OPTIMIZING AQUACULTURE AREA MAPPING IN FLOOD-PRONE COASTAL REGIONS THROUGH THE APPLICATION OF TEXTURE MODELS ON SENTINEL-1 RADAR IMAGERY

A CASE STUDY OF DEMAK REGENCY, CENTRAL JAVA

(*Optimasi Pemetaan Area Tambak di Daerah Rawan Banjir Rob Melalui Penerapan Model Tekstur Pada Citra Radar Sentinel-1, Studi Kasus: Kabupaten Demak, Jawa Tengah*)

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ABSTRACT

This study aims to improve the accuracy of aquaculture area mapping in regions prone to tidal inundation, where coastal flooding (rob) causes similarities in characteristics between seawater and coastal aquaculture areas. Rob flooding often leads to the mixing of seawater with aquaculture areas, posing challenges in classification due to spectral and textural similarities. To address this issue, we utilize Sentinel-1 data, and a texture model based on the Gray Level Co-occurrence Matrix (GLCM). This approach aims to distinguish aquaculture areas from other regions with similar characteristics, such as rice fields and aquaculture ponds frequently submerged by rob flooding. By integrating Sentinel-1 radar data with the GLCM texture model, more varied and specific information is provided to enhance classification accuracy. The results indicate that the texture model approach applied to Sentinel-1 radar imagery significantly improves the accuracy of aquaculture area mapping compared to traditional methods. This study provides mapping accuracy results of 81.71% using a texture model for areas affected by tidal flooding. These findings highlight that the texture modeling technique using Sentinel-1 radar imagery provides a more effective solution to overcome mapping challenges in rob flood-prone areas. This approach offers important benefits for land management and flood risk assessment in coastal areas, particularly in Demak Regency, Central Java.

Keywords: Aquaculture, coastal flooding, GLCM, Sentinel-1

ABSTRAK

Penelitian ini bertujuan untuk meningkatkan akurasi pemetaan area tambak di daerah rawan inundasi tidal, di mana banjir rob menyebabkan kemiripan karakteristik antara air laut dan area tambak pesisir. Banjir rob sering mengakibatkan percampuran air laut dengan area tambak, yang dapat menimbulkan tantangan dalam klasifikasi karena kesamaan spektral dan tekstural. Untuk mengatasi masalah ini, kami memanfaatkan data Sentinel-1 serta model tekstur berbasis Gray Level Co-occurrence Matrix (GLCM). Pendekatan ini bertujuan untuk membedakan area tambak dari daerah lain yang memiliki karakteristik serupa, seperti sawah dan tambak yang seringkali terendam air rob. Dengan mengintegrasikan data radar dari Sentinel-1 dengan model tekstur GLCM, akan memberikan informasi yang lebih bervariatif dan spesifik untuk meningkatkan akurasi klasifikasi. Hasil penelitian menunjukkan bahwa pendekatan model tekstur pada citra radar Sentinel-1 secara signifikan meningkatkan akurasi pemetaan area tambak dibandingkan metode tradisional. Penelitian ini memberikan hasil akurasi pemetaan sebesar 81.71% menggunakan model tekstur untuk area yang terdampak banjir rob. Temuan ini menekankan bahwa teknik pemodelan tekstur pada citra radar Sentinel-1, menyediakan solusi yang lebih efektif untuk mengatasi tantangan pemetaan di daerah rawan banjir rob. Pendekatan ini memberikan manfaat penting untuk manajemen lahan dan penilaian risiko banjir di kawasan pesisir, khususnya di Kabupaten Demak, Jawa Tengah.

***Kata kunci**: Tambak, banjir rob, GLCM, sentinel1*

INTRODUCTION

Indonesia, as an archipelagic country with a coastline of about 104,000km and consisting of around 17,504 islands, both large and small (Haris et al., 2021), has huge potential for the development of coastal areas. Since the 15th century, the practice of brackish water cultivation has begun on the coast of Java (Gusmawati, et al., 2016; Haris et al., 2021, 2022). One important form of brackish water aquaculture is ponds, which are an integral part of the aquaculture sector (Azahra et al., 2019). With the rapid growth of the human population, increasing socio-economic needs, and the ever-growing demand for protein, the aquaculture sector has become one of the fastest-growing food production sectors in the world in recent decades (Porporato et al., 2020).

