



## ARTIFICIAL NEURAL NETWORKS FOR THE CLASSIFICATION OF SHRIMP FARM FROM SATELLITE IMAGERY

Ilada AROONSRI<sup>1</sup>, Satith SANGPRADID<sup>2</sup>

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### ABSTRACT:

Shrimp production was the high demand for the popular in the global market in Thailand. The change of land use is important for the management and monitoring of land use changed. The objectives of this paper to (1) classification of shrimp farm using artificial neural networks (ANN) technique from the Sentinel-2 imagery. (2) change detection of land use changes map among 2015, 2018, and 2020. The land use classification based on ANN technique and the accuracy assessment by used the confusion matrices and kappa coefficient. The classify of land use classes divide into built-up, forest, water bodies, paddy field, shrimp farm, and field crop. The change detection methods used was the image differencing technique was performed to the land use changes map. The result of land use classification show that the field crop area was 80% cover the most area. The result of land use changed show that built-up, paddy field, and shrimp farm increased throughout between year 2015 to 2020. The shrimp farm between year 2015 to 2020 to increasing trend of related with the shrimp production was the high demand for the popular in the global market.

**Key-words:** *Sentinel-2 imagery, Supervise classification, Land use change detection, artificial neural networks (ANN).*

### 1. INTRODUCTION

Nowadays, shrimp farming in Thailand has been cultivating shrimp for domestic consumption and exports for a long time over the past 20 years. In the year 2020, the exports of production from shrimp farming are expected to increase to 350,000 tonnes (Thai Shrimp Association, 2019). Shrimp production was the high demand for the popular in the global market in Thailand. According to the shrimp is the most popular food consumed due to the reasons the farmers changed an agricultural area into the shrimp farming. The rapid change from agriculture to shrimp farming should be an issue associated with land degradation and water pollution. Therefore, it is necessary to plan and manage environmental impacts and social conflicts that have occurred in the area. The shrimp farming mapping is important for monitoring the land use changed in these areas.

The study of land utilization is very importance for managing dynamics for land use and demand of the population (Yaday et al., 2010). Planning and managing the change of land use in the area is the first priority for future land use planning to resource and sustainable development process.

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<sup>1</sup> Department of Business Digital, Faculty of Management Sceinces, Valaya Alongkorn Rajabhat University Under the Royal Patronage, 1, Moo 10, Klong 1, Klong Luang, Pathum Thani 13180, Thailand; E-mail: ilada@vru.ac.th

<sup>2</sup> Research unit of Geo-informatics for Local Development and Department of Geoinformatics, Faculty of Informatics, Mahasarakham University, Kantarawichai District, Maha Sarakham 44150, Thailand; E-mail: satith.s@msu.ac.th

Currently, the geo-informatics technology has been applied for the land use changed by used the processed from the satellite images. It has been very useful to classified the land use mapping for the monitor and analyze of land use in the area (Jomsrekrayom et al., 2021; Pradabmook & Laosuwan, 2021). Satellite Imagery an important in the sustainable development of shrimp aquaculture by providing information about land use/land cover, water quality, and coastal infrastructure (Rajitha et al., 2007). Satellite imagery has been used to monitoring areas of shrimp aquaculture, as well as to classify of land use change related aquaculture or specifically of land use in an area. Satellite imagery can support both of small and large-scale mapping of aquaculture for a better understanding and management and improve the quantifying of fish and shrimp ponds and associated production volumes to ensure comparable statistics between countries and regions (Ottinger et al, 2017; Stiller et al., 2019).

There several techniques for land use classification from satellite imagery based on supervised classification method such as parallelepiped, minimum distance, maximum likelihood, and mahalanobis distance. The maximum likelihood technique is the most popular for classify the land cover in coastal landscapes and classify of shrimp aquaculture (Alonso-Perez et al., 2003). However, the classifier method based rely upon field severing to collect the data or visual interpretation to identify shrimp pond shape samples as inputs of models (Dorber et al., 2020). The maximum likelihood technique assigned a class of land used based on the probability that a pixel belonging to a particular class that a normally distributed dataset exists, and that the statistical parameters. The classification accuracy of the maximum likelihood technique depending on the training samples are then used to train the classifier to classify the spectral data into a thematic map (Du & Wang, 2007). Machine learning is an emerging advanced classification methodology with supervised classification methods, such as random forest (RF), support vector machine (SVM), and artificial neural networks (ANN), there are can perform better than traditional classification method (Erbek et al., 2004; Maung & Sasaki, 2021).

