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RESEARCH ARTICLE

Enhancing Accuracy in Detection and Counting of Islands Using Object-Based Image Analysis: A Case Study of Kepulauan Seribu, DKI Jakarta

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Abstract. Based on previous observations, a series of steps using digital image processing methods is proposed for the automatic detection and counting of islands to avoid inaccuracies from satellite imagery by leveraging morphological properties of object. The need for accurate spatial data regarding the number of islands in Indonesia is crucial for various developmental purposes. Many small islands known to have beautiful landscapes remain unaccounted for due to the vast territorial waters of the country, posing challenges to manual evaluation of the numbers and distributions. Remote sensing methods offer a viable solution for efficiently counting and inventorying islands. Therefore, this study aimed to detect islands in Kepulauan Seribu, located north of DKI Jakarta, through the thresholding-based segmentation process and count the total number using morphological information. The methodology applied was Object-Based Image Analysis (OBIA), including image gray-scaling, thresholding, morphological operations, connected component labeling, and region-based object counting. The results obtained showed 111 islands, compared to direct observation of image from which 104 were found, with detection accuracy of 93.27%. The discovery not only contributes valuable insights into the specific region but also serves as a basis for potentially applying digital image processing methods on a larger scale to recalculate the number of Indonesian islands. Such recalculations could play a crucial role in informing and guiding future developmental initiatives.

1. Introduction

Indonesia contains one of the largest archipelagos globally and two-thirds of the territory is situated in the oceans, covering an area of 6.32 million km^2. This country has the second-longest coastline, spanning 99,093 km, after Canada (Soemarmi & Diamantina, 2019). In addition, it consists of five major islands (Java, Sumatra, Sulawesi, Kalimantan, and Papua) alongside approximately 17,475 small islands measuring less than 200 km^2. Despite the rapid development of the larger islands, numerous smaller islands, including Kepulauan Seribu, often face neglect and oversight (Farhan & Lim, 2012).

Kepulauan Seribu known as Seribu Islands situated in the administrative district of DKI Jakarta, Indonesia, comprises a group of islands in Jakarta Bay. In 2020, this area contained 29,230 people, constituting 0.26% of the total population (11,196,633) found in DKI Jakarta(BPS, 2017). The term "Kepulauan Seribu" literally meaning "The Archipelago of a Thousand Islands" alludes to the historical assumption that there were around a thousand islands, although the exact number remains elusive. Several studies reported different figures ranging from 105 (Cleary et al., 2006; Farhan & Lim, 2012; Zubaida et al., 2020), 110 (BPS, 2017; Hakim et al., 2007; Madduppa et al., 2013), to 120 islands (Fauzi & Buchary, 2002), while the remaining areas are sandbars and coral reefs visible at the sea surface.

Apart from the diverse ecosystem, Kepulauan Seribu has economic potential, particularly in sectors such as fisheries, mining, and tourism (Hakim et al., 2007; Rivai et al., 2018). Additionally, it harbors Kepulauan Seribu National Park (TNKS), a marine conservation area (Fauzi & Buchary, 2002; Rudianto et al., 2019). Despite environmental challenges, the region is still relatively rich in marine resources, including coral reefs, reef-associated fish, seabirds, invertebrates, and turtles (Cleary et al., 2006; Prakoso et al., 2019). The ecological landscape shows a surrounding expanse of sandy beaches, mangrove trees, seagrass beds, and seaweed (Pasaribu et al., 2020).

Small Indonesian islands are known to often elude proper recording due to natural processes (Ramadhan et al., 2016). Farhan & Lim (2012) reported that both outer and inner small islands regions such as Kepulauan Seribu District had been neglected by the central and local governments for decades, rendering the precise number of islands in this location unreliable. Periodic counting to ensure updated data becomes essential, but the manual procedure often applied is inefficient, prompting the need for a digital image processing method for automatic detection and counting using satellite imagery (Farhan & Lim, 2012; Prabowo & Salahudin, 2016).

Object-Based Image Analysis (OBIA) involves utilizing digital image-processing methods that, when implemented, lead to the segmentation (i.e., partitioning) of an image into distinct, non-overlapping units based on specific criteria. Alternatively, these techniques can be employed to delineate specific multiscale characteristics, forming the foundation for subsequent segmentation (Davis, 2019). Digital image processing, consisting of image digitization, filtering, and computational analysis (Gonzalez & Woods, 2018), plays a crucial role in detection and counting of specific object. Image segmentation methods facilitate the separation of foreground object from the background, enhancing detection and classification (Gonzalez & Woods, 2018; Wei et al., 2018; Yuan et al., 2014)

Studies including Liu et al. (2016), Lumauag & Nava (2018), Shafri et al. (2011), Barbedo (2014), Frost et al. (2016), Li et al. (2017), Chao et al. (2020) and Guo & Yu (2013) conducted automatic object counting through digital image processing. For instance, Shafri et al. (2011) semi-automatically detected and counted oil palm trees with high spatial resolution airborne imagery, while Fernandez-Gallego et al. (2020) developed an automatic wheat ear counting using machine learning based on RGB UAV imagery. Reliable segmentation processes are crucial for accurate object detection and counting. Wang et al. (2020) reported five types of remote sensing image segmentation methods, comprising the pixel-based method which consists of the thresholding-based segmentation and clustering algorithm.