However, this rapid development also poses various challenges, including the destruction of natural habitats (Hardy et al., 2019), ecosystem degradation in coastal areas (Peng et al., 2013), and land fragmentation (Ren et al., 2019). Therefore, monitoring coastal areas is essential to ensure sustainable management. One of the methods that can be used for this monitoring is land cover mapping, including mapping of human-managed ponds, to support sustainable aquaculture practices (Duan et al., 2020). However, direct monitoring of ponds by individuals requires significant time and cost, given the large area of ponds that must be monitored (Gusmawati et al., 2016).

Remote sensing data offers a valuable solution for mapping and identifying pond areas. The use of this data has increased, due to its advantages, including digital format, temporal monitoring capabilities, and wide area coverage, as well as the ability to generate different types of data that are often difficult to obtain directly in the field (Alexandridis et al., 2008; Moharrami et al., 2024; Shang et al., 2018). Optical imagery, such as those generated by Landsat satellites, has been widely used for pond mapping at various scales (Ottinger et al., 2022; Ren et al., 2019), but its use is limited in areas that are often covered by clouds, such as in Southeast Asia (Ottinger et al., 2016, 2022). Alternatively, imagery from the Synthetic Aperture Radar (SAR) system can penetrate clouds and reduce the impact of weather on imaging, making it an effective choice for tropical regions such as Indonesia (Ottinger et al., 2022; Prasad et al., 2019).

Gray Level Co-occurrence Matrix (GLCM) is one of the methods in texture analysis that is widely used to extract texture features from digital images (Mohammadpour et al., 2022). GLCM works by calculating the frequency of occurrence of adjacent pixel intensity value pairs in each direction, distance, and angle. The results of this calculation result in a matrix that depicts the spatial distribution of pixel intensity values, which can then be analyzed to extract various texture features such as contrast, homogeneity, energy, and correlation (Mohanaiah et al., 2013; Tavus & Kocaman, 2023).

In the context of mapping land using radar imagery, such as Sentinel-1, the GLCM method provides additional capabilities to distinguish objects that have similar spectral characteristics but have different textures (Tavus & Kocaman, 2023), such as pond areas and coastal areas affected by tidal floods. The use of radar and texture data has also been applied in the coastal areas of Indramayu Regency in mapping rice fields adjacent to pond areas to minimize identification errors (Fathoni et al., 2017). By analyzing the texture of the radar imagery, GLCM allows for improved classification accuracy (Haris et al., 2021; Mohanaiah et al., 2013), especially in regions that are often difficult to distinguish only with conventional spectral analysis (Tavus & Kocaman, 2023). This makes GLCM an important tool in improving the accuracy of mapping complex areas, such as ponds in flood-prone areas.

In this context, this study aims to improve the accuracy of identification and mapping of pond areas by utilizing radar imagery capabilities and the application of texture models on the coast of Demak Regency, Central Java Province. By using the index transformation and guided classification approach, it is hoped that the results of this study can provide clear insights and practical recommendations regarding the selection of the most suitable imagery for mapping and identification of pond areas.

METHOD

This study focuses on the analysis of radar images for the extraction of land use information, especially ponds in coastal areas, as an effort to improve the ability of radar images. Next, a texture model approach is performed on radar imagery to improve the accuracy of classification. This study utilizes backscatter information on radar imagery and applies filters and texture models. The combination of the Sentinel-1 radar polarization and texture models is used as a reference in the classification process to improve the accuracy of the classification results.

Research Location

The location of the research was carried out in Demak Regency. Astronomically it is located between 6°41'47.07"S - 6°58'47.32"S and 110°26'34.47"E - 110°38'58.21"E.