Recently, machine learning methods have been used widely in satellite imagery to classify land use classification, monitoring, land use change detection, and prediction of land use change. The supervised machine learning classifier such as RF, SVM, and decision tree (DT) (Toosi et al., 2019; Ahmad, 2013; Ge et al., 2020). Currently, the application of Sentinel-2 has used widely in generally for land use monitoring (Urban et al., 2021; Migas-Mazur et al., 2021; Punalekar et al., 2021), precision agriculture (Santaga et al., 2021), fire monitoring (Kovacs, 2019; Vanderhoof et al., 2021), drought assessment (Varghese et al., 2021) and maritime monitoring (Costantino et al., 2020). In addition, Sentinel-2 has been spatial resolution varies from 10 m to 60 m and temporal resolution are only available every 5 days. In this paper, focused on ANN technique was used widely to classify the satellite image data to accuracies higher than of the tradition classification techniques (Foody et al., 1995; Toshniwal, 2005; Mahmon & Yaacob, 2014). The objective of this paper to (1) classification of shrimp farm using ANN technique from the Sentinel-2 imagery. (2) change detection of land use changes map among 2015, 2018, and 2020.

## 2. MATERIALS AND METHODS

### 2.1. Study area and data collection

This study was conducted at Yang Talad district, Kalasin province, Thailand (**Fig. 1**). The study area has tropical monsoon weather and the average temperature ranges from 26.9 - 28.2 degrees Celsius. The study are lies between 16.28° to 16.60° N Latitude and 103.15° to 103.50° E Longitude.

Sentinel-2 Imagery is a European wide-swath, high-resolution, multi-spectral imaging mission. The spectral resolution of Sentinel-2 imagery shown in **Table. 1** (USGS EROS Center,2015).

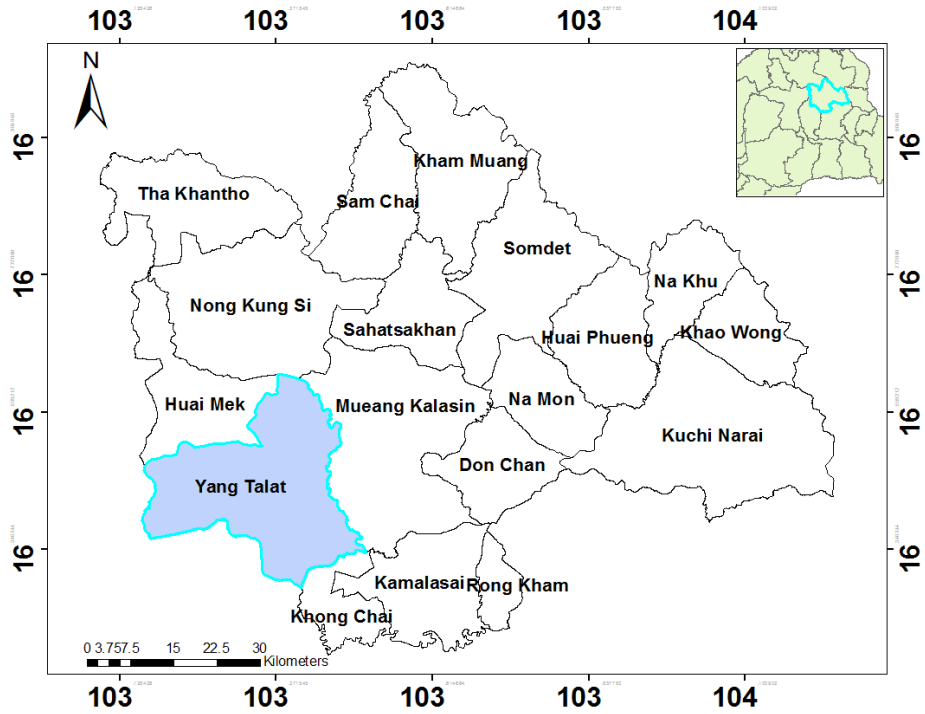


Fig. 1. Study area.

Table. 1

Characteristics of the Sentinel-2 Imagery.

