

Automatic extraction of rivers from satellite images using image processing techniques

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Abstract

Automatic extraction of water bodies from satellite imagery has been broadly studied for many reasons, including mapping of natural resources (i.e., forest and water resources), drinking water supplies, food production, agricultural planning, and disaster management. With the growth of global warming, it became essential to maintain the sustainable management of these resources for the preservation of human life. Several methods attempted to allocate water bodies from different satellite imagery in both spatial and spectral domains. In this paper, we present an automatic segmentation method to extract the water body from Landsat satellite imagery. The proposed segmentation approach consists of several stages, including histogram stretching, de-correlation, binarization of the image, and clutter removal using morphological operations. The segmentation results are promising.

Keywords

Rivers detection, Satellite images, Enhancement, Segmentation, Recognition, De-correlation.

1. Introduction

River water is an essential natural resource that is a vital component affecting the global carbon cycle and climate change [1]. Thus, river water is an essential component of the environment, which has a vital role in the survival of humans, plants, animals, as well as economic development. Generally, river water is utilized for multiple purposes such as agriculture, drinking, hydropower projects, etc. Accordingly, it is important to take care of the rivers and identify the areas of water pollution in the river as well. However, extracting rivers from satellite imagery remains a difficult problem because rivers have complex shapes with diverse branches and directions [2]. Synthetic Aperture Radar (SAR) images have been used growingly for water monitoring, due to their ability to register images independently of weather conditions [3]. Many algorithms for extracting water using SAR images rely on optimum thresholding techniques [4–6].

However, these simple techniques generated many false classification results, particularly when the bodies of water are small. For example, five different thresholding methods applied to three satellite images to determine the most effective technique for image segmentation was presented in [7]. These threshold methods include the P-tile method, Histogram Dependent Technique (HDT), the Mean method, and the Edge Maximization Technique (EMT). Al-Amri and Kalyankar [7] found that HDT and EMT methods yielded the best results. HDT technique is histogram-based, where the histogram depends on the value of the threshold. The allocated threshold value separates the area of the image where the feature of interest blends into the background. EMT method is used when there is a distinct contrast in illumination between the feature of interest and the background. Gong et al. [8] proposed an automatic adaptive threshold segmentation approach based on the fuzzy c-means algorithm and the Otsu threshold method to extract tidal creeks.

Sakurai-Amano et al. [9] presented a fully automated method to extract the location of narrow rivers in tropical rain forests-based images collected from JERS-1 SAR images. Their method was examined by

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comparing the outcomes from optical JERS-1 VNIR in the Amazon basin and the Congo basin. Commonly, images obtained via remote sensing suffer from poor contrast and low resolution [10]. The importance of overcoming these challenges and successfully processing satellite images for research is relevant to fields such as astronomy, agriculture, and environmental industries and water management [11].

As discussed above, water management research has particularly gained momentum as environmental bid, including growing overpopulation and pollution surrounding water resources are on the rise. Protecting natural water supplies has become a top priority as water is an important life-sustaining resource [12]. In such a context, the detection of water bodies and extracting them from satellite imagery is beneficial operations for many designing and evolution activities such as coastline mapping, river erosion mapping in addition to water resource management. Scientific research in the field of water resources management and planning worldwide has explored various satellite data to understand the spatial, spectral, and temporal characteristics to produce maps of land with a special interest in water bodies [13]. Detecting water resources was not only limited to the use of satellite remote sensing images, but an Unmanned Aerial Vehicle (UAV) was utilized for the same purpose [14, 15]. For example, Randazzo et al. [16] proposed an image processing framework for coastal extraction as well as shallow water depth on the GeoEye-1 satellite image and mosaic image collected by a drone on the coast of San Vito Lo Capo. Several researchers have endeavored to analyze river water using machine learning tools and high-resolution satellite images. In this regard, we review some popular works of water body extraction during the period from 2015 to 2020.

There are several published works of various methods involving the segmentation of features in satellite images. Although not much has been explored with extracting rivers, in particular, several objects have been successfully detected and extracted. Dhanachandra et al. [17] successfully extracted rivers from satellite images and the two methods were explored. The first included the extraction of rivers using a color histogram technique, and hill-climbing algorithm and k-means clustering method. The second one included the use of the thresholding of a grayscale image and morphological erosion. The results achieved were reasonable based on both methods. Syrris et al. [18]

discussed the importance of image enhancement and contrast adjustment when extracting features from low-resolution satellite data. The authors built a case study that encompasses the use of enhancement techniques such as linear and decorrelation stretching. They showed that low-resolution satellite imagery could be improved or “corrected” and thus more effective when extracting features.

