Passive remote sensing uses sunlight to get information on the ground. The sensor will receive the ground signal. The active remote sensing does, in fact, produce a

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signal, and this signal is the information the object's reflected radiation sends back to the sensor (Joshi et al., 2016). Two forms of passive remote sensing are available: multispectral and hyperspectral. This study only focuses on multispectral passive remote sensing. Multispectral remote sensing information typically comprises of between 3 and 10 bands which are measured by the reflected energy wavelength. The bands comprise visible green, visible blue, visible red, Near-infrared (NIR), etc. Remote sensing data range from low resolution to high resolution in different spatial resolution. Spatial resolution defines the detail in the human eye in the pixel. The more specific information can be viewed and retrieved the greater the spatial resolution (Qu et al., 2017; Yokoya et al., 2017). However, remote sensing with a high resolution typically takes extra time to analyze your data. For example, Landsat, Worldview 2, Moderate Resolution Imaging Spectroradiometer (MODIS), IKONOS and sentinel are the most important for remote sensing data. Huge parts of global aquaculture activities happen in tropical and subtropical areas. Cloud cover limits the data acquisition from optical sensors and is a major constraint in tropical region. However, cloud cover effect is minimal in this study because the scale of study area is small. Remote sensing is an ideal method for the spatial assessment of aquaculture areas because it is cheap option compared to broad field surveys done by local authorities.

Besides that, it gives sight over huge areas of the Earth’s surface and even cover remote places which access may be troublesome. Earth observation can help in aquaculture management such as, site selection and mapping, environmental monitoring, and aquaculture ponds inventory (Ottinger et al., 2016). However, remote sensing data which are earth observing data have been growing enormously in terms of amount of data and rising degree of diversity and complexity are regarded as RS ‘Big Data’. RS ‘Big Data’ refers to volume, velocity, variety and complexity of remote sensing data that outstrip storage and processing power. Besides that, processing the huge RS ‘Big Data’ such as storing data, putting data into memory, processing, and evaluating data can be burdensome. One of the best solutions for this issue is cloud computing which process RS ‘Big Data’ on very powerful servers, which virtualize supercomputer for the users efficiently. Amazon EC2, Microsoft Azure and Google Earth Engine are examples of cloud computing platform for RS ‘Big Data’ processing (Ma et al., 2015).GEE is a free cloud computing platform unlike Microsoft Azure and Amazon EC2 are platform for cloud computing on a pay-as-you-go basis. It provides up to 40 years of petabyte scale remotely sensed imagery like Landsat, Modis and Sentinel 1, 2, 3 and 5-P including raw imagery, pre-processed, cloud-removed and mosaicked images which can be found in its data catalog. Computational time can be decreased because GEE platform is supported by the computing infrastructure of Google to enable simultaneous processing of geographical data. There is a Git repository provided by Earth Engine servers for storing and sharing of APIs (JavaScript and Python) script of users’ codes which can facilitate joint effort with other users. Code editor in GEE is a web-based Integrated Development Environment (IDE) is used to write, create, and execute sophisticated programs using the JavaScript API. The GEE’s code editor is all user friendly consists of various algorithms image processing, picture collecting, geometry-feature, reduction, and machine learning are just a few examples. which the users do not need other software to perform task. GEE's explorer is a web tool for inspecting data catalogues., visualization and to run simple analyses by users (Gorelick et al., 2017; Kumar & Mutanga, 2018; Tamiminia et al., 2020). Therefore, GEE is a suitable platform for aquaculture pond mapping for management and monitoring.

Machine learning is among the most dependable methods of non-linear classification. It is useful to comprehend the system's behaviour based on input observations and can estimate values without knowing the connection between data beforehand. This means that machine teaching is a viable option in classifying remote sensing pictures when the features of the whole research field cannot be fully understood (Lary et al., 2016). As complicated data and higher-resolution satellite imaging are readily available, classifiers for machine learning in remote sensing are already widely utilized (Pal & Mather, 2005; Pal & Mather, 2004). Even with complicated data and more input characteristics, machine-learning classifiers generate greater accuracy (Aksoy et al., 2005; Huang et al., 2012). Few of the most common classifications include k-Nearest Neighbor (k-NN), SVM, RF, ARN, CART etc. While some classifiers like CART create a single decision-making, panel based on training data provided, RF utilizes random subsets of training data for several decision-making panels. Classifiers such as SVM, on the other side, identify a subset of training data as vectors by fitting a hyperplane that best selects two classes (Huang et al., 2002). In all these classification situations, most research shows that SVM and RF are above the level of other machine classification scenarios (Belgiu & Dragut, 2016; Nery et al., 2016). CART is a basic binary classifier created by (Breiman et al., 1984). It is based on hierarchical decision trees. The primary benefit of such structures is that the classification choices may be regarded as a white box system that readily understands and interprets input-output connections compared with multilayer neuronal networks (Tso & Mather, 2009). The CART algorithms' input and output are linked through a sequence of nodes, each of which is divided into two branches, eventually leading to leaf nodes that represent class labels in classification trees and continuous variables in regression trees, respectively. The recurrent splitting of nodes continues until a threshold criterion is met. CART determines the input characteristics that will result in the optimal split at each node based on the Gini Impurity Index (Tso & Mather, 2009). The split may be univariate, with decision boundaries parallel to the axis of the input feature, or multivariate, with input features combined linearly (Tsoi & Pearson, 1991). Multivariate decision boundaries provide each class boundary more flexibility.

Tumer and Ghosh (1996) established that integrating the output of several classifiers for the purpose of predicting an event results in very high classification accuracy. This is the underlying principle of the ensemble classifier RF, which combines the output of several decision trees to determine the label for fresh input data based on the highest vote. Random Forest randomly chooses a portion of the training sample through replacement to construct a single tree, i.e., it employs a bagging method in which data is chosen from the original full training set for each tree. This may result in the same samples being chosen for several trees while others are not chosen at all (Breiman, 1996). The non-training data (out-of-bag samples) are utilized internally to evaluate the classifier's performance and give an impartial estimate of the generalization error.