Spatial resolution (m)	Band Number	S2A		S2B	
		Central Wavelength (nm)	Bandwidth (nm)	Central Wavelength (nm)	Bandwidth (nm)
10	2	492.4	66	492.1	66
	3	559.8	36	559	36
	4	664.6	31	664.9	31
	8	832.8	106	832.9	106
20	5	704.1	15	703.8	16
	6	740.5	15	739.1	15
	7	782.8	20	779.7	20
	8a	864.7	21	864	22
	11	1613.7	91	1610.4	94
	12	2202.4	175	2185.7	185
60	1	442.7	21	442.2	21
	9	945.1	20	943.2	21
	10	1373.5	31	1376.9	30

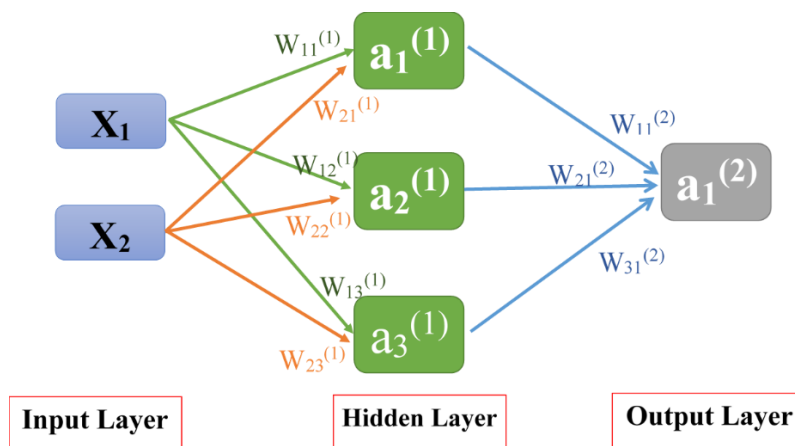
The Sentinel-2 imagery was acquired on dates 22 October 2015, 26 October 2018, and 23 October 2020 in order to classify the land use classification historical and current of shrimp farm cover. The spatial resolution of Sentinel-2 imagery is  $10 \times 10$  m was used for colour composites of Bands 8,4, and 3 to select the training area and classification of land use. Band combination is created by band combining of spectral data to improve a particular land use. A significant advantage of multispectral images is important to detected the difference surface of the area by the spectral of band combination. Band 8 (Near InfraRed) is very important in terms of ecological monitoring, since the Near InfraRed is the spectrum reflected by the water present in plants. False colour composite of Bands (RGB 8,4,3) was used for classified the vegetation appear red color and water bodies or shrimp farm with appear navy or black color.

## 2.2. Image classification from Sentinel-2 imagery

To survey the land use classes of shrimp farm in the Yang Talad study area, a field survey for collection of training samples and validation were primarily collected from field observations. Data collection by record the land use types including: built-up (Bu), forest (F), water bodies (W), paddy field (Pf), shrimp farm (Sf), and field crop (Fc), respectively.

### 2.2.1 Image classification using artificial neural networks (ANN)

An ANN is a computing system designed based on the structure of the biological neural network of the human nervous system and processes information. The systems of ANN have many layers is also call a multi-layer perceptron with the input layer, a hidden layer, an output layer, each of these layers has a specific purpose. These layers consist of nodes for takes input from the previous layer according to the requirements and transfers them to the next layer show in **Fig. 2**.



**Fig. 2.** Structure of a neural network.

The input nodes receive data in a format that can be expressed as numbers. The data is presented as the activation value, where each node receives a number. This data is passed to the network, depending on the strength of the connection (weight). These weights to calculate the weighted sum of inputs and applying an activation function (sigmoid, unit step, linear, etc.) in hidden layer to generate data their output layer. The several ANN models have been applied in land use classification such as Hopfield network, self-organizing competition, radial basis function, multilayer perception,

and multilayer perception with back propagation (Mas & Flore, 2008; Xiong et al., 2008; Shrestha et al., 2012). This paper used standard backpropagation for the classifier of land use classes. The error backpropagation was used for back propagated through the network and weight adjustment using a recursive method.