The thresholding-based method operates on a simple principle, requiring no prior knowledge, thereby facilitating easy implementation. Similar to the quality improvement process, image segmentation is experimental, subjective, and dependent on the objectives to be achieved (Wang et al., 2020). In the aspect of linear features segmentation, most academicians concluded that no optimum methods exist universally and spatial resolution does not substantially influence overall precision. Instead, precision relies on morphological characteristics such as the shape and orientation of image or object to be measured (Cipolletti et al., 2012). This conclusion corresponded with the results of Soille & Pesaresi (2002) which showed the capability of mathematical morphology to enhance processing and analysis methodologies of earth observation data, particularly in segmentation tasks. Additionally, morphological arithmetic operations were reported as an established image analysis method applicable in almost all science and engineering disciplines dealing with digital spatial data.

While studies by Liu et al. (2016), Shafri et al. (2011), and Fernandez-Gallego et al. (2020) have successfully employed digital image processing for object counting, the specific challenges of counting islands in the intricate marine environment of Kepulauan Seribu remain largely unexplored. This research gap emphasizes the the need for a customized strategy that integrates the benefits of OBIA. Also, existing segmentation methods, including the thresholding-based segmentation and clustering algorithm, provide a foundation for digital image processing. However, the application of these methods to detect islands in a maritime setting, particularly with varying shapes and orientations, requires refinement. The introduction of OBIA addresses this gap by offering a more context-aware and sophisticated approach to image analysis.

Based on the previous observations, a series of steps using digital image processing methods is proposed for the automatic detection and counting of islands from satellite imagery by leveraging morphological properties of object. The novelty of this research lies in its application of Object-Based Image Analysis (OBIA) for the automatic detection and counting of islands in the Kepulauan Seribu region of DKI Jakarta, Indonesia. The study addresses the challenges of accurately assessing the number and distribution of islands, particularly in a vast territorial waters area like Indonesia. The research also leverages the morphological properties of objects in the satellite imagery to enhance the accuracy of island detection and counting. This suggests a more nuanced and context-aware approach to image analysis. The research emphasizes the importance of accurate spatial data for various developmental purposes. The discovery and estimation of small islands in Kepulauan Seribu region is crucial, with the anticipation of contributing to a comprehensive record of all small Indonesian islands. The findings could potentially serve as a basis for applying similar digital image processing methods to recalculate the number of islands in the entire country, providing valuable insights for community welfare initiatives.

2. Methods

This study applied several steps in Object-Based Image Analysis (OBIA) to detect and count Kepulauan Seribu features from satellite imagery. The first stage of the methodology involved the comprehensive collection of satellite imagery depicting the Kepulauan Seribu region. This step is crucial for providing a reliable foundation for subsequent image processing and analysis. Following data collection, a crucial step was undertaken to enhance the visual quality and interpretability of the images. This involved a two-step process: 1.) RGB to Grayscale Conversion: employed to simplify the image by transforming it into a single-channel representation; 2.) Image Normalization:

A process that ensures consistent illumination and contrast levels, mitigating variations in the original images and enhancing the overall quality for subsequent segmentation. The third stage was dedicated to the critical task of segmentation, aimed at detecting the islands within the pre-processed images. This stage comprised multiple sub-steps: 1.) Thresholding: applied to create a binary image, distinguishing between foreground (islands) and background. This technique set pixel intensity thresholds to highlight relevant features, forming the basis for subsequent segmentation. 2.) Morphological Operations: crucial for refining the segmented image. These operations included Closing, Hole Filling, and Opening. The final stage involved the quantification of detected islands through two distinct processes: 1.) Connected Component Labeling: able to identify distinct regions in the segmented image, attributing unique labels to individual islands. This facilitated the isolation of each island as an independent object. 2.) Region-Based Object Counting: utilized the labeled components to determine the total number of islands present in the image. This step provided a quantitative measure of the islands detected during the segmentation process. This multi-stage methodology ensures a comprehensive and systematic approach to the detection and counting of islands in the Kepulauan Seribu region, employing advanced image processing techniques to enhance accuracy and reliability in the final results. Figure 1 illustrates the Object-Based Image Analysis (OBIA) methodology proposed in this research.