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Additionally, RF conducts a random selection of variables from training samples at each node to find the optimal split for tree construction. While this decreases the strength of individual trees, it decreases the correlation between them, resulting in a reduction in generalization error (Breiman, 2001). To determine the optimal split, RF employs the Gini Index, which is a measure of impurity inside a node. The split is carried out in such a manner that the entropy decreases, and the information gain increases after the split. However, the effectiveness of tree-based classifiers is more dependent on the pruning techniques used than on the optimal split selection measure (Pal & Mather, 2003). RF is resistant to these effects since it grows trees without the need of trimming methods (Pal & Mather, 2005). In the area of remote sensing, SVM is one of the frequently used classifiers. SVM gained prominence owing to its ability to achieve high classification accuracy with few training sets, which is often a constraint in land use land cover classification situations (Mantero et al., 2005). SVM is a linear binary classifier based on the idea that training samples closer to class limits better distinguish a class than other training samples. SVM thus aims to find a perfect hyperplane separating the samples of the input training of different classes. These samples are collected as supportive vectors for the actual training, at the borders of a class and at a minimal distance from the hyperplanes.

Remote sensing has been used to map aquaculture ponds in several studies, using many types of sensors, GEE platforms, and algorithms several recent studies regarding application of GEE for aquaculture pond mapping have been produced. For instance, a study created a flowchart for retrieving aquaculture ponds by combining existing multi-source remote sensing data on the Google Earth Engine platform. The method of Multi-threshold Connected Component Segmentation and the Random Forest algorithm were utilised to automatically retrieve aquaculture ponds using Shanghai as a study region. The data show that this method is capable of accurately mapping Shanghai's aquaculture ponds from 2016 to 2019, with a classification accuracy of 91.8 % in 2018 (Xia et al., 2020). Next, a study proposed using Landsat 8 images and the Google Earth Engine (GEE) platform to map aquaculture ponds on a country scale. The study used a decision tree classifier that combined spectral, spatial, and morphological characteristics to successfully extract aquaculture pond regions in the Chinese coastal zone in 2017, with an overall accuracy of 0.96 (0.94–0.97, 95 % confidence interval) and a kappa coefficient of 0.82. The results revealed a detailed geographical dispersion of aquaculture ponds in the Chinese coastal zone, with a total area of 15632.64 km^2 (14386.98 km2–17924.95 km2, 95 % confidence interval) (Duan et al., 2019). Besides that, a study of the three-decade evolution of aquaculture, including the spatiotemporal dynamics of both the Yellow River Delta (YRD) and the Pearl River Delta (PRD), during a 30-year period (PRD). Long-term patterns of change in aquaculture are derived by merging a Sentinel-1-generated reference layer on existing aquaculture ponds for 2015 with annual data on water bodies from the Landsat archive. Significant expansion in aquaculture area were found in the studied target deltas, with the YRD increasing 18.6-fold between 1984 and 2016, and the PRD increasing 4.1-fold between 1990 and 2016. The research also uses linear regression analysis to find aquaculture growth hotspots for the deltas, revealing that hotspots may be identified along the YRD's coastal regions and along the PRD's Pearl River. When compared to high-resolution Google Earth data, the proposed method detects spatio-temporal changes in aquaculture with an overall accuracy of 89 % (Stiller et al., 2019). In addition, a subtle analysis was conducted which an application for the mapping of national coastal aquaculture ponds with new categorization schemes utilizing Sentinel-1 series data was created using Google Earth Engine (GEE). Clustering indices relevant to aquaculture ponds, which use water index, texture, and geometric metrics derived from radar backscatter, are mostly seen in pond aquaculture. With this method, the study categorized using decision tree aquaculture ponds with a total accuracy of 90.16% over the whole area of the coastal region in Vietnam (based on independent sample evaluation). In order to monitor and manage aquaculture ponds effectively, wall-to-wall mapping and area evaluation are important. Aquaculture ponds have been shown to be extensively spread in the coastal region of Vietnam and are focused inside the Mekong River Delta and Red River delta (85.14 % of the total area) (Sun et al., 2020). Another study that was conducted which a decision-tree classifier was utilised to detect large-scale aquaculture ponds in the province of Jiangsu via the 7-fold diaphragm between 1988 and 2018 using Landsat cloud data generated from Google Earth Engine (GEE). The results have shown that, in Jiangsu Provinces, the area allotted to aquaculture ponds has continuously increased from 660,29 km^2 in 1988 to 4097,95 km2 in 2018 and three regions with dense distributions of aquacultural ponds have been found throughout the province of Jiangsu's coastlines as well as in the south and the center. The overall accuracies were greater than 0.91, and kappa coefficient was greater than 0.79 (Duan et al., 2020). In addition, a study carried out targeted at addressing a knowledge gap by development and evaluation on the platform of Google Earth Engine (GEE) of an automated process for fishpond mapping, using Sentinel-2 pictures. The workflow comprises two main steps: (1) an automated flooding identification approach that employs a pixel selection technique and an image segmentation method is used in the spectrum filtering step. and (2) the space filtering phase, in order to further classify flooded bodies in fishponds and non-fishponds through object-based features (OBF). A case study in Singra Upazila, Bangladesh, was condcuted to assess the effectiveness of the workflow and can effectively map inland fish tanks with an accuracy of 0.788. This study compared different classifis which are decision tree and logistics regression and found out that logistics regression is more accurate compared to decision tree (Yu et al., 2020). Based on previous study, only two machine learning classifiers algorithms were compared which are logistic regression and decision tree. There are still no studies comparing three most common machine learning classifiers algorithms for aquaculture pond mapping which are, Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CART).