Jiang et al. [19] adopted a multilayer Perceptron-Artificial Neural Network (ANN) to determine the surface water in Landsat 8 satellite imagery. A study presented in [20] used ANN and a threshold technique with a set of mathematical morphology operations to extract lakes from satellite imagery. A segmentation approach based on Convolutional Neural Networks (CNN) was used for extracting water bodies from remote sensing images with high resolution that were gathered from Google earth imagery [21]. A deep learning approach was developed in [22] to interactively extract water bodies, farmlands, forests, and other nonartificial regions from satellite images with high resolution. Their approach was performed on two datasets with different object types and varied, complicated scenes [22].

Meng et al. [23] presented an automated Lake and Reservoir Extraction Process (LREP). This method implemented a Modified Two-Mode (MTM) method for extracting water from partial images using 154 Gaofen-2 images covering Zigong, Xianning, and Liaoyuan cities. A study given in [24] reported an enhanced deep convolutional encoder-decoder network to extract body water from remote sensing images through the application of superpixel segmentation and conditional random fields.

Rishikeshan and Ramesh [25] presented a flexible Mathematical Morphological (MM) driven approach for extracting water bodies from much different satellite imagery of different spatial resolution. An operational automated water extraction method was used for the extraction of water bodies for a large number of lakes in China using Landsat 8 land images. This method does not demand the determination of histogram peaks, but instead searches for the minimum values in the threshold range to arrive at an automated dynamic threshold [4].

Moreover, a variety of image processing and machine learning methods have been adopted for the detection of pollution in river water. Analysis of different

satellite sensors, image processing methods and many classification methods to classify river water was provided in [26]. Navarro et al. [27] presented an unsupervised approach using the local Moran index of spatial association combined with morphological processes for extracting inland water bodies. Dereli and Tercan [28] developed a method to detect shoreline changes of Lake Salda in Turkey from the year 1975 to the year 2019. A segmentation approach using the stepwise thresholding technique was drawn to track and map the change in the extent of surface water using SAR images in Ontario, Canada from 2008 to 2016 [5].

A method combining Google Earth Engine (GEE) and a multiscale CNN was presented in [29] for detecting water from Landsat images. An approach that combined global salience features, multi-feature fusion method based on principal component analysis, and an Active Contour Model (ACM) to extract rivers from SAR imagery was proposed in [30]. In [31], the authors presented an assessment to the accuracy of a new automated water detection method by integrating the automatic water extraction index, GEE platform, and Landsat 8 OLI data throughout the years 2014, 2015, 2016, 2017 and 2018 to study the case of New Zealand. The proposed image fusion method was successfully utilized to test the real changes of the lakes at a more accurate scale.

In light of the importance of automatic extraction of water bodies from satellite images, the main goal of this work is to present an automatic method to extract the water body from Landsat satellite images based on a method consisting of several image processing stages. These stages include enhancement, segmentation, and clutter removal of images. We used several images collected from the Connecticut River in the state of Connecticut. The images were acquired through Google Earth at an altitude between 14,000 and 15,000 meters. The paper is structured as follows. In Section II, we provide a discussion of our proposed methodology. Section III describes the experimental setup and the developed results. Finally, we provide our conclusions and future work.

2. Proposed methodology

Our proposed method for extracting the water body from a Landsat satellite imagery is based on several steps. They include enhancement, binarization, morphological operation, and clutter removal. Image enhancement and pre-processing techniques include histogram equalization and de-correlation stretching. Image enhancement is often thought of as only

visually improving an image. However, by improving the contrast and overall quality of the raw image before the segmentation process, one will potentially yield better results [18]. Thresholding is also an essential step to image segmentation as it aids in the separation of objects in the foreground from the background. Converting an image to grayscale, then to binary by selecting a threshold value, is key to foreground object and feature detection [32].