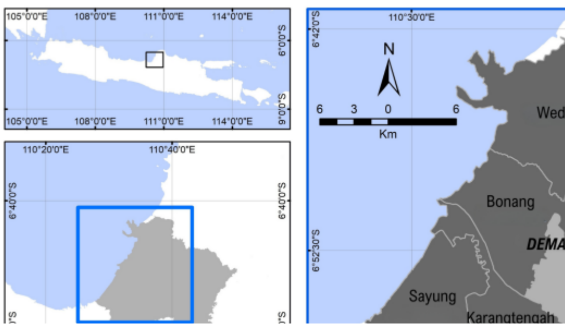

Figure 1. Research location, Demak Regency, Central Java Province.

Geographically, Demak Regency is bordered by Jepara Regency and the Java Sea to the north, Grobogan Regency and Semarang Regency to the south, Kudus Regency to the east, and Semarang City to the west. This research covers coastal areas in four districts, namely Wedung, Bonang, Karangtengah, and Sayung Districts.

Tools and Materials

This study uses Sentinel-1 Level 1-GRD radar image data corrected for ellipsoid projections based on terrain height. Image processing, from correction to analysis, was carried out using the SNAP application, while accuracy testing was carried out with QGIS, and map layout was prepared using ArcMap.

Table 1. Data used in the study.

Analysis	Data used	Source
Pond Extraction from Active Sensors	Sentinel-1, 10m resolution (April 2020-March 2021)	Open Access ESA Copernicus
Terrain Correction	DEM 30m Resolution	Online Progress on the SNAP application
Study Area Boundaries	Administrative Map of Demak Regency	Indonesia Geospatial Portal (tanahair.indonesia.go.id/)

Data Processing

In this study, data processing was carried out using Sentinel-1 radar data and a texture model based on *the Gray Level Co-occurrence Matrix* (GLCM) to improve the accuracy of mapping pond areas in coastal areas of Demak Regency that are prone to tidal floods. Tidal floods pose a challenge in classification due to the spectral similarity between seawater and pond areas, so a special approach is needed to differentiate between the two. The selection of the GLCM model compared to other models such as Local Binary Pattern (LBP) or Wavelet Transform. The LBP model is less sensitive to larger and more complex texture variations than GLCM. And for the Wavelet Transform model, this method is more complex and requires more computation than GLCM. In addition, the interpretation of the results can be more difficult.

The data processing steps are presented in a flowchart that includes the main stages (**Figure 2**), from Sentinel-1 data acquisition, application of the GLCM texture model, to analysis of the results to improve mapping accuracy.

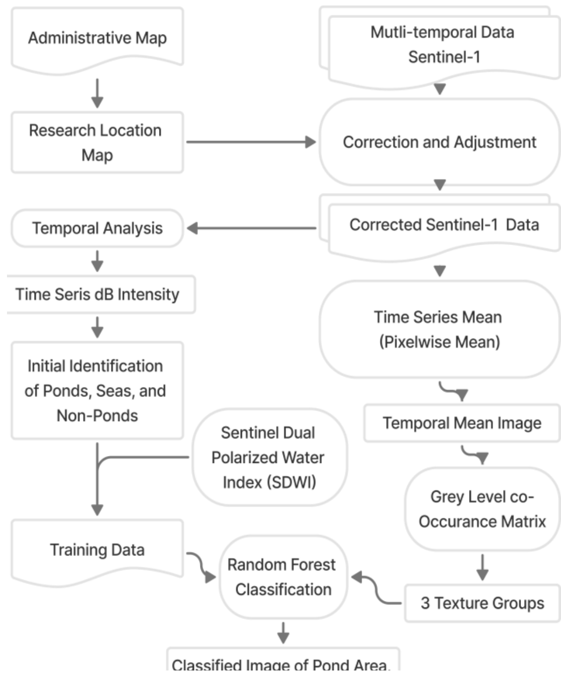

Figure 2. Data processing flow chart.