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3. Materials and Methods

The study area, Sungai Udang is located in Seberang Perai Selatan district of Penang, within latitudes 5°09′ N and longitudes 100°25′ E. It is a Chinese fishery village with population of 2045 (as of census 2010) as shown in Figure 1. The area which this study was conducted in Sungai Udang is 9.51 km². For secondary datasets, high resolution image from Google Earth Pro were used and referred for sampling selection and to obtain area of aquaculture pond which is then used to compare with the area obtained from classified image using Google Earth Engine. The workflow for this study is shown in Figure 2. Primary dataset which is the 10m Sentinel 2 Level-1C orthorectified top-of-atmosphere reflectance images were obtained directly from Google Earth Engine platform. Next, cloud mask band (QA 60) was used to mask cloud in the images followed by annual composite function was used to replace the cloud pixels removed. This processed was used to obtain images free from cloud from the year 2016 to 2020. Next, the image was clipped to the user's preference of designated study area (shapefile). The shapefile of the study area which is a vector data was created using the ArcMap 10.5 software. The shapefile was uploaded into GEE personal Asset folder.

Figure 1: Study Area Sungai Udang, Penang

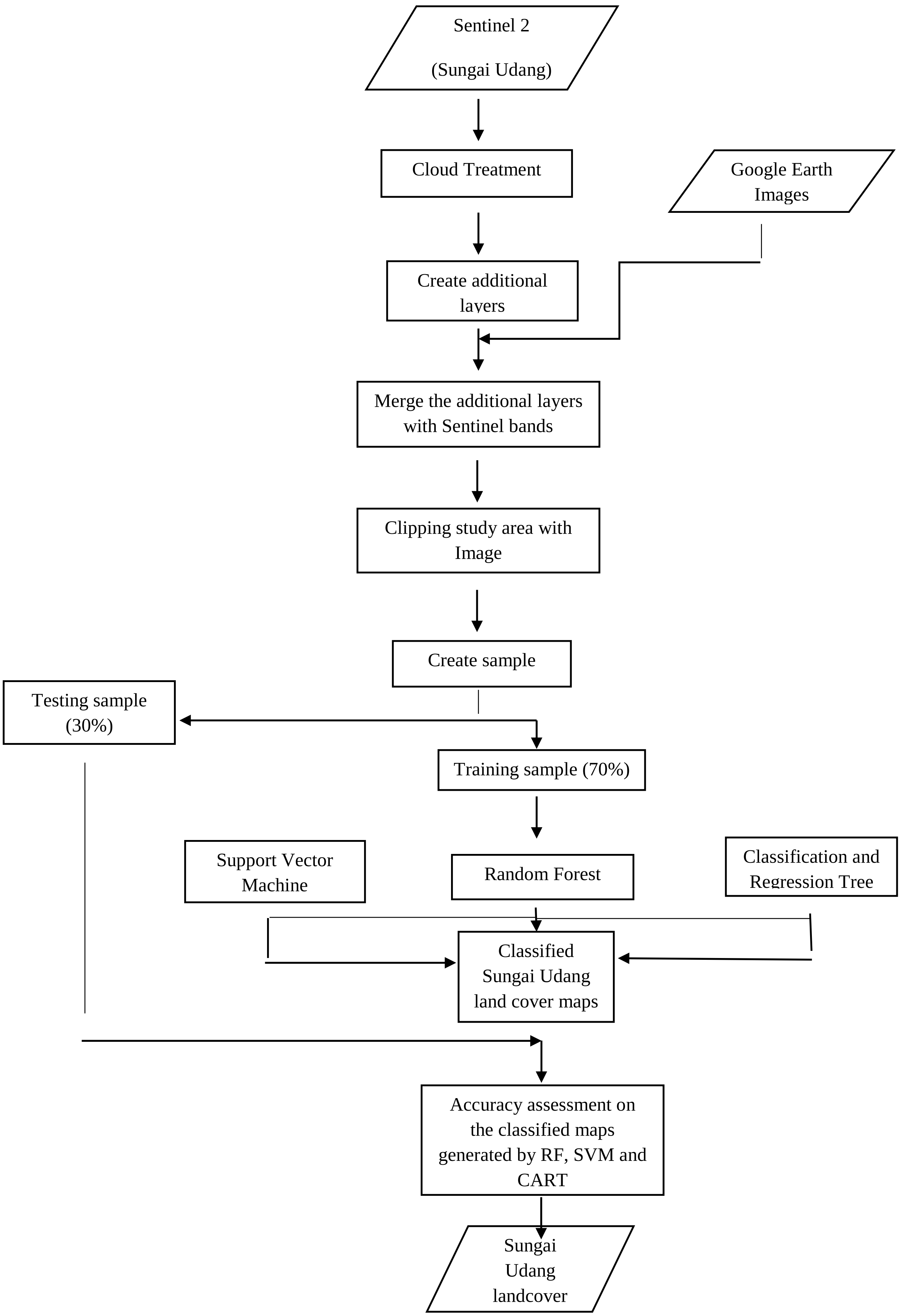

Figure 2: Methodological steps conducted for this research

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This study uses primary datasets and secondary datasets to produce and analyse aquaculture pond maps over Sungai Udang, Penang. For primary datasets, 10m Sentinel 2 data from 2016 to 2020 (7 original bands) which details can be found in Table 1 and additional data including NDVI, MNDWI and NDBI which details can be found in Table 2.

Samples were created in Google Earth Engine platform where 3 classes were identified: vegetation, urban and aquaculture pond. This samples were formed using the point option in GEE covering the whole study area by using random sampling. With the help of Google Earth Pro high resolution images, the samples were chosen. Next, the selected samples were separated into training and testing. 70% from the whole created samples (98 points) were used to classify the Sentinel images and the balance 30% of the samples (42 points) were used for validation and accuracy assessment of the machine learning classifiers used. Some sample selection biases appeared as this sample selection is done manually.