Segmentation plays a critical role in providing the ability to analyze and gain information from an image. This process involves the separating and grouping of pixels based on similar characteristics allowing features to have higher contrast and to become distinguishable. The process and technique used to achieve segmentation largely depend on the task at hand [32]. Image segmentation can be performed on either grayscale or color images, making it useful in several image processing applications. A survey of global thresholding methods for mapping, open water bodies was presented in [33, 34]. A recent study in the Tianjin Binhai New Area was implemented to extract the surface water using a Modified Normalized Difference Water Index (MNDWI) method to extract surface water and detect its change [35]. The finding claims that the environment evaluation method shows that the water quality of the Haihe River section was poor. It was suggested to strengthen the environmental protection protocol in this area.

A. Enhancement via decorrelation

Color enhancing is an essential process for object detection in satellite images. To show multispectral images that fall outside the range of the human spectrum, an appropriate transformation must be rendered for representing the data in color. Therefore, need to use an appropriate method to enhance the image for better detection of water resources locations such as rivers.

Decorrelation stretching is one method that can be used to enhance the color domains of an image with considerable band-to-band correlation. The inflated colors expand the visual understanding of the image and make feature perception clearer. In the past, the decorrelation stretching was explored by many researchers as a successful tool to handle multispectral imaging that can space channels in the spectral domain, and hence, achieve exceptionally high inter-channel correlation [36, 37]. In our proposed method we plan to use the decorrelation method.

The decorrelation stretching process is used to enhance (i.e., stretch) the color differences in satellite images. The method depends on removing the inter-channel correlation obtained in the image pixels; this is why we call the process "decorrelation stretch". The decorrelation stretch is a procedure that enhances the three color bands independently from each other. The RGB space represents only one of the possible bases for the color space. If we think of R, B, G, as X, Y, Z for a normal Cartesian space, then every point in the color space has an R coordinate, a G coordinate, and a B coordinate. Moving along R increases "redness" from a very dark red to a very light red, and similarly, for G and B.

The decorrelation stretching algorithm normalizes each band and then rotates the bands into eigenspace. The algorithm finds the rotated orthogonal coordinate system along which the colors in the images are maximally extended and then stretches the colors along with those coordinates to the maximal extent. In this step, the bands lose their relationship (or correlation) to each other. Then, the bands are rotated back to the original RGB space, where they retain their normalized and decorrelated values [38]. The net impact of the process is to get an output image in which the pixels are well distributed between all possible colors while maintaining the relative meaning of hue, saturation and intensity components of the input image [36]. *Figure 1* shows the block diagram of the proposed methodology. In *Figure 2*, we show a satellite image utilized by decorrelation

stretching along with the histogram of both images. To show how the band of color stretched, we have shown the color scatter plot before and after stretching in *Figure 3*.