The integration of radar data with the texture model aims to provide more detailed and accurate information, helping to overcome difficulties in distinguishing pond areas from other areas that are often submerged in tidal water. The steps of data processing are explained as follows.

Preparation of Radar Imagery (Sentinel-1)

Thermal noise removal is applied to reduce noise, and then the image is calibrated to convert the digital number into sigma nought (σ°) backscatter. Speckle filtering with Lee filter (**Equation 1**) (7x7 size) is used to remove speckle noise, because it can eliminate noise while preserving the integrity of the pixel values and the edges within the image (Rana & Suryanarayana, 2019). After that, the terrain correction is adjusted to the field conditions and the value of σ° is converted to decibels (dB) as backscatter.

$$\hat{I}^3 - \bar{I}\hat{I}^2 + \sigma(\hat{I} - DN) = 0 \quad \textbf{(1)}$$

where:
$\hat{I}^3$ = Required value
$\bar{I}$ = Average value
DN = Input value
σ = Original image variant

Application of Texture Models

The use of texture models in radar imagery is expected to improve the accuracy of land cover/use classification, especially in coastal pond areas. The texture of the image is measured through the difference in grayness level (contrast), the size of the change area (window), and a certain direction (omnidirectional). The texture matrix (GLCM) calculates the probability of a certain pair of grayness levels occurring in an image. This matrix

(**Equation 2**) shows the probability of the occurrence of the grayness level j when the grayness level i moves as far as in the direction θ. With G as the maximum number of grayscale levels in the image, GLCM is a square matrix *of* $G \times G$ that depicts the spatial relationships between pixels. Probability is calculated by:

$$p_x(i) = \sum_{j=1}^{G} p_{ij},\ p_y(j) = \sum_{j=1}^{G} p_{ij} \quad \textbf{(2)}$$

GLCM is used to calculate the frequency of pixel pairs with specific spatial relationships, aiding in classification. In this study, the SNAP application was used to analyze 10 texture models grouped into three groups: Contrast (Contrast, Dissimilarity, Homogeneity), Orderliness (ASM, Energy, Max, Entropy), and Descriptive Statistics (Mean, Variance, Correlation). This texture model is used to determine the best classification approach on radar imagery.

Validation Sample

Sample determination was carried out by Proportional Random Sampling Technique in marine classes, ponds, and non-ponds. This method is adapted to field conditions to ensure that each class is represented in the classification and testing process. The test samples were in the form of points, obtained from the field, as well as areas interpreted from Google Earth imagery, aided by field data. The number of samples used is 119 sample points consisting of 36 sea samples, 35 non-pond samples, and 48 pond samples. The filed survey was conducted in August 2021 by paying attention to the time of sea tides. So that the survey data obtained is in accordance with the original cover of the land being studied. The use of random point samples is avoided because it does not provide consistent results (Danoedoro & Utara, 2015).

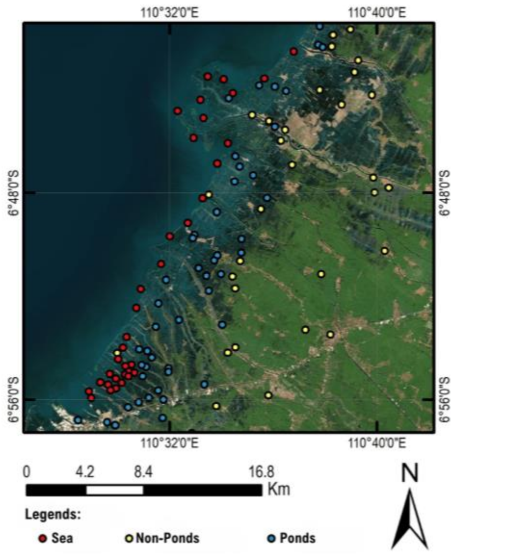

Figure 3. Distribution map sample testing accuracy of classification results.