This study uses a pixel-based supervised classification with 3 most common land cover classification machine learning classifiers algorithms which are Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART). The samples for training were used to train the machine learning classifiers. The hyperparameter for RF and SVM was tuned based on trial and error. CART algorithm in GEE does not need to be tuned and default hyperparameter will be automatically used. For RF, the number of trees selected was 10. For SVM, kernel type was set to RBF, gamma was set to 0.5 and cost was set to 10.

Confusion matrices was used to assess the accuracy of supervised classifiers. The testing samples was introduced and allocated to the classifier. The overall accuracy and kappa coefficient function were used, and the result was displayed at the console section of GEE platform.

Google Earth Pro was used as secondary dataset due to available high-resolution image. Each pond was visually identified, and a polygon was created around it. Next, the polygon of the ponds (KMZ) was imported into ArcMap 10.5 to create shapefile and to count the area of the aquaculture ponds which is then used to compare with the area obtained from classified image.

Table 1: Shows information of Sentinel 2 bands

Name	Description	Pixel size (m)	Wavelength (μm)
B2	Blue	10 meters	496.6nm (S2A) / 492.1nm (S2B)
B3	Green	10 meters	560nm (S2A) / 559nm (S2B)
B4	Red	10 meters	664.5nm (S2A) / 665nm (S2B)
B5	Red Edge 1	20 meters	703.9nm (S2A) / 703.8nm (S2B)
B8	NIR	10 meters	835.1nm (S2A) / 833nm (S2B)
B9	Water vapor	60 meters	945nm (S2A) / 943.2nm (S2B)
B11	SWIR 1	20 meters	1613.7nm (S2A) / 1610.4nm (S2B)

Table 2: Shows additional layers that were included in classification

Name	Formula	Source
NDVI	$\frac{NIR - Red}{NIR + Red}$	(Bannari et al., 1995)
MNDWI	$\frac{Green - SWIR1}{Green + SWIR1}$	(Xu, 2005)
NDBI	$\frac{SWIR1 - NIR}{SWIR1 + NIR}$	(Zha et al., 2003)

4. Results and Discussion

The goal of this research was to compare SVM, RF and CART machine learning classifier algorithms on GEE to create an aquaculture pond map across Sungai Udang, Penang. Three different land use classes including aquaculture, urban, and vegetation were used in this study. Nevertheless, the classification output analysis focused solely on aquaculture ponds because the resulting aquaculture pond map will be utilised to assess the spatial distribution of aquaculture pond maps in Sungai Udang, Penang.

Three types of vegetation were identified in this research, including plantation features such as oil palm and paddy fields, woodland, bushes, and other crops. Buildings, metals, concrete, and roadways are all classified as urban. Aquaculture ponds that are classed as aquaculture. Additional layers such as NDVI, MNDWI, and NDBI were included to improve the classification, particularly in differentiating one class from another, because the goal of the study was to test the performance of machine learning algorithms to retrieve aquaculture pond from 10 m Sentinel 2 images in the GEE platform. The aquaculture map from 2016 to 2020 created offers information on the distribution of aquaculture ponds, and it may also be utilised in future studies to assess the effect of aquaculture land cover in more detail.

30% of testing samples (vegetation: 15, urban: 6, aquaculture pond: 21) were utilised to validate the classified land cover maps, and the overall accuracies and kappa coefficient acquired for each classifier and years were calculated as shown in (Table 3). The total area of aquaculture pond in Sungai Udang, Penang produced by CART, SVM and RF for the year 2016 were 265.24 ha, 256.55 ha and 286.80 ha while for the year 2020 were 313.20 ha, 314.80 ha and 296.74 ha. SVM produced the highest overall accuracy with an average of 97.36% followed by CART with 93.86% and RF 93.48%. The overall accuracies produced were calculated via confusion matrix based on the accuracies of the 3 classified classes.

By referring to the Google Earth Pro high resolution imagery, the area of aquaculture pond produced by SVM, CART and RF were compared for each year. Table 4 shows the difference of aquaculture pond area produced by SVM, CART and RF by comparing the produced results area obtained from Google Earth Pro. However, due to narrow river and drainage, RF, CART and SVM have exaggerated the aquaculture pond area. The value of overestimation is not high. For example, in the year 2020, RF

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overestimated 25.61 ha, CART overestimated 24.73 ha and SVM overestimated 8.27 ha. This is because the narrow river and drainage have similarity of the reflectance value of the pixels. All three algorithm have underestimated but the value is not high too. For example, for the year 2019, RF underestimated 4.06 ha, CART underestimated 4.05 and SVM underestimated 0.97 ha. Aquaculture pond area increased from the year 2016 to 2020 for all 3 classifiers. However, for the year 2019 the area decreased. This is due to some ponds become inactive. Figure 3 shows classified map for the year 2020 for all 3 classifiers. Based on observation there are some misclassification pixels. For example, some urban pixels are misclassified in CART and RF.

Table 3: Overall accuracy and Kappa coefficient for land cover class of each classifier

		2016	2017	2018	2019	2020
RF	Overall Accuracy (%)	82.05	97.37	91.84	96.16	100
	Kappa Coefficient	0.723	0.958	0.861	0.933	1
CART	Overall Accuracy (%)	90.48	93.75	95.12	95.65	94.29
	Kappa Coefficient	0.845	0.891	0.919	0.924	0.905
SVM	Overall Accuracy (%)	98.08	97.44	100	97.14	94.12
	Kappa Coefficient	0.967	0.968	1	0.953	0.905

Table 4: Comparison of machine learning classifers in aquaculture ponds mapping.

