Estimation of salt pond area in Madura based on satellite imagery

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Abstract. Salt is one of the essential commodities in Madura. Still, this commodity is often a problem related to the volume of production that cannot be determined with certainty. Sometimes, the estimation and actual production in the field is much different. The satellite image is a picture of an area photographed by satellite remote sensing of an area according to conditions in the field. Satellite imagery can be used to estimate the area of production of a commodity at a specific location. This study aimed to estimate the total area of salt pond in the Madura Island, specifically Sampang district, using a Landsat 8 satellite image. The method used spectral analysis that extracts multispectral data Landsat 8 to result from different areas. Field observations were conducted to validate the area. The results show that the accuracy of satellite image interpretation of salt ponds and non-salt ponds was 67.5%. Based on the result, it is possible to estimate salt pond area production in the Sampang district using Landsat 8. However, classification results must be improved by using other classification methods.

1. Introduction
Madura Island is known as the Salt Island because Madura contributes about 25% of national salt production. It is because Madura Island is known to have a long dry season, not many rivers and freshwater sources. Salt production on the island of Madura can be conducted two to four times in one season with an average production of about 70 tons/ha/year, with a production period of around May to September. At that time, the stock of salt in the market was very abundant. One of the salt problems that arises is the uncertainty of the number of real salt stocks available. The government estimates that national salt production is insufficient, so it is necessary to import salt.

On the other hand, the salt stock should be sufficient for the national salt fulfillment target based on field conditions. These problems can be caused by several factors [1], ranging from uncertain estimates of the volume of salt production, the quality of the salt produced is not up to standard, the amount of stock in the warehouse is not clear to the need for salt that cannot be determined. Therefore, this condition makes the problems in the salt sector very complex.

There are several studies on salt production and productivity of salt ponds in Madura, Indonesia. Cahyadi et al. [2] developed an Artificial Neural Network Model to estimate salt fields productivity. Purnama et al. [3] analyzed the salt pond of Sampang District using the ALOS PALSAR image. ALOS PALSAR was a radar image acquired by an active microwave sensor that uses L-band frequency. Only one study uses satellite imagery to estimate salt production; Muharram and Khakhim [4] have investigated the use of worldview-1 imagery to estimate salt production in Sampang Regency.
One possible solution to the problem is to redesign the method for estimating the volume of salt production, especially in Madura. Production volume estimation by satellite imagery to determine salt ponds correlated with productivity in the observed ponds. The next challenge is how estimating salt production volume based on satellite imagery can make policies related to salt commodities, primarily associated with the volume of salt production in Madura.

Based on these conditions, it is crucial to develop mitigation of salt production volume in Madura based on satellite imagery. It is expected to increase the accuracy of the prediction of salt pond production volume based on actual conditions in the field. Thus, it is no longer possible to manipulate salt ponds' production volume data to land productivity.

This study aimed to estimate the area of salt pond production in Madura, especially the Sampang district using a satellite image interpretation approach. The estimated area should be used to predict volume salt production. The results of this study are expected to help determine public policies regarding salt commodities.

2. Materials and methods

2.1. Materials

There are two data used in this study, spatial data and non-spatial data. Spatial data using Landsat 8 OLI/TIRS satellite imagery has accompanied by multispectral. Spatial data used Sampang district that acquired from earthexplorer.usgs.gov. The data accessed from April – November 2015 that selected with minimum cloud cover area. The 2015 data was used as Indonesia experienced strong El Nino that correlates with increased salt production [5]. Based on these conditions, the area of salt ponds and non-salt ponds can be distinguished. Spatial data administration about Sampang district was received from tanahair.indonesia.go.id/portal-web. Non-spatial data consisted of primary data and secondary data. Primary data includes salt ponders, landowners, observations about salt ponds, and the salt production process stages. Primary data also includes data on land area, productivity. In contrast, secondary data includes literature from previous research published in books, journals, or productions related to research data needs.

2.2. Methods

The research method for determining the area of salt ponds based on satellite imagery is presented in Figure 1. The stages of this research refer to the steps of the study conducted by Syam et al. [6] and Nahib et al. [7]. First, Landsat data is processed by radiometric correction. Second, Landsat data was clipped to highlight the problematic region, especially the salt pond area. Third, the data were analyzed using a band combination to observe better the salt pond area, rivers, seashore, and urban area.

The band combination was acquired from Dwivedi and Rao [8]. The salt pond map was created and then classified using the maximum likelihood method to differentiate salt pond and non-salt pond areas. This method is based on Zhang et al. [9] and Zhang et al. [10]. Two hundred forty areas, i.e., 120 salt ponds and 120 non-salt ponds, were observed at four sub-districts, Sampang, Torjun, Jrengik, and Sreseh. The area was chosen because it has the largest salt pond area in East Java [11]. The distribution
of salt pond areas for the 4 sub-districts is shown in Figure 2. Three-fourth of data observation is used to train the classification model and the rest for test validation model classification.

![Figure 2. Map of distribution of salt pond at Sampang district.](image)

The best correlation model is used to determine salt production in the sub-model of supplying consumption salt and sub-model of providing industrial salt, which is included in a dynamic model of mitigating the volume of salt production. The preparation of the dynamic model of salt production volume mitigation refers to the research stages carried out by Dharmayanti et al [1].