The accuracy test was carried out by applying the Confusion Matrix and Kappa Coefficient methods which were analyzed using the QGIS application. Accuracy tests were applied to the classification results using VH Polarization data, Contrast Texture Model, *Orderliness,* and *Statistical Descriptive.* The use of VH polarization is advantageous because the waves are transmitted vertically and received horizontally (Ottinger et al., 2022). This configuration is particularly effective for monitoring objects with vertical structures and variations (Chen et al., 2020). Consequently, it is employed to enhance the monitoring of pond embankment structures. This method has been commonly used by researchers to test the accuracy of land use classification/mapping results (Haris et al., 2021, 2022).

RESULTS AND DISCUSSION

Processing radar image data in pond identification, in the form of 10m spatial resolution Sentinel-1 data consisting of VH and VV polarization bands. The data used was in the form of time-series data for 12 months. Then it is processed into a single data that aims to reduce the noise in the data by using the mean model in the 12 months of the data. The use of bands with VH and VV Polarization aims to form a data transformation in the form of SDWI that can distinguish water bodies and non-water bodies (Sun et al., 2020). Meanwhile, what is used in the classification is only VH Polarization data which is good for land use data extraction (Chen et al., 2020; Ottinger et al., 2022) and the application of texture models to the Polarization. The results are explained as follows.

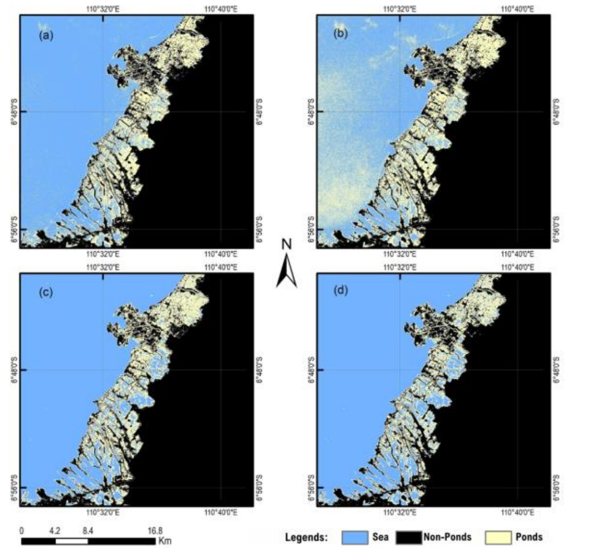

Figure 4. Map of pond identification results using radar imagery, (a) VH polarization, (b) *contrast* group, (c) *orderliness* group, (d) *descriptive statistical* group in Demak Regency.

Based on **Figure 4,** be it for VH Polarization (a), Contast group (b), Orderliness group (c), and Desc Statistic group. (d) provide good results for non-pond areas visually. For the pond class in the Contrast group, it was found that there was a classification error to the sea area and there was little in the sea area for VH polarization. This can be caused by water conditions that are calculated on average (Bioresita et al., 2019) for 12 months of data used.

Table 2. Backscatter value in Sentinel-1 Imagery Demak Regency.

Class	**Mean (backscatter)**			
Polarization Data	**SDWI**	**VH**	**VV**	
Sea	0.4074	-23.7758	-18.9384	
Other (non-Ponds)	-0.8507	-15.9247	-8.4292	
Ponds	0.2666	-24.4825	-16.3812	
Contrast Group	**Contrast**	**Dissimilarity**	**Homogeneity**	
Sea	0.0002	0.0002	1.9988	
Other (non-Ponds)	2.2528	0.4033	1.8613	
Ponds	0.2414	0.2894	1.8535	
Orderliness Group	**ASM**	**Energy**	**Entropy**	**Max**
Sea	3.9962	1.9987	1.3858	1.9982
Other (non-Ponds)	3.4321	1.8130	0.8208	1.7580
Ponds	3.3173	1.7867	0.7908	1.7133
Statistic Desc. Group	**Correlation**	**Mean**	**Variance**	
Sea	0.1516	0.0002	0.0002	
Other (non-Ponds)	0.9723	2.6797	5.5891	
Ponds	0.4881	0.4723	0.4300	