Year	Area (ha) Google Earth Pro	RF		CART		SVM	
		Classified	Variation	Classified	Variation	Classified	Variation
2016	264.42	256.55	-7.87	265.24	0.82	286.80	22.38
2017	265.22	298.28	33.06	303.42	38.20	293.16	27.94
2018	284.96	284.81	-0.16	289.68	4.71	275.21	-9.75
2019	286.84	282.78	-4.06	282.79	-4.05	285.86	-0.97
2020	288.47	314.08	25.61	313.20	24.73	296.74	8.27

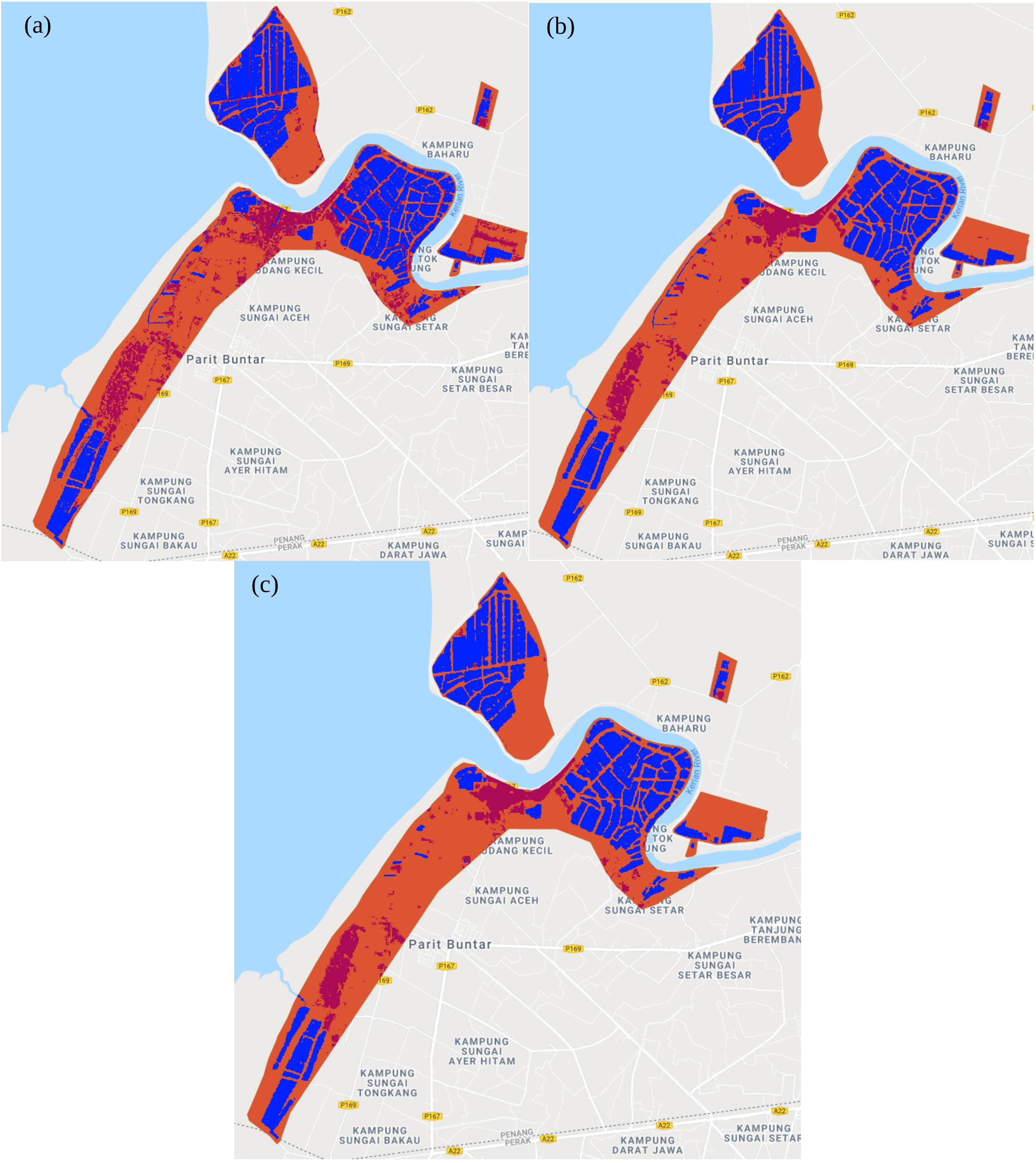

Figure 4: Classified map for (a) CART, (b) RF and (c) SVM for the year 2020

In this study, we used a pixel-based supervised image classification to produce the aquaculture pond map. It is a traditional method in classification and easy to implement. Unlike pixel-based, object-based is a technique that works through image segmentation. Each segmented area or object consists of homogeneous pixels that have been grouped together. Several previous studies have used object-based to perform aquaculture pond classification. However, the technique used is either complicated or complex to implement. It requires time to extract aquaculture pond spatial information. Besides that, the object-based approach is suitable for large scale study areas due to the presence of complex features with a similar spectral response. However, our study area is small scale, and no other features identical to aquaculture pond spectral response is present in the

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study area. Even though this technique is simple to be implemented and suitable for small scale, the overall accuracy produced for each year and classifiers are considered high, and area variation is minimal.

5. Conclusion

Aquaculture pond maps were created using 10 m Sentinel 2 data and sampled annual cloud free composite images from 2016, 2017, 2018, 2019, and 2020 in this study. The GEE platform was used for all image acquisition, processing, and analysis. GEE is a good choice for aquaculture pond mapping because it is simpler and more convenient than the traditional method. There are several methods for creating an aquaculture pond map based on previous research. However, when compared to other methods used in previous studies, the method proposed here is simpler. Users with little experience with geospatial analysis can quickly learn and use GEE.

The images were classified using three popular machine learning classifiers for land cover: SVM, CART, and RF. In comparison to CART and RF, SVM produced a more accurate classified map based on accuracy assessment. Thus, SVM is the most suitable classifier compared to RF and CART to produce aquaculture pond map with the highest accuracy. For all years, all three classifiers produced satisfactory overall accuracy of more than 90%. There isn't much of a difference between the aquaculture pond area obtained from Google Earth Pro and the aquaculture pond area obtained from the classified image. In this study, the issue we faced is the distinction arises from the classification of a narrow river and its drainage as an aquaculture pond. GEE can perform object based (OBIA) classification, which is something that should be investigated further in the future. However, in the GEE platform, OBIA classification can be time-consuming and difficult. Learning and performing OBIA classification will take more time, but guidance is available on the GEE developer's website and other online resources. The Sentinel 1 dataset, which employs active sensors, is also available in GEE.