3. Results and discussion

3.1. Satellite image analysis process

The satellite images were processed to classify the non-salt field and salt field. Classifying the salt field and not the salt field was done using the polygons feature technique during the image enhancement stage [7]. The polygon feature draws on Landsat data where observed salt field data exist. The results show that field-produced salt crystals have a dark blue that generally lasts during the dry period (April-September). Different results in the interpretation of salt crystals depend on the type of satellite image used; using Quickbird satellite imagery, the salt field had a bright hue [7].

Figure 3 illustrates a classification map with four classes: salt pond, water bodies, buildings, and agricultural area. Each class had a micro class; the salt pond contained salt crystal (crystallization ponds) and the salt field (evaporation pond). Water bodies contain the foreshore, rivers, and sea. Buildings enclose urban areas. Agriculture includes both paddy fields and non-paddy fields. It was not easy to distinguish between a salt pond and a body of water. This condition causes false detection of areas that should be foreshore but are instead detected as sea ponds and vice versa. Compared to other micro classes, the wavelength between the foreshore and the salt crystal is slightly higher. Figure 4 shows a spectral plot revealing the wavelength value for each micro class. The classification map helped distinguish between salt ponds, agricultural areas, and urban areas. Other classification methods, such as neural networks, could assist in differentiating between sea ponds and water bodies [10].
Other information from the interpretation of satellite imagery was a pattern of the salt pond between salt ponds managed by people and corporations. The pattern of people's salt pond: size, placement, and arrangement of each salt pond were not even. However, corporate salt ponds had a regular pattern of shapes ranging from evaporation ponds, condensation ponds, and crystallization ponds. A regular pattern of the salt pond was required to have a standard size of smallholder salt ponds, allowing for a more precise estimation of salt production [4].

3.2. Process for comparison of land measurement results
A comparison of the measurement results was carried out on satellite imagery and field observations at Sampang district. The measurement accuracy is divided into two parts. First, the measurement accuracy of the difference in the area resulting from the interpretation of satellite images and field observations; and second, the accuracy of image interpretation was aimed at assessing the success of satellite image processing classification in distinguishing salt and non-salt ponds. Determination of accuracy was based on Muharram and Khakhim [4], who compiled a confusion matrix to present the classification success.
The vertical and horizontal measurement accuracy results differ by 1.1m and 0.6m, respectively. These findings are consistent with Dolloff and Settergren [12], who found that the vertical and horizontal measurement error rates are 1.2m and 0.7m, respectively. Table 1 shows the accuracy of satellite image interpretation. The four results of a confusion matrix were true positive, false positive, false negative, and true negative. There were three other measurements based on that result: accuracy, precision, and recall. The classification result had a precision of 100 percent, indicating that the predicted class by model classification was accurate. Its accuracy and recall were low, and its parameter revealed that the model classification failed to distinguish between salt and non-salt ponds and vice versa. In general, the maximum likelihood classification result was inadequate at distinguishing between the salt pond and non-salt pond, especially salt pond and foreshore.

Table 1. Confusion matrix of distinguishing between the salt pond and non-salt pond.

| Confusion matrix | Field survey results | Amount |
|------------------|----------------------|--------|
|                  | Salt ponds | Not salt ponds |        |
| Salt pond        | 120       | 0           | 120    |
| Not salt pond    | 78        | 42          | 120    |
| Amount           | 198       | 42          | 240    |
| Accuracy         | 67.5%     | 60.6%       |
| Precision        | 100%      |             |
| Recall           |           |             |

The total area of the salt pond as interpreted by Landsat 8 OLI/TIRS was 5685.48 ha. The total area is determined by pixel counting then multiplication by width and height of each pixel, 30, 30 respectively. Based on each sub-district area, the largest salt pond in order, Sreseh, Torjun, Sampang, and Jrengik (Table 2). The determined area was slightly different from the actual salt pond area for each sub-district. The difference was 31% between counting area by pixel and actual area. The gap needed to be completed to ensure an accurate estimation of salt production based on total area. This difference in results can be due to heterogeneous satellite imagery coverage [13]. A satellite image can include a variety of sizes, colors and locations making it difficult to determine an object by a single color. A factor that also affects the accuracy of broad determination is the determination of the exact spectral index[14][15].

Table 2. Total area salt pond between counting by pixel and actual area.

| District | Actual area (ha) | Determined area (ha) |
|----------|------------------|----------------------|
| Sreseh   | 2006.5           | 2634.2               |
| Torjun   | 1549.9           | 2034.8               |
| Sampang  | 557.8            | 732.3                |
| Jrengik  | 216.5            | 284.2                |

4. Conclusions
Landsat 8 OLI/TIRS satellite imagery could classify salt ponds and non-salt ponds. Salt ponds in particular that have produced salt crystals were shown in black blue. The arrangement of the salt ponds needs to be standardized to facilitate interpretation using satellite imagery. The measurement accuracy based on satellite imagery is 1.1m for vertical and 0.6m for horizontal measurement. Classification result showed unsatisfied result, accuracy and recall parameter just slightly a top of half value. Model classification resulted in low performance to distinguish between salt crystal and foreshore. Classification methods used other machine learning need to be further studied.
Acknowledgment
The authors would like to acknowledge the Institute for Research and Community Service (LPPM) University of Trunojoyo Madura for providing financial support through the Research Group schemes 2021.

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