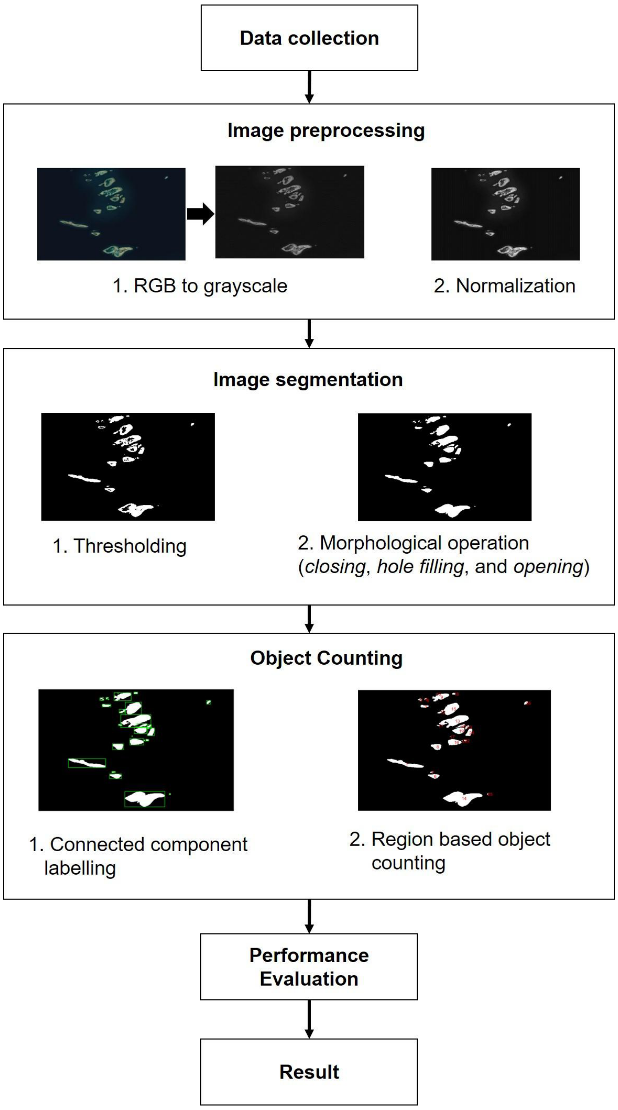


Figure 1. Workflow of the OBIA method

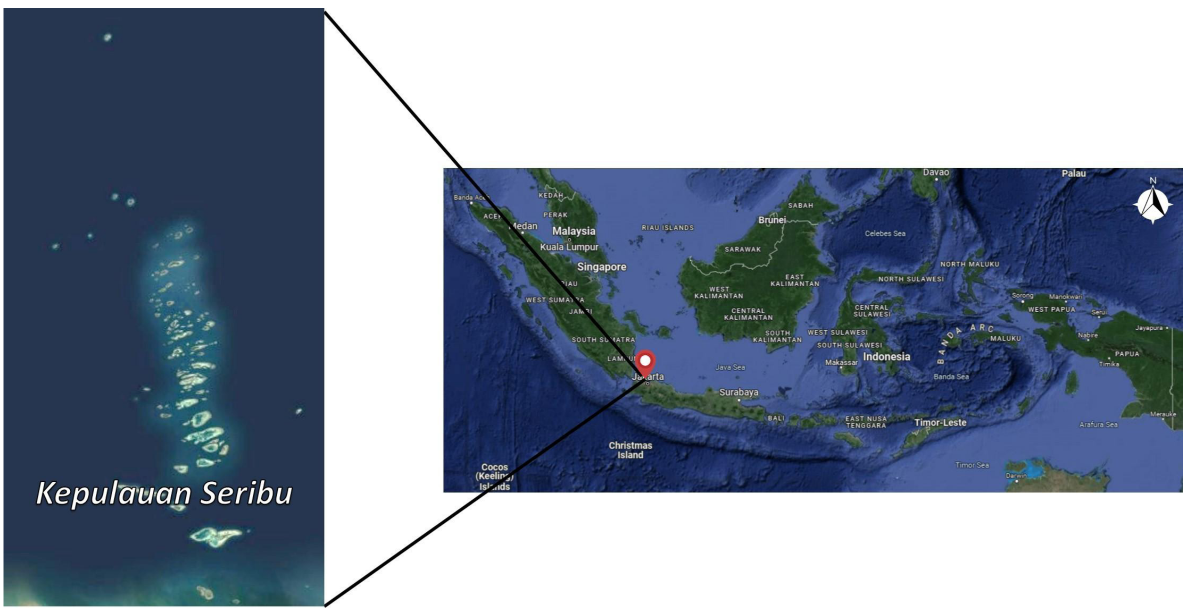


Figure 2. The study area of Kepulauan Seribu Regency

Study Area

The Administrative District of Kepulauan Seribu is located between 106°19'30" - 106°44'50" East Longitude and 5°10'00" - 5°57'00" South Latitude in the DKI Jakarta Province, with a total area of approximately 4,745.62 km2 (District, 2021), consisting 105 to 120 small islands (Farhan & Lim, 2012; Fauzi & Buchary, 2002; Madduppa et al., 2013). Furthermore, it is bordered to the north, east, and west by the Java Sea/Sunda Strait and to the south by the North Jakarta Administrative City (District, 2021).

Figure 2 shows the map of Kepulauan Seribu selected for this study because of its strategic geographical location near the capital city of Indonesia, DKI Jakarta. Additionally, it contains a marine national park (Fauzi & Buchary, 2002; Rudianto et al., 2019) and has the potential for various industrial developments (Hakim et al., 2007; Rivai et al., 2018).

Data

Based on the geographical location of Kepulauan Seribu (District, 2021), satellite imagery of this region was acquired from the Google Earth application with a good spatial resolution to ensure high accuracy during the mapping of land use and waters (Collin et al., 2014). Google Earth image is presented free as well as easy to use and recognize by users. For islands interpretation, 3, 2, 1 composite band or true color constituting wavelengths 3 (red), 2 (green), and 1 (blue), were applied respectively. This composite was selected to determine the condition of object on the surface of the earth in accordance with their original appearance. The collected data was in PNG format with a fixed scale in August 2021. The input image file size was about 1.65 MB to speed up the computing process.

Numerous recent studies focused on machine learning applications in improving object classification accuracy by introducing new classification, segmentation, and optimization methods. The methods applied were more efficient due to the high spatial resolution data. However, the mid-resolution satellite spatial data play essential roles including offering free access policies and ensuring scientific robustness when verifying these methods (Bui et al., 2019).