Overall, GEE was successful in achieving all of its goals. The primary goal, which is to create an aquaculture pond map, is critical. This is because the map and data can be used by a variety of organisations, including the government, non-governmental organisations, and aquaculture pond owners, to manage and monitor aquaculture pond fish production. In addition, the environment degradation caused by aquaculture ponds can be monitored. This research will aid in decision-making and the development of long-term aquaculture ponds.

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References

Ahmed, M., & Lorica, M. H. (2002). Improving developing country food security through aquaculture development—lessons from Asia. *Food Policy*, *27*(1652), 125–141.

Aksoy, S., Koperski, K., Tusk, C., Marchisio, G., Tilton, J. C., & Member, S. (2005). Learning Bayesian classifiers for scene classification with a visual grammar. *IEEE Transactions on Geoscience And Remote Sensing*, *43*(3), 581–589.

Allison, E. H. (2011). *Aquaculture, Fisheries, Poverty and Food Security* (65).

Azra, M. N., Azman, N., Othman, R., Afiz, G., Ruslan, G., Mazelan, S., Bin, Z., & Sar, G. (2021). Impact of COVID-19 on aquaculture sector in Malaysia: Findings from the first national survey. *Aquaculture Reports*, *19*. https://doi.org/10.1016/j.aqrep.2020.100568

Bannari, A., Taylor, P., Morin, D., Bonn, F., & Huete, A. R. (1995). A review of vegetation indices. *Remote Sensing Reviews*, *13*(June 2013), 95–120. https://doi.org/http://dx.doi.org/10.1080/02757259509532298

Barbosa, C. C. D. A., Atkinson, P. M., & Dearing, J. A. (2015). Remote sensing of ecosystem services : A systematic review. *Ecological Indicators*, *52*, 430–443. https://doi.org/10.1016/j.ecolind.2015.01.007

Belgiu, M., & Dragut, L. (2016). Random forest in remote sensing: A review of applications and future directions gut. *ISPRS Journal of Photogrammetry and Remote Sensing*, *114*, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Beveridge, M. C. M., Thilsted, S. H., Phillip, M. J., Metian, M., Troell, M., & Hall, S. J. (2013). Meeting the food and nutrition needs of the poor : the role of fish and the opportunities and challenges emerging from the rise of aquaculture. *Journal of Fish Biology*, *83*, 1067–1084. https://doi.org/10.1111/jfb.12187

Breiman, L. E. O. (2001). *Random Forests*. 5–32.

Breiman, L, Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees*. Chapman and Hall/CRC.

Breiman, Leo. (1996). Bagging Predictors. *Machine learning*, *24*, 123–140.

Campbell, B., & Pauly, D. (2013). Mariculture: A global analysis of production trends since 1950. *Marine Policy*, *39*, 94–100. https://doi.org/10.1016/j.marpol.2012.10.009

Cao, L., Wang, W., Yang, Y., Yang, C., Yuan, Z., Xiong, S., & Diana, J. (2007). Environmental impact of aquaculture and countermeasures to aquaculture pollution in China. *Environmental Science Pollution Research*, *14*(7), 452–462. https://doi.org/http://dx.doi.org/10.1065/espr2007.05.426

DOF. (2020). *Malaysian Fishing Industry Scenario*. Department of Fisheries Malaysia. https://www.dof.gov.my/index.php/pages/view/42

Duan, Y, Li, X., Zhang, L., Liu, W., Liu, S., Chen, D., & Ji, H. (2020). Detecting spatiotemporal changes of large-scale aquaculture ponds regions over 1988–2018 in Jiangsu Province, China using Google Earth Engine. *Ocean and Coastal Management*, *188*. https://doi.org/10.1016/j.ocecoaman.2020.105144

Duan, Yuanqiang, Li, X., Zhang, L., Chen, D., Liu, S., & Ji, H. (2019). Mapping national-scale aquaculture ponds based on the Google Earth Engine in the Chinese coastal zone. *Aquaculture*, *520*(November 2019), 734666.