In Demak Regency, the backscatter data from the Sentinel-1 image (**Table 2** and **Figure 5**) shows clear differences between classes. For the sea, the average backscatter value is 0.4074 on SDWI, -23.7758 on VH, and -18.9384 on VV. Non-pond objects recorded values of -0.8507 in SDWI, -15.9247 in VH, and -8.4292 in VV, while pond objects had values of 0.2666 in SDWI, -24.4825 in VH, and -16.3812 in VV. Based on **Table 2** and **Figure 6**, in the contrast group, the sea has low contrast and dissimilarity values and high homogeneity. Non-pond objects show high contrast and dissimilarity with slightly lower homogeneity, while pond objects have moderate values in all three metrics. In the regularity group, the ocean has the highest ASM, energy, and max values, while non-pond objects have slightly lower values for all metrics, and pond objects show the lowest values.

In the descriptive statistical group, the sea showed low correlation and mean values with a very small variance; non-pond objects have a high correlation with the greatest mean and variance, while pond objects fall somewhere in between the two. For a specific explanation of the texture model applied to the study location, it can be seen as follows.

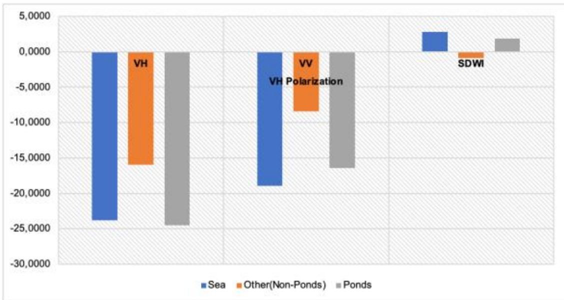

Figure 5. Graph of backscatter values VH, VV, polarization and SDWI Sentinel-1 data in Demak Regency.

GLCM Model: Contrast Group

The texture model in the Contrast Group measures contrast based on distance from the GLCM diagonal (Hall-Beyer, 2017; Haralick et al., 1973) and takes advantage of the characteristics of the Sentinel-1 radar imagery, especially its reverse scattering (Chen et al., 2020). The application of this model in Demak Regency shows the variation in pixel values for the Contrast and Dissimilarity classes, which are higher than the Homogeneity class (**Table 2** and **Figure 6**). This difference is due to regional characteristics such as the type of pond (Sridhar et al., 2008) and different land uses, as well as the placement of training data that affects the distribution of value.

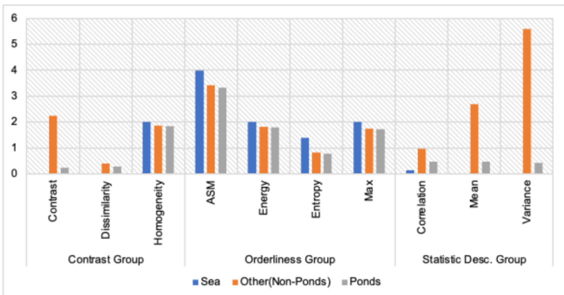

Figure 6. Graph of backscatter values of contrast group, orderliness group, and statistic descriptive group of Sentinel-1 data in Demak Regency.

GLCM Model: Orderliness Group

The use of texture models in Orderliness Groups focuses on measuring the regularity of pixel values within an imagery. The more uniform the value is among neighboring pixels, the higher the texture value (Hall-Beyer, 2017). In this model, four main texture models, such as ASM and Energy, are used to measure the variation in pixel values. Although each model has a different range of values, they all share the same basic concept, which is to assess uniformity and regularity.

Based on the data shown in **Table 2** and **Figure 6**, the texture model applied in Demak Regency shows a tendency to have higher pixel values, especially in the ASM model. The model assesses the degree of uniformity, where the more uniform the pixels in the image, the higher the value produced. This indicates that the use of land and the type of ponds in Demak Regency make a significant contribution to the high value of this uniformity. For example, pond land in these areas may be more uniform, which is then reflected in higher texture values.