Image Preprocessing

A digital image is interpreted as a two-dimensional function f(x,y), where x and y are coordinate positions and f is the amplitude at (x,y) called intensity or grayscale (Gonzalez & Woods, 2018). Furthermore, it often passes through preprocessing in RGB color format before entering the main phase. This initial processing ensures image produces the desired output, with the results anticipated to be used optimally in subsequent steps (Muchtar et al., 2016).

Color or RGB image (Lainez & Gonzales, 2019) consists of three layers denoted as R, G, and B (red, green, and blue), forming a 3-dimensional matrix. In contrast, a grayscale image, lacking color, contains only brightness information, with its data matrix representing intensity. Generally, this type of image comprises 8 bits/pixel, permitting 256 grey brightness levels (0-255), facilitating faster operations. Since certain algorithms apply to 2-D image alone, RGB image is converted to grayscale (Padmavathi & Thangadurai, 2016).

Most collected image in this study featured a blue background requiring removal during segmentation. To simplify this process, the segmentation stage reduced the blue color using the weighted methods of converting RGB image to grayscale. The weighted method, also known as the luminosity method, includes the application of function f(x) to convert RGB values to grayscale through a weighted sum. Considering that the red, green, and blue components have three different wavelengths contributing to image formation, the average value is calculated accordingly. Another reason for using different weights is the higher sensitivity of human eyes to red and green components than blue. Moreover, the blue component being the darkest of the three receives the least weight and the improved formula is as follows (Olaniyi et al., 2017):

$$f(x) = 0.299Rd + 0.587Gr + 0.114Bl \tag{1}$$

where f(x) is the grayscale image, while Rd, Gr, and Bl represent the Red, Green, and Blue colored channels in the input image, respectively. Grayscale image is normalized using enhancement methods to achieve gray degree transformation of the selected region (Givens et al., 2012). Each band is then rescaled to the appropriate intensity range using Matlab's mat2gray function between 0 to 255, resulting in a better 8-bit image ready for segmentation.

Image Segmentation

Image segmentation stage was conducted after preprocessing using common a pixel-based thresholding method for object detection in remote sensing imagery. According to Wang et al. (2020), this stage operates on a simple principle, requires no prior knowledge, and is easily implementable in remote sensing.

The goal of the thresholding step is to generate a binary image where the value of each pixel is 1 or 0 for islands object or background, respectively. Moreover, pixel-based segmentation of grayscale image was performed to objectively quantify the number of foreground object (islands) extracted from the input image.

In this study, the segmentation values for low to high ranged from 80 to 255. From a direct eye view, the segmented islands object showed a whitish appearance, approaching the maximum color range of the grayscale image, which was 255, while the dark blue color of the sea tended toward the lowest range, nearly 0, without seeming overly dark. Therefore, 80 was set as the minimum pixel value and considered the foreground. Figure 3 shows the means of conducting the thresholding process by determining the low and high values. The region of interest is defined as:

$$ROI = (x(i,j) >= low) \; \& \; (x(i,j) <= high) = 1 \tag{2}$$

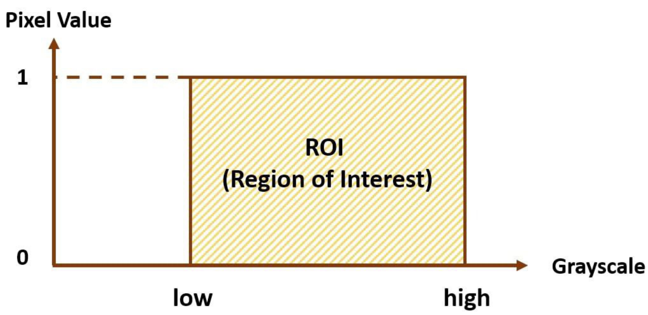


Figure 3. Setting the thresholding values between low and high to define the ROI

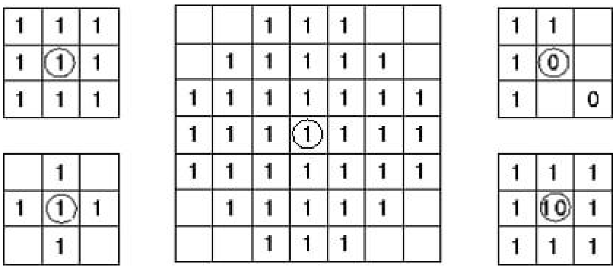


Figure 4. Example of SE (Fisher et al., 1997)

where ROI is the region of interest or foreground object and x(i,j) denotes the grayscale image. Equation (2) produces a binary image with a value of 1 for each pixel in the grayscale image within the specified ROI area [low, high].

After thresholding, morphological image analysis or morphological operations were applied to detect islands. Morphology refers to the shape and structure properties of object (Gonzalez & Woods, 2018), while morphological operations alter the structure using two inputs, specifically image and a kernel, which is a small matrix known as a structuring element (SE) (Putra, 2010). The purpose of the operations used was to acquire information about morphological properties of islands object by adjusting the SE size and shape. These were also applied because of the advantages mentioned by Soille & Pesaresi (2002), namely, to enhance processing and analysis methodologies, including segmentation in remote sensing. Morphological operations are recognized as an established image analysis method applicable in almost all disciplines handling digital spatial data.

The SE comprises a pattern described as the coordinates of several discrete points relative to an origin, often using Cartesian coordinates and represented by a small image on a rectangular grid (Fisher et al., 1997). Moreover, the shape of SE is arbitrary when depicted as a binary image of a given size (Gonzalez & Woods, 2018). Figure 4 shows various SE of different sizes, with the circled position denoting the centers of the coordinates.