Geografi Vol.9(2), 86- 106
ISSN 2289-4470 /eISSN 2462-2400

https://doi.org/10.1016/j.aquaculture.2019.734666
FAO. (2002). *CWP Handbook of Fishery Statistical Standards*. Section J: AQUACULTURE. CWP Data Collection [WWW Document]. FAO Fish. Aquac. Dep. http://www.fao.org/fishery/cwp/handbook/J/en
FAO. (2014). *The State of World Fisheries and Aquaculture 2014*.
FAO. (2016). *The state of world fisheries and aquaculture 2016. Contributing to food security and nutrition for all*.
FAO. (2020). *The State of World Fisheries and Aquaculture 2020. Sustainability in action.* https://doi.org/https://doi.org/10.4060/ca9229en
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine : Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *2016*. https://doi.org/10.1016/j.rse.2017.06.031
He, Z., Cheng, X., Kyzas, G. Z., & Fu, J. (2016). Pharmaceuticals pollution of aquaculture and its management in China. *Journal of Molecular Liquids*, *223*, 781–789. https://doi.org/10.1016/j.molliq.2016.09.005
Herbeck, L. S., Unger, D., Wu, Y., & Jennerjahn, T. C. (2013). Effluent , nutrient and organic matter export from shrimp and fish ponds causing eutrophication in coastal and back-reef waters of NE Hainan , tropical China. *Continental Shelf Research*, *57*, 92–104. https://doi.org/10.1016/j.csr.2012.05.006
Holmstrom, K., Graslund, S., Wahlstrom, A., Poungshompoo, S., Bengtsson, B.-E., & Kautsky, N. (2003). Antibiotic use in shrimp farming and implications for environmental impacts and human health. *International Journal of Food Science and Technology*, *38*, 255–266.
Hossain, M. S., Uddin, M. J., & Fakhruddin, A. N. M. (2013). Impacts of shrimp farming on the coastal environment of Bangladesh and approach for management. *Reviews Environmental Science and Bio/technology*, *12*, 313–332. https://doi.org/10.1007/s11157-013-9311-5
Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, *23*(4), 725–749. https://doi.org/10.1080/01431160110040323
Huang, G.-B., Zhou, H., Ding, X., & Zhang, R. (2012). Extreme Learning Machine for Regression and Multiclass Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, *42*(2), 513–529.
Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., Jepsen, M. R., Kuemmerle, T., Meyfroidt, P., Mitchard, E. T. A., Reiche, J., & Ryan, C. M. (2016). A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring. *Remote Sensing*, *8*(70), 1–23. https://doi.org/10.3390/rs8010070
Keesing, J. K., Liu, D., Fearns, P., & Garcia, R. (2011). Inter- and intra-annual patterns of Ulva prolifera green tides in the Yellow Sea during 2007 – 2009 , their origin and relationship to the expansion of coastal seaweed aquaculture in China. *Marine Pollution Bulletin*, *62*, 1169–1182. https://doi.org/10.1016/j.marpolbul.2011.03.040
Kumar, L., & Mutanga, O. (2018). Google Earth Engine Applications Since Inception :

Usage, Trends, and Potential. *Remote Sensing*, *10*(1509), 1–15. https://doi.org/10.3390/rs10101509

Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2016). Machine learning in geosciences and remote sensing. *Geoscience Frontiers*, *7*(1), 3–10. https://doi.org/10.1016/j.gsf.2015.07.003

Lee, J. H., Pang, I., Moon, I., & Ryu, J. (2011). On physical factors that controlled the massive green tide occurrence along the southern coast of the Shandong Peninsula in 2008 : A numerical study using a particle-tracking experiment. *Journal of Geophysical Research*, *116*, 1–12. https://doi.org/10.1029/2011JC007512

Liang, P., Wu, S., Zhang, J., Cao, Y., Yu, S., & Wong, M.-H. (2016). The effects of mariculture on heavy metal distribution in sediments and cultured fi sh around the Pearl River Delta region , south China. *Chemosphere*, *148*, 171–177. https://doi.org/10.1016/j.chemosphere.2015.10.110

Ma, Y., Wu, H., Wang, L., Huang, B., Ranjan, R., Zomaya, A., & Jie, W. (2015). Remote sensing big data computing : Challenges and opportunities. *Future Generation Computer Systems*, *51*, 47–60. https://doi.org/10.1016/j.future.2014.10.029

Mantero, P., Moser, G., & Serpico, S. B. (2005). Partially Supervised Classification of Remote Sensing Images Through SVM-Based Probability Density Estimation. *IEEE Transactions on Geoscience and Remote Sensing*, *43*(3), 559–570.

Marini, Y., Emiyati, P. T., Hanzah, R., & Hasyim, B. (2013). Fishpond aquaculture inventory in Maros Regency of south sulawesi province. *Int. J. Remote Sens*, *10*, 25–35.

Natale, F., Hofherr, J., Fiore, G., & Virtanen, J. (2013). Interactions between aquaculture and fisheries. *Marine Policy*, *38*, 205–213. https://doi.org/10.1016/j.marpol.2012.05.037

Naylor, R. L., Goldburg, R. J., Primavera, J. H., Kautsky, N., Beveridge, M. C. M., Clay, J., Folke, C., Lubchenco, J., Mooney, H., & Troell, M. (2000). Effect of aquaculture on world fish supplies. *Nature*, *405*, 1017–1024.

Nery, T., Sadler, R., Solis-aulestia, M., White, B., Polyakov, M., & Chalak, M. (2016). Comparing supervised algorithms in land use and land cover classification of a landsat time-series. *IGARSS 2016*, 5165–5168.

Ottinger, M., Clauss, K., & Kuenzer, C. (2016). Aquaculture : Relevance , distribution , impacts and spatial assessments - A review. *Ocean and Coastal Management*, *119*(2016), 244–266. https://doi.org/10.1016/j.ocecoaman.2015.10.015

Pal, M., & Mather, P. M. (2005). Support vector machines for classification in remote sensing. *International Journal of Remote Sensing*, *26*(5), 1007–1011. https://doi.org/10.1080/01431160512331314083

Pal, M., & Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, *86*, 554–565. https://doi.org/10.1016/S0034-4257(03)00132-9

Pal, M., & Mather, P. M. (2004). Assessment of the effectiveness of support vector machines for hyperspectral data. *Future Generation Computer Systems*, *20*, 1215–1225. https://doi.org/10.1016/j.future.2003.11.011

Pattanaik, C., & Prasad, S. N. (2011). Assessment of aquaculture impact on mangroves of Mahanadi delta (Orissa), East coast of India using remote sensing and GIS. *Ocean*

Geografi Vol.9(2), 86- 106
ISSN 2289-4470 /eISSN 2462-2400

and Coastal Management, *54*(11), 789–795. https://doi.org/10.1016/j.ocecoaman.2011.07.013

Paul, B. G., & Vogl, C. R. (2011). Impacts of shrimp farming in Bangladesh : Challenges and alternatives. *Ocean and Coastal Management*, *54*(3), 201–211. https://doi.org/10.1016/j.ocecoaman.2010.12.001

Pauly, D., & Froese, R. (2012). Comments on FAO ' s State of Fisheries and Aquaculture , or ' SOFIA 2010 .' *Marine Policy*, *36*(3), 746–752. https://doi.org/10.1016/j.marpol.2011.10.021

Peng, Y., Chen, G., Li, S., Liu, Y., & Pernetta, J. C. (2013). Use of degraded coastal wetland in an integrated mangrove e aquaculture system: a case study from the South China Sea. *Ocean and Coastal Management*, *85*, 209–213. https://doi.org/10.1016/j.ocecoaman.2013.04.008

Primavera, J. H. (2006). *Overcoming the impacts of aquaculture on the coastal zone*. *49*, 531–545. https://doi.org/10.1016/j.ocecoaman.2006.06.018

Qu, Y., Qi, H., Ayhan, B., Kwan, C., & Kidd, R. (2017). Does multispectral / hyperspectral pansharpening improve the performance of anomaly detection? *IGARSS 2017*, 6130–6133.