### 2.2.2 Land use Classification Types

Land use classes of the paper were categorized into six land types: built-up (Bu), forest (F), water bodies (W), paddy field (Pf), shrimp farm (Sf), and field crop (Fc) using the ANN classifiers with the regions of interest (ROI) for the training samples of land use classes. The training polygons or ROI was selected as represented of each class in the satellite imagery by digitized on the image based on the prior knowledge of the field surveyed and visual interpretation. The accuracy assessment of this paper using confusion matrices base on binomial probability theory with the desired level of confidence of 85 percent. The 300 samples of the reference point evaluate the classification procedure by using overall accuracy and the kappa coefficient.

### 2.2.3 Land use change detection

The percentage of land use change from the classification map from the map 2015, 2018, and 2020 in the study area. The process to identify the difference of classification map between map 2015 – 2018, and 2018 – 2020 was used the change detection technique. The various technique of change detection techniques has been applied to the monitoring of land use change including image differencing (Lu et al., 2004; Panuju et al.,2020), principal component analysis (Lu et al., 2004; Panuju et al.,2020), and change vector analysis (Lu et al., 2004; Panuju et al.,2020; Sangpradid, 2018). This paper used the image differencing technique was performed to classification the map by subtracts the first date image from a second date image on the digital image value between pixel by pixel.

## 3. RESULTS

### 3.1. The result of land use classification

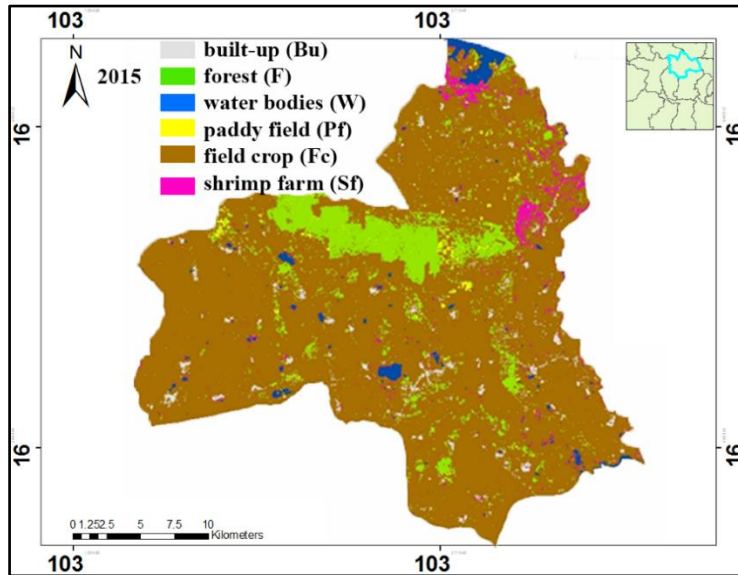
The results of land use classification map for the years 2015, 2018, and 2020 as shown in **Fig. 3, 4, and 5**, respectively. The area of the land use classifications from the ANN technique shown the percentage values of an area shown in **Table. 2**. The land use classes for the year 2015 in this table show that the area cover by built-up was 2.16%, forest was 12.64%, water bodies was 1.93%, paddy field was 1.71%, field crop was 79.88%, and shrimp farm was 1.67%.

**Table 2.**

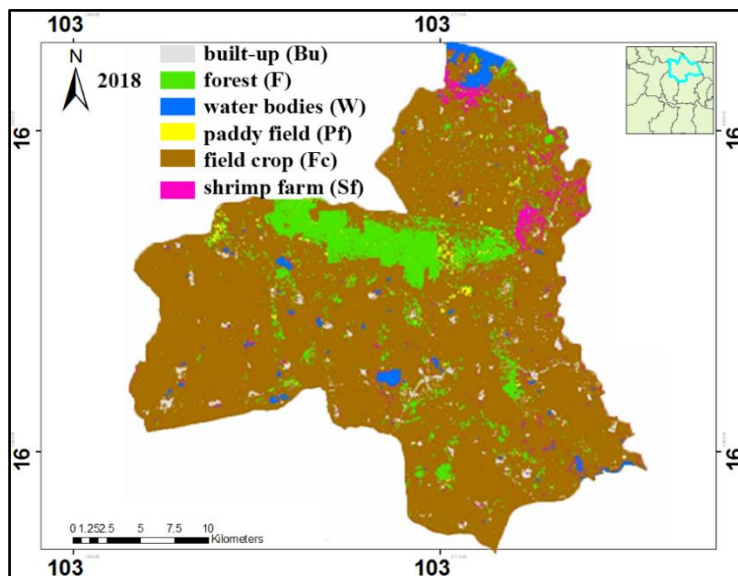
**The areas and percentage values of LU classes for the years 2015, 2018, and 2020.**