There are two fundamental morphological operations, specifically dilation and erosion, forming the basis for various processes such as opening and closing (Pasrun et al., 2020). Erosion includes removing all islands object in image except the largest one (object) by scraping image and applying an SE smaller than object to be saved. Subsequently, the dilation operation expands the remaining object using the same SE. The erosion, dilation, opening, and closing operation of A by B are defined in equations (3), (4), (5), and (6) as follows (Gonzalez & Woods, 2018):

$$A \ominus B = \{z \mid (B)_z \subseteq A\} \quad (3)$$

$$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \emptyset\} \quad (4)$$

$$A \circ B = (A \ominus B) \oplus B \quad (5)$$

$$A \bullet B = (A \oplus B) \ominus B \quad (6)$$

where A means the binary image, B is SE, and z denotes the set of points. Erosion of A by B is the set of all points z, with B translated by z being contained in A. Meanwhile, dilation is used for repairing breaks and intrusions in the binary image, denoted as $A \oplus B$ in Equation (4). Opening operations generally smoothen contour object, break narrow isthmuses, and eliminate thin protrusions, aiming to minimize the impact of noise more subtly. To perform the opening operation of A by B, the erosion of A by B is first conducted, followed by dilation of the resulting image by B. Closing tends to smoothen contours, but merges narrow breaks, lengthens thin gulfs, and fills gaps in the contour (Gonzalez & Woods, 2018; Goyal, 2011), with the goal to conduct hole filling, enlargement of regions, and background shrinking. The closing of A by B is achieved through the dilation of A by B and subsequently eroding the resulting structure with B, denoted as $A \bullet B$ in equation (6).

The proposed series of steps for applying morphological operations in detecting the main object (islands) are as follows:

1. Apply the closing operation using a disk-shaped SE with a radius of three pixels. This process enlarges regions, shrinks backgrounds, and eliminates small holes.
2. Perform a hole-filling operation to saturate the hole in specific object by equalizing pixel values surrounded by the same value.
3. Apply the opening morphological operation to remove small object in image with less noise.

Object Counting

After each detected pixel group formed a connected region in morphological opening stage, the connected component labeling algorithm by Samet & Tamminen (1988) was applied. At this stage, labels were assigned numbers for each region with connections, enabling the identification of each detected region. Moreover, a binary input image was used, and the connected component could label each pixel linked to the foreground.

Region selection comprised measuring various characteristics of image regions, including those specific to Kepulauan Seribu image. Subsequent to labeling each foreground object, islands were selected using *regionprops* function in the MATLAB software. *Regionprops*, which measured several binary image quantities, was particularly used to extract Area, Centroid, Perimeter, and *Boundingbox*. One crucial property is the centroid, providing the (x,y) locations where the middle of each object is positioned. To calculate the mass center of the desired object, *regionprops* outputs show a structure detailing the centroid of each object in a black and white image (Jeyalaksshmi & Prasanna, 2018).

The Reference Image

The reference or ground truth image was generated and labeled manually by an expert using editing software such as Adobe Photoshop. This served as a reference for calculating detection accuracy and counting islands in Kepulauan Seribu. Figure 5 presents an example of the ground truth image used in this study. According to expert manual observation, there are 104 islands in Kepulauan Seribu.

Figure 5. Example of the ground truth image

Evaluation Metric

The evaluation of the applied method was conducted by calculating detection and counting accuracy using the evaluation metric recommended by Lumauag & Nava (2018) as well as Lainez & Gonzales (2019). Detection accuracy is presented in the following equation (7):

$$D = 1 - \frac{|t-r|}{t} D = 1 - \frac{|t-r|}{t} \tag{7}$$

where detection accuracy (D) is the overall detection accuracy of islands, the reference image or ground truth (t) is determined by manually verifying the actual number of islands in all image by an expert, and the result (r) denotes islands detected by the applied method.

Object detection process may encounter problems of undercounting or overcounting. Undercounting is experienced when the applied methods fail to extract the desired object, while overcounting occurs during misidentification, leading to an excessive count. Therefore, counting accuracy (AC) was calculated to establish the precision of the applied method in counting object (islands), as defined in equation (8).

$$Ac = 1 - \left(\frac{\sum O + \sum U}{t}\right) Ac = 1 - \left(\frac{\sum O + \sum U}{t}\right) \tag{8}$$

where Ac is counting accuracy, O represents the number of overcounted object, U signifies the number of undercounted object based on the reference image, and t means the reference image or the ground truth.