In addition to ASM, the Energy texture model, which is the root of ASM, also contributes to the measurement of uniformity, although Energy values tend to be lower than those of ASM due to their mathematical characteristics (Hall-Beyer, 2017; Mohanaiah et al., 2013). Overall, the pattern of pond uniformity and land use in Demak Regency showed a close relationship with higher texture values in the models in the Orderliness group, thus providing an overview of how the physical characteristics of the land affect the results of image texture analysis.

GLCM Model: Statistic Descriptive Group

In the GLCM analysis for the Descriptive Statistics Group in Demak Regency, the new pixel value is calculated by considering the neighbor's pixel value, not just the primary pixel value. Models such as Mean, Variance, and Correlation consider the value of the surrounding pixels in their processing (Hall-Beyer, 2017; Haralick et al., 1973). The data (**Table 2** and **Figure 6**) show that marine objects in Demak Regency have pixel values that tend to be lower than pond and non-pond objects. Texture variations affect the pixel value of the imagery, with non-farm objects showing higher value variations (Bai et al., 2021; Chen et al., 2020; Nizalapur & Vyas, 2020; Ottinger et al., 2013). This difference is due to the different conditions of the sea waters in Demak Regency, which affects the results of texture analysis (Grover et al., 2018).

Mapping Accuracy

Table 3. Overall scenario accuracy using radar imagery.

No	Scenario	Accuracy: *Overall Accuracy*	*Kappa Coeficient*
1	VH Polarization	80.87%	0.69
2	Contrast Group	79.92%	0.66
3	Orderliness Group	79.89%	0.67
4	Statistic Descriptive Group	81.71%	0.67

Pond identification in Demak Regency using radar images resulted in an overall accuracy of between 79-82%. Based on **Table 3**, it was found that the scenario using the Statistic Descriptive Group Model produced the highest mapping accuracy of up to 82%. These results are in accordance with research conducted by Herold et al., (2004), which used the Variance Texture model in the Statistic Descriptive Group. By obtaining an increase in accuracy from 56% to 75%. This accuracy is influenced by the characteristics of relatively homogeneous ponds, with most ponds in the form of silvofishery. The homogeneity of this type of pond affects the return scattering value on the radar imagery, which is in accordance with the findings Sridhar et al., (2008) and has an impact on the results of the application of the texture model (Mohanaiah et al., 2013; Nizalapur & Vyas, 2020) These factors contribute to the level of accuracy achieved in the mapping of ponds in the coastal area of Demak Regency.

Previous research using texture models provides a relevant picture for this study. For example, Sun et al., (2020) used Sentinel-1 radar data and SDWI water index transformations to minimize classification errors, resulting in similar results even with different classification systems. Herold et al., (2004) used a Statistic Descriptive texture model with a large window size, improving accuracy and reducing classification errors. Chen et al., (2020) show that the Orderliness texture model has a significant influence, especially on non-pond areas. Some other studies, such as Haris et al., (2021) reported an overall accuracy 90.96% using GLCM on the VH Band, while Fathoni et al., (2017) achieved an accuracy up to 88% accuracy in the contrast group. These studies demonstrated a high accuracy range, which is influenced by the type of land cover in coastal areas, including ponds in Demak Regency. Haris et al., (2021) Fathoni et al., (2017). From several similar studies that use radar imagery in pond mapping, there are consistent results direction. Provides quite good accuracy and is very dependent on the condition of the land cover at the study location.

CONCLUSION

The use of Sentinel-1 radars imagery and texture models in Demak Regency resulted in a mapping accuracy of around 79-82%. The application of the Statistic Descriptive group texture model provides better results than other texture and polarization models, although it is only 1% different from VH Polarization. However, in general, the results from radar imagery and texture models provide good results, especially for non-pond areas with mapping accuracy that has a small difference. The Descriptive Statistics and VH Polarization Group is recommended for coastal areas with disturbances or diverse land cover distributions such as those that occur in Demak Regency with coastal conditions that are often affected by tidal floods.

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