Classes	2015		2018		2020	
	sq.km	%	sq.km	%	sq.km	%
built-up	15.00	2.16	15.71	2.26	20.99	3.03
forest	87.69	12.64	65.35	9.42	59.88	8.63
water bodies	13.42	1.93	12.88	1.86	12.93	1.86
paddy field	11.85	1.71	5.76	0.83	13.70	1.98
field crop	554.03	79.88	579.85	83.61	567.59	81.84
shrimp farm	11.55	1.67	14.01	2.02	18.45	2.66

The land use classes for the year 2018 show that the area cover by built-up was 2.26%, forest was 9.42%, water bodies was 1.86%, paddy field was 0.83%, field crop was 83.61%, and shrimp farm was 2.02%. The land use classes for the year 2020 show that the area cover by built-up was 3.03%, forest was 8.63%, water bodies was 1.86%, paddy field was 1.98%, field crop was 81.84%, and shrimp farm was 2.66%. The accuracy assessment of land use classified technique using the confusion matrices and kappa coefficient were used the 300 points of randomly by the stratified sampling methods. The overall accuracy and the kappa coefficient as shown in **Table 3,4, and 5**.



**Fig. 3.** The land use classes map for the years 2015 of the Yang Talad, Kalasin province, Thailand.



**Fig. 4.** The land use classes map for the years 2018 of the Yang Talad, Kalasin province, Thailand.

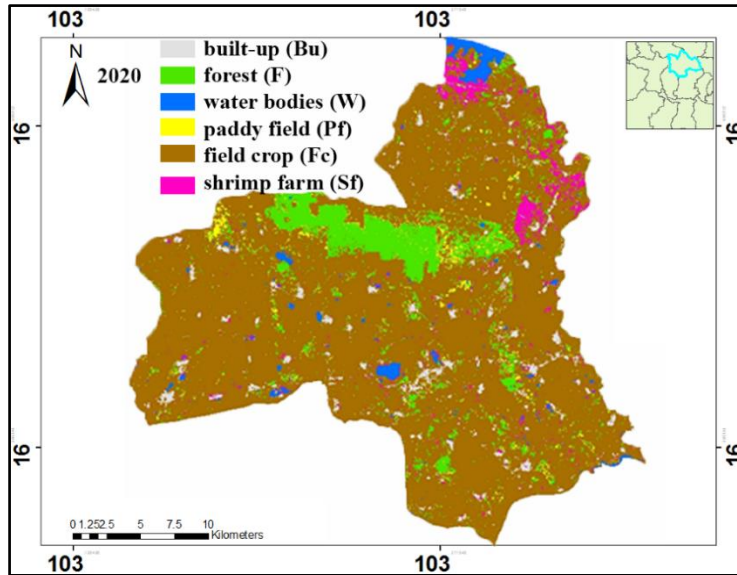


Fig. 5. The land use classes map for the years 2020 of the Yang Talad, Kalasin province, Thailand.

Table 3.

Confusion matrices and kappa coefficient of land use classified for the years 2015.

Classes	Reference data						total
	Bu	F	Wb	Pf	Fc	Sf	
Bu	47	0	0	0	2	0	49
F	0	46	0	2	0	1	49
Wb	0	0	47	0	0	0	47
Pf	0	4	0	46	0	1	51
Fc	3	0	0	2	47	2	54
Sf	0	0	3	0	1	46	50
total	50	50	50	50	50	50	300

Table 4.

Confusion matrices and kappa coefficient of land use classified for the years 2018.

Classes	Reference data						total
	Bu	F	Wb	Pf	Fc	Sf	
Bu	47	0	1	0	0	0	48
F	0	46	0	3	0	1	50
Wb	1	0	46	0	2	0	49
Pf	0	4	0	45	0	1	50
Fc	2	0	1	2	47	2	54
Sf	0	0	2	0	1	46	49
total	50	50	50	50	50	50	300

The accuracy assessment of land use classification using the confusion matrices for year 2015 show that the overall accuracy was 93 % and the kappa coefficient was 0.916 as shown in **Table 3**. The accuracy assessment of land use classification using the confusion matrices for year 2018 show that the overall accuracy was 92.33 % and the kappa coefficient was 0.910 as shown in **Table 4**. The accuracy assessment of land use classification using the confusion matrices for year 2020 show that the overall accuracy was 91.66 % and the kappa coefficient was 0.90 as shown in **Table 5**.