3. Results and Discussion

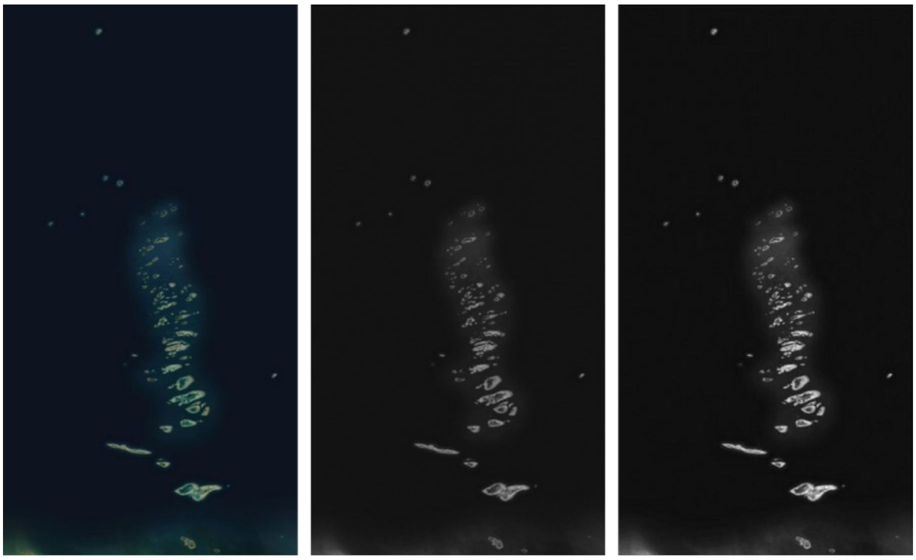
The method in this study was implemented using MATLAB software, applying four test image extracted from Kepulauan Seribu image. The first test image named ‘Image 1’ represented the mid-resolution satellite imagery of Kepulauan Seribu. Meanwhile, ‘Image 2,’ ‘Image 3,’ and ‘Image 4’ were derived from the same source, with ‘Image 1’ divided into three parts for a more comprehensive experiment analysis.

The four images were processed using the applied methods, while the evaluation stage calculated detection and counting accuracy of the methods. The discussion section included the analysis of errors in detection or counting stages that affected accuracy, hence future studies are suggested to improve this method.

The preprocessing stage results are presented in Figure 6, showing ‘Image 1’, which contains all Kepulauan Seribu object (a), and it was converted to grayscale and normalized.

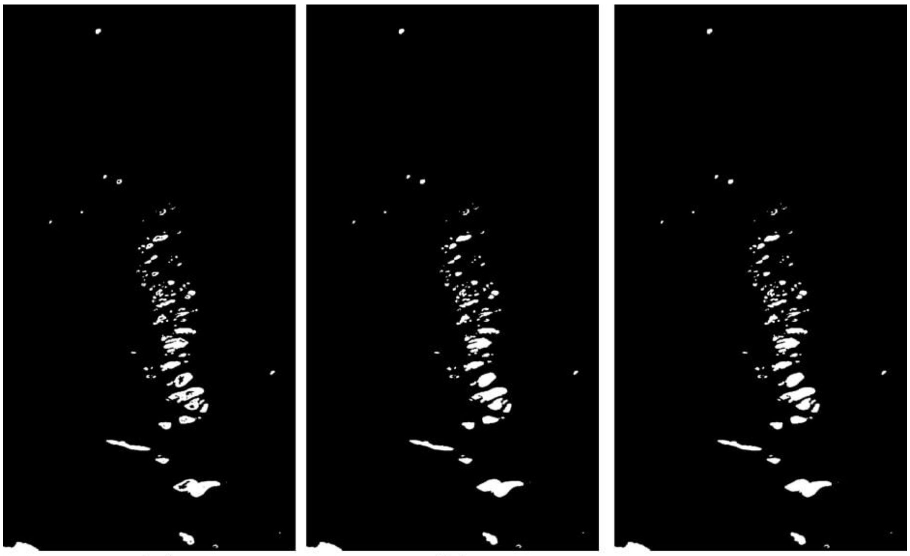
The following images in Figure 7 are the results from thresholding (a), morphological hole filling (b), and opening operations (c).

Figure 8 shows detection stage results, with the green box showing the detected islands object. The red numbers represent islands label, which were successfully counted. After identifying object, masking was conducted by overlapping the original image with the resulting binary one. From the experiment performed on ‘Image 1,’ a total of 111 islands were found in Kepulauan Seribu, while the actual number according to the reference image was 104. Moreover, detection and counting accuracy was calculated, as detailed in Table 1.



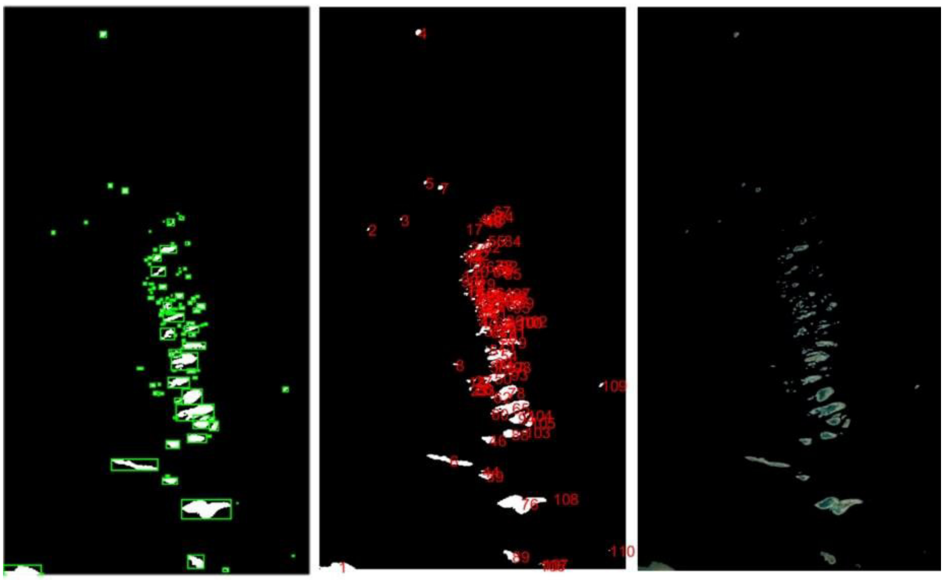
(a) (b) (c)

Figure 6. (a) Original image, (b) Grayscale image, and (c) Normalized image



(a) (b) (c)

Figure 7. Results of (a) Thresholding, (b) Hole filling, and (c) Opening



(a) (b) (c)

Figure 8. Results of (a) Islands detection, (b) Islands counting, and (c) Masking

The second, third, and fourth test image was processed similarly, and the accuracy calculation results are shown in Table 1. After applying the methods, a green box was obtained, which marked and calculated object area (island). Figure 9 depicts 'Image 2', where the system automatically detected 11 out of 12 islands, meaning one was not recognized, leading to an undercount of 1.