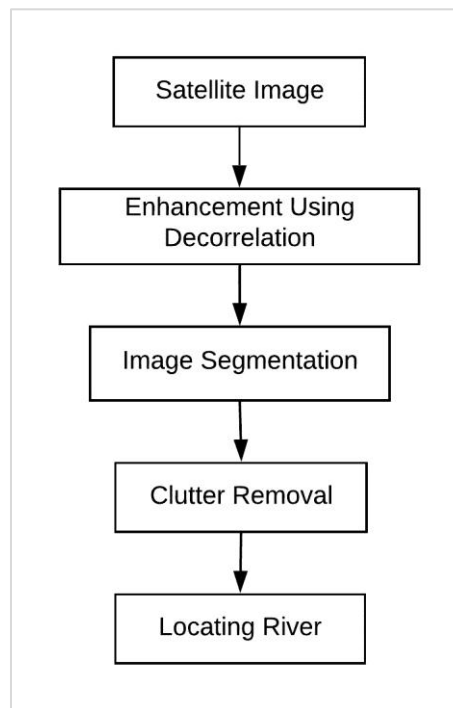


Figure 1 Block diagram of proposed methodology

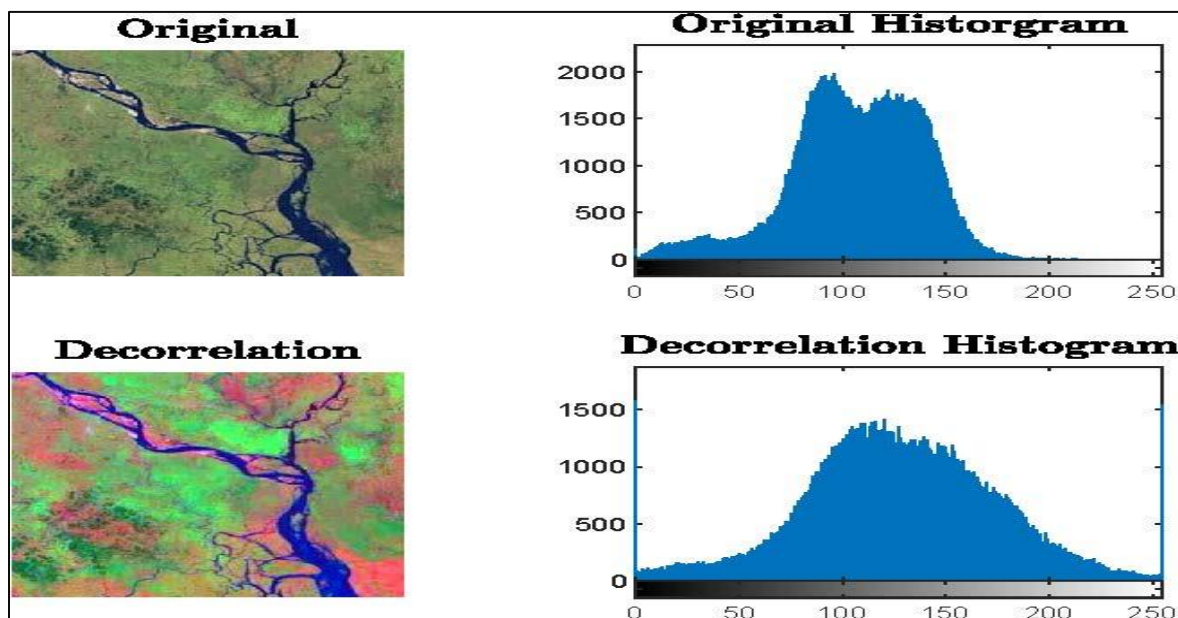


Figure 2 (a) Original satellite image (b) decorrelated image

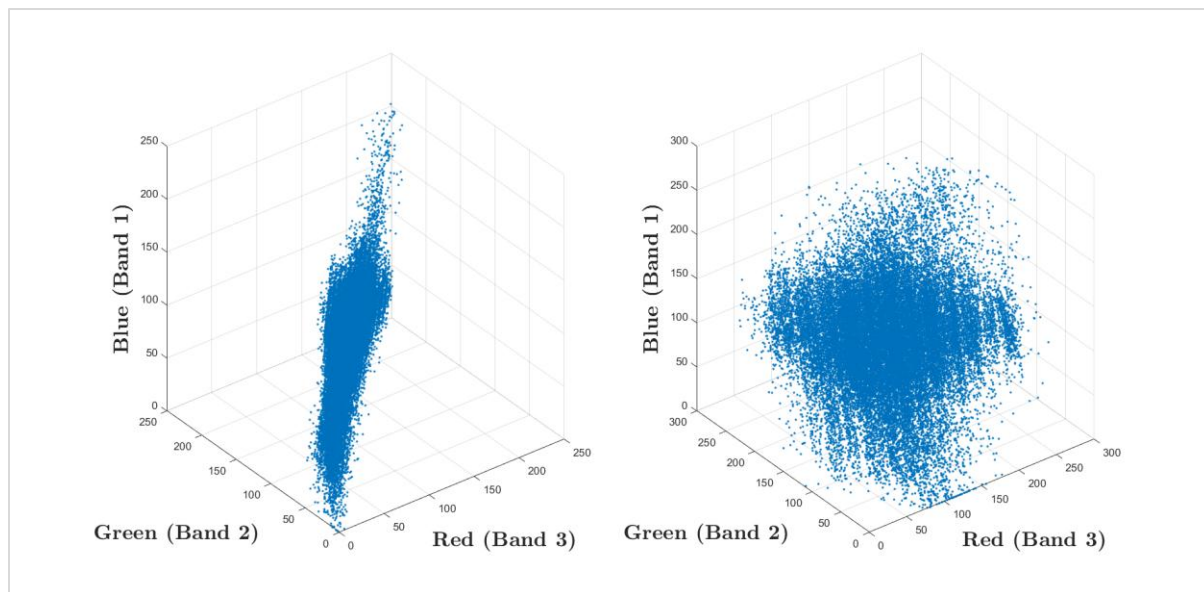


Figure 3 Color scatterplot before (a) and after (b) decorrelation

B. Segmentation

Image segmentation is the process of splitting an image of interest into several regions or categories. Each region is corresponding to different objects. Every pixel in an image will be classified based on a pre-defined criterion. In the case of grayscale images, the goal is to identify the similar grayscale pixels and recognize the relationship of these pixels as an object. Objects can later be recognized based on a set of selected features extracted from clustered objects.