**Table 5.****Confusion matrices and kappa coefficient of land use classified for the years 2020.**

Classes	Reference data						total
	Bu	F	Wb	Pf	Fc	Sf	
Bu	45	0	0	0	1	1	47
F	0	47	0	1	0	0	48
Wb	0	1	46	1	0	2	50
Pf	2	1	0	46	2	0	51
Fc	3	1	1	1	46	2	54
Sf	0	0	3	1	1	45	50
total	50	50	50	50	50	50	300

**3.2. The result of Land use change detection**

The results of the land use change detection were performed by image differencing method show that in **Table 6**. The area of land use change between year 2015 and 2018 show that built-up area increased was 4.67%, forest area decreased was 25.48%, water bodies decreased was 3.99%, paddy field decreased was 51.44%, field crop increased was 4.66%, and shrimp farm increased was 21.28%. The area of land use change between year 2018 and 2020 show that built-up area increased was 33.66%, forest area decreased was 8.37%, water bodies increased was 0.36%, paddy field increased was 138.05%, field crop decreased was 2.11%, and shrimp farm increased was 31.74%. The area of land use change between year 2015 and 2020 show that built-up area increased was 28.52%, forest area decreased was 46.44%, water bodies decreased was 3.79%, paddy field increased was 13.50%, field crop increased was 2.39%, and shrimp farm increased was 37.41%.

**Table 6.****The area of land use change detection on years 2015, 2018, and 2020.**

Classes	Chang detection (2015-2018)		Chang detection (2018-2020)		Chang detection (2015-2020)	
	sq.km	%	sq.km	%	sq.km	%
built-up	0.70	4.67	5.29	33.66	5.99	28.52
forest	-22.34	-25.48	-5.47	-8.37	-27.81	-46.44
water bodies	-0.54	-3.99	0.05	0.36	-0.49	-3.79
paddy field	-6.10	-51.44	7.95	138.05	1.85	13.50
field crop	25.81	4.66	-12.26	-2.11	13.56	2.39
shrimp farm	2.46	21.28	4.45	31.74	6.90	37.41



#### 4. DISCUSSION AND CONCLUSIONS

As the result of the land use classification for the year 2015, 2018, and 2020 found that the area of Yang Talad district about 80 % cover by field crop area. Meanwhile, the shrimp farm area covers about 2.66 %. The classification accuracy of the ANN technique shows that the overall accuracy and kappa coefficient higher than 91.66 % and 0.90, respectively. The results accuracy assessment by the producer's accuracy of the ANN technique for the year 2015 show that built-up was 94%, forest was 92%, water bodies was 94%, paddy field was 92%, field crop was 94%, and shrimp farm was 92%. The producer's accuracy of the ANN technique for the year 2018 show that built-up was 94%, forest was 92%, water bodies was 92%, paddy field was 90%, field crop was 94%, and shrimp farm was 92%. The producer's accuracy of the ANN technique for the year 2020 show that built-up was 90%, forest was 94%, water bodies was 92%, paddy field was 92%, field crop was 92%, and shrimp farm was 90%. The results of land use classes map of the year 2015, 2018, and 2020 show that the pink color of land use maps show the area of shrimp farm compared with the surveyed and visual interpretation was the accurate with the shrimp farm area existing.

In addition, the comparison of the results of the land use classify show with similar research such as Dorber et al. (2020) presented the remote sensing can be use to provide spatially explicit land-use change information of shrimp aquaculture. The results of accuracy assessment show that the accuracy of the spatial resolution of Sentinel-2 similar with Costantino et al. (2020). The land use change detection show that forest area decreased throughout between year 2015 to 2020 was 46.44%. The land use of built-up, paddy field, and shrimp farm increased throughout between year 2015 to 2020. The shrimp farm between year 2015 to 2020 to increasing trend of related with the shrimp production was the high demand for the popular in the global market in Thailand (Thai Shrimp Association. (2019). The shrimp farm area increased was 37.41%. Furthermore, the results of land use change of shrimp farm can be used for predicting the future land use by using the prediction model such as land change modeler or Ca-Markov model.

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