Figure 10 presents 'Image 3' and its processing for object detection, in which the number of object (islands) were marked and counted through the green box. For this third test image, the system automatically detected 81 islands instead of 76, with an overcount of 6 inappropriate object.

Figure 11 shows 'Image 4' and its processing for object detection. For this fourth test image, 26 islands were detected without any overcounts or undercounts. Table 1 presents detection and counting accuracy of 'Image 2,' 'Image 3,' and 'Image 4'.

By applying accuracy calculation method from equations (7) and (8), Table 1 shows the ground truth values for all islands based on the reference image obtained. The 'Result' column presents successfully counted or detected object, those undercounted, and overcounted non-object after implementing the methods. The proposed system needs improvements to address the issue of overcounting caused by several close pixels being labeled as a group from the same object, and vice versa, specifically during hole filling in morphological operation stage.

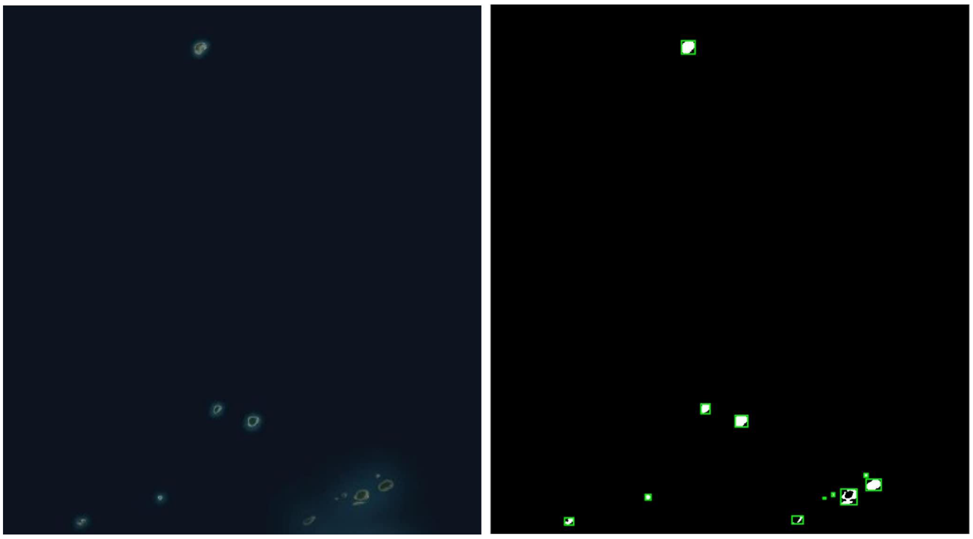


Figure 9. The original second image testing (left) and islands detection result (right)

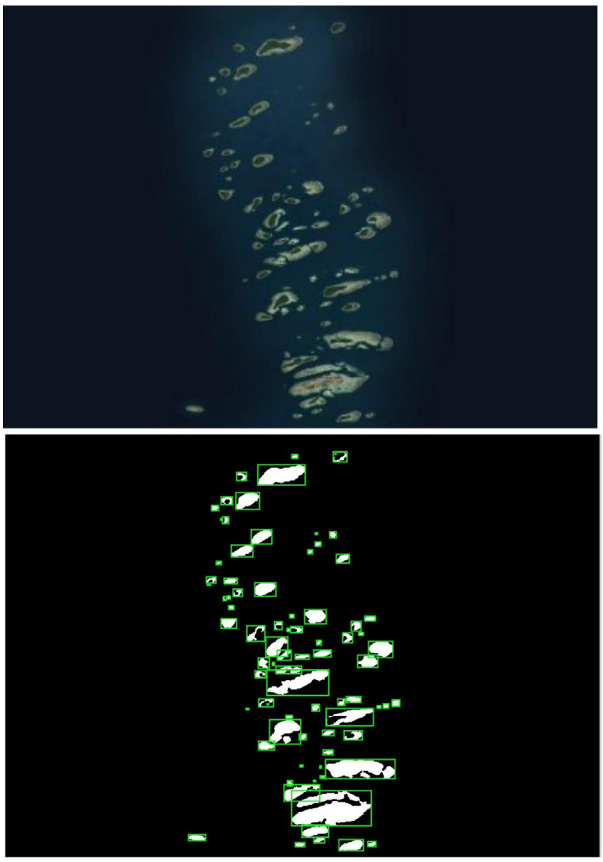


Figure 10. The green frame of the detected islands in 'Image 3'

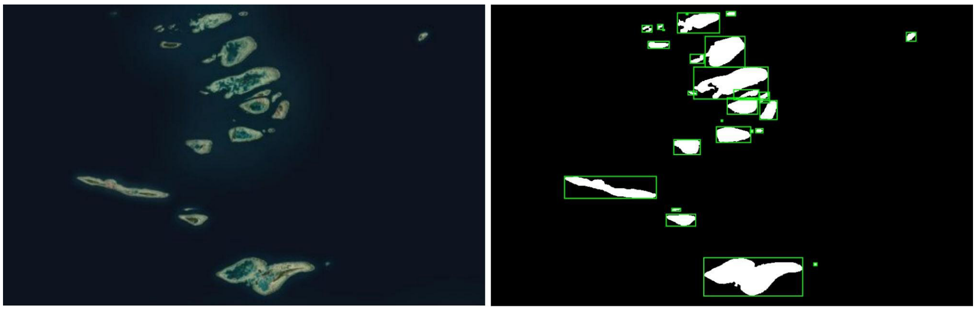


Figure 11. Testing image and successfully detected islands marked in the green box

Table 1. Evaluation Results

Test Image	Ground Truth	Result	Undercount	Over Count	Detection Accuracy	Counting Accuracy
Image 1	104	111	1	11	93.27%	88.46%
Image 2	12	11	1	0	91.67%	91.67%
Image 3	76	81	0	6	93.42%	92.11%
Image 4	26	26	0	0	100%	100%

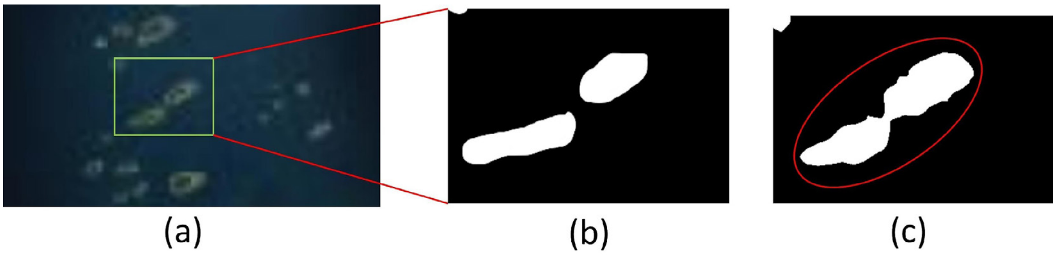


Figure 12. (a) original image; (b) reference image; (c) image detected by applied methods

Figure 12 shows an example of detection error where two islands were mistakenly considered as one due to their color closely resembling the background appearance (dark blue). Future studies should focus on refining islands detection and counting through satellite imagery to reduce noise and background image while preserving foreground details.

The study employed a series of digital image processing techniques to detect and count islands in the Kepulauan Seribu region. The results indicate promising outcomes with an overall detection accuracy ranging from 91.67% to 100%. Notably, the system successfully identified a total of 111 islands in 'Image 1,' outperforming the reference image count of 104. However, instances of undercounting and overcounting were observed in subsequent test images ('Image 2,' 'Image 3,' and 'Image 4'). The evaluation outcomes, detailed in Table 1, provide a comprehensive overview of the detection and counting accuracy for each test image. The analysis of the results highlights the effectiveness of the proposed digital image processing methods in detecting islands. However, challenges such as undercounting and overcounting were observed, particularly during morphological operations, suggesting the need for refinement in the methodology.

Detection errors, as illustrated in Figure 12, underscore the importance of addressing color similarities between islands and the background to enhance accuracy. While the study successfully applied the proposed OBIA method for island detection, it acknowledges the presence the cases of overcounts. The hypothesis that the applied methods would accurately detect and count islands in all scenarios is proven partially incorrect. The issue of overcounting, attributed to the labeling of closely located pixels during morphological operations, highlights a limitation that needs to be addressed in future research. Incorporating advanced machine learning algorithms, enhancing color differentiation techniques, and optimizing morphological operations can contribute to improved accuracy. Additionally, exploring real-time applications and scalability to larger geographical areas can broaden the practical implications of the developed methodology. In summary, this research provides valuable perspectives in the field of digital image processing for identifying islands. Despite achieving noteworthy accuracy, the recognized challenges present opportunities for continued improvement and investigation. The results establish a foundation for future research initiatives dedicated to refining the accuracy of island detection and counting.

4. Conclusion

In conclusion, this study showed the significant potential possessed by Kepulauan Seribu across various sectors, including tourism, mining, conservation, and fisheries. However, numerous small Indonesian islands remained unrecorded, leading to an unclear count, particularly in the neglected inner regions. Periodic counting of these small islands appeared to be essential for maintaining accurate and updated data. The manual detection and counting process, being time-consuming, necessitated the adoption of a digital image processing method for automatic islands enumeration through satellite imagery.

The segmentation method had been the most frequently used for object detection because of its reliability, but most existing methods relied on high-resolution data, leading to computational challenges. Therefore, in this study, low to mid-sized satellite image was used to enhance computational efficiency and mitigate noise associated with a high-resolution image. The application of a pixel-based segmentation method, along with various morphological operations, facilitated the automatic detection and counting of islands in Kepulauan Seribu. Moreover, the implemented method consisted of a systematic series of steps, yielding average experimental accuracy rates of 94.59% for islands detection and 93.06% for counting.

The experimental results showed several instances of undercounting due to object closely resembling the background, as well as overcounting, where a single island was erroneously identified as two. Although the applied methods were tailored for processing Kepulauan Seribu satellite imagery data, their potential applicability extended to detecting object in diverse settings and fields requiring accurate object detection and counting tasks. To address the entire described challenges, further in-depth studies were suggested.

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