Image segmentation plays a key role in many image processing tasks throughout partitioning an image into homogenous areas or objects that share similar properties. The extracted regions of interest of a particular image become more meaningful and can be utilized for further analysis and processing [39]. There exist well-known segmentation techniques reported in the literature such as:

- Threshold-based Segmentation
- Edge-based Segmentation
- Region-based Segmentation
- Clustering-based Segmentation

Threshold-based segmentation: The threshold-based segmentation method is modest and efficient in segmenting grayscale images that can fulfill the segmentation task by comparing the intensity of the image under study to one or more intensity thresholds [40]. Threshold-based methods are categorized into global and local thresholding techniques [41].

- Global thresholding is the best option for dividing the objects and backgrounds if an image has objects with homogeneous intensity or the contrast between the objects and the background is too large. Choosing the proper threshold becomes hard when the contrast of an image is low.
- On the other hand, local thresholding can be identified by estimating a threshold value for different regions from the intensity histogram. The threshold values of local thresholding can be generally estimated using local statistical properties such as the mean intensity value [42].

An image described as f with grayscale levels from 0 to 255 consists of a light object and a dark background, with pixels distributed in two dominant modes, where $f(x, y)$ represents the pixel intensity at coordinates (x, y) . A single threshold value, T , is used to group the pixels of f into black (i.e., with a value of 0) and white (i.e., with a value of 255), which results in extracting the region of interest within the image for segmentation. An increase in the threshold values gives the increased number of intensity values in the segmented image. For the application of thresholding-based segmentation technique, it is necessary to apply the correct threshold values to achieve appropriate segmentation results. Specifically, the pixels below threshold T will be categorized as class $C1$ with the rest of pixels as class $C2$ as shown in Equation 1, where these two classes differ from each other.

$$g(x,y) = \begin{cases} C1, & \text{if } f(x,y) > T \\ C2, & \text{if } f(x,y) \leq T \end{cases} \quad (1)$$

In many cases, the threshold value of t is selected manually by the user. It is more likely a trial and error process to explore various objects in an image. The best value of t can help to identify the objects of interest. Histogram Thresholding algorithm can be described briefly as shown in Algorithm 1.

Algorithm 1: Histogram thresholding.

Result: Segmented image

1. Divide each input image into two halves (horizontal, vertical);
2. Calculate the histogram for both parts of the image under consideration;
3. Compute the difference between the histograms (two halves);
4. Calculate the threshold value T from the difference value in the previous step;
5. Segment the image as per

$$\begin{aligned} f(x,y) &\geq T; \text{ Background} \\ f(x,y) &\leq T; \text{ Object} \end{aligned}$$

C. Clutter removal

Small unwanted objects in the image are removed by using an area opening morphological operator. Per the image characteristics, a maximum pixel amount to be imputed. As a result, all objects having fewer than the selected number of pixels will be removed from the image.

3. Experimental results

In this section, we present the results of our proposed methodology, which consists of image enhancement, segmentation, and clutter removal, with the final output, which is the segmented river.

A. Data set

The dataset used in this research consisted of images collected from the Connecticut River in the state of Connecticut. The images were acquired by Google Earth at an altitude between 14,000 and 15,000 meters. The results of the proposed segmentation method for a selected image are shown in *Figure 4*.

B. Analysis of results

Figure 4 (a) shows the original satellite image that is targeted to a segment based on the proposed image

segmentation approach. In the first phase of the image segmentation problem is the application of the enhancement phase. In this phase, a decorrelation and stretch algorithm is applied to the original satellite image in *Figure 4 (a)*. The output of this enhancement phase is a decorrelated RGB band with a contrast stretch as exhibited in *Figure 4 (b)*. The next phase of the image segmentation problem is to segment the image regions. In this phase, first, the image is converted to binary, and then a global thresholding technique with a thresholding level, α , of an arbitrary value between 0 and 1 is applied to the enhanced image. The result of the thresholding segmentation phase is presented in *Figure 4 (c)*.

In the final phase of the image segmentation method, the clutter removal procedure is applied. In this phase, clutter with specific sizes β is removed based on the characteristics of the image. In the case presented in *Figure 4*, β took values up to 1000 pixels. Finally, the location and outlines of the detected River are shown in *Figure 4 (d)*. The proposed image segmentation method was also applied to several different river images with various degrees of complexity and in various shapes. A set of examples of segmented satellite images is shown in *Figures 5 to Figure 8*.

The original images in *Figures 5-8* show normal variation with a moderately complex background. Each image in *Figures 5-8 (b) - (d)* shows a separate phase of the proposed image segmentation method, with the output of each case showing a reasonable level of accuracy in the phase processed. It can be concluded that the whole proposed image segmentation approach is sensible and that each phase of this approach is appropriate to assist the proposed approach to detect the outlines of the river in the target image. The only limitation of this approach is we could not generalize the set of parameters that can be used for all image segmentation and background removal since the images were collected from various resources and under different environmental conditions. The lack of accessibility of a database of images collected from a unified sensor is a limitation that needs to be investigated.

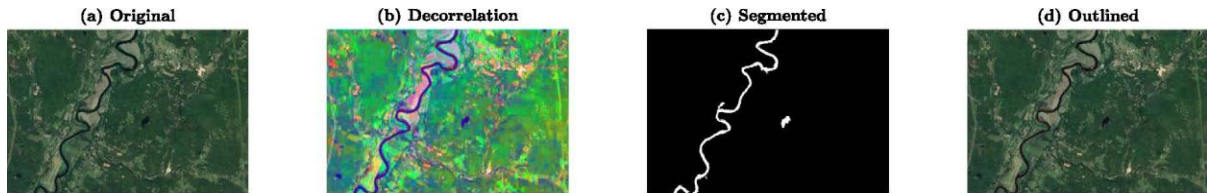


Figure 4 Image segmentation for satellite image 1: (a) original image (b) decorrelated image (c) segmented image (d) outlines of the original image

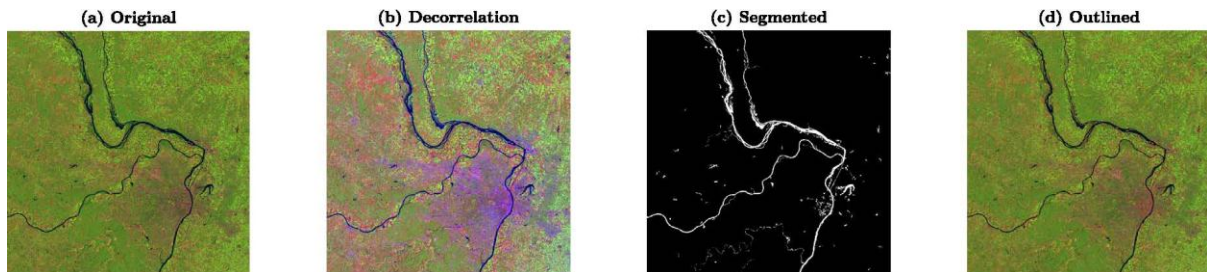


Figure 5 Image segmentation for satellite image 2: (a) original image (b) decorrelated image (c) segmented image (d) outlines of the original image

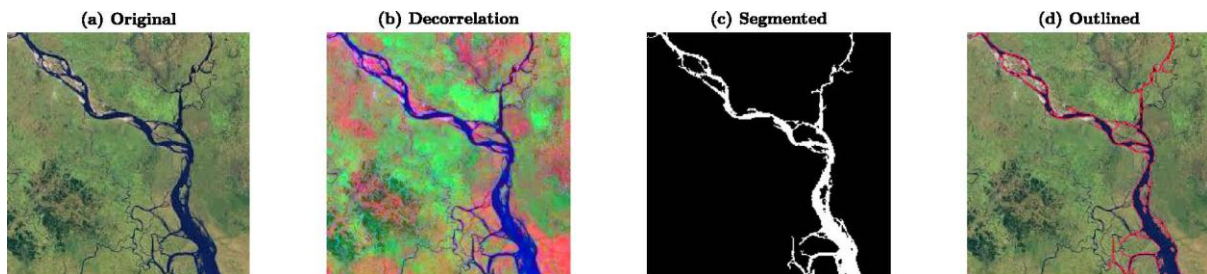


Figure 6 Image segmentation for satellite