Sabra, F. S., & Mehana, E. E. (2015). Pesticides toxicity in fish with particular reference to insecticides. *Asian Journal of Agriculture and Food Sciences*, *3*(01), 40–60.

Schumann, G. J.-P., Neal, J. C., Mason, D. C., & Bates, P. D. (2011). The accuracy of sequential aerial photography and SAR data for observing urban flood dynamics , a case study of the UK summer 2007 floods. *Remote Sensing of Environment*, *115*(10), 2536–2546. https://doi.org/10.1016/j.rse.2011.04.039

Shaharum, N. S. N., Shafri, H. Z. M. S., Ghani, W. A. W. A. K., Samsatli, S., Al-habshi, M. M. A., & Yusuf, B. (2020). Oil palm mapping over Peninsular Malaysia using Google Earth Engine and machine learning algorithms. *Remote Sensing Applications: Society and Environment*, *17*(100287). https://doi.org/10.1016/j.rsase.2020.100287

Slater, M. J., Mgaya, Y. D., Mill, A. C., Rushton, S. P., & Stead, S. M. (2013). Effect of social and economic drivers on choosing aquaculture as a coastal livelihood. *Ocean and Coastal Management*, *73*, 22–30. https://doi.org/10.1016/j.ocecoaman.2012.12.002

Smith, M. D., Roheim, C. A., Crowder, L. B., Halpern, B. S., Turnipseed, M., Anderson, J. L., Asche, F., Bourillón, L., Guttormsen, A. G., Khan, A., Liguori, L. A., Mcnevin, A., Connor, M. I. O., Squires, D., Tyedmers, P., Brownstein, C., Carden, K., Klinger, D. H., Sagarin, R., & Selkoe, K. A. (2010). *Sustainability and Global Seafood*. AAAS. https://doi.org/10.1126/science.1185345

Stiller, D., Ottinger, M., & Leinenkugel, P. (2019). Spatio-temporal patterns of coastal aquaculture derived from Sentinel-1 time series data and the full Landsat archive. *Remote Sensing*, *11*(14), 1–18. https://doi.org/10.3390/rs11141707

Sun, Z., Luo, J., Yang, J., Yu, Q., Zhang, L., Xue, K., & Lu, L. (2020). Nation-scale mapping of coastal aquaculture ponds with sentinel-1 SAR data using google earth engine. *Remote Sensing*, *12*(18), 1–18. https://doi.org/10.3390/RS12183086

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications : A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *164*(March), 152–170. https://doi.org/10.1016/j.isprsjprs.2020.04.001

The World Bank, F. to 2030. (2013). *Prospects for Fisheries and Aquaculture*.

Troell, M., Naylor, R. L., Metian, M., Beveridge, M., Tyedmers, P. H., & Folke, C. (2014). *Does aquaculture add resilience to the global food system ?* PNAS. https://doi.org/10.1073/pnas.1404067111

Tso, B., & Mather, P. M. (2009). *Classification Methods for Remotely Sensed Data*. CRC Press.

Tsoi, A. C., & Pearson, R. A. (1991). Comparison of three classification techniques, CART, C4.5 and Multi-Layer Perceptrons. *NIPS'90: Proceedings of the 3rd International Conference on Neural Information Processing Systems,* 963–969.

Tumer, K., & Ghosh, J. (1996). *Analysis of Decision Boundaries in Linearly Combined Neural Classifiers* (Patent No. 0031-3203(95)00085-2). Pattern Recognition Society.

Vaghefi, N. (2017). Penang's Aquaculture Industry Holds Great Economic Potential By. In *Penang Institute Issues*. https://penanginstitute.org/publications/issues/1005-penang-s-aquaculture-industry-holds-great-economic-potential/

Verdegem, M. C. J., & Bosma, R. H. (2009). Water withdrawal for brackish and inland aquaculture , and options to produce more fish in ponds with present water use. *Water Policy*, *1*, 52–68. https://doi.org/10.2166/wp.2009

Wang, S., Tang, D., He, F., Fukuyo, Y., & Azanza, R. V. (2008). Occurrences of harmful algal blooms (HABs) associated with ocean environments in the South China Sea. *Hydrobiologia*, *596*, 79–93. https://doi.org/10.1007/s10750-007-9059-4

Xia, Z., Guo, X., & Chen, R. (2020). Automatic extraction of aquaculture ponds based on Google Earth Engine. *Ocean and Coastal Management*, *198*. https://doi.org/10.1016/j.ocecoaman.2020.105348

Xu, H. (2005). A study on information extraction of water body with the modified normalized difference water index (MNDWI). *Journal of Remote Sensing*, *9*, 589–595.

Yokoya, N., Grohnfeldt, C., & Chanussot, J. (2017, June). Hyperspectral and Multispectral Data Fusion. *IIEEE Geoscience and Remote Sensing Magazine*, 29–56. https://doi.org/10.1109/MGRS.2016.2637824

Yu, Z., Di, L., Rahman, M. S., & Tang, J. (2020). Fishpond mapping by spectral and spatial-based filtering on google earth engine: A case study in singra upazila of Bangladesh. *Remote Sensing*, *12*(17). https://doi.org/10.3390/RS12172692

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized di ff erence built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, *24*(3), 583–594. https://doi.org/0.1080/01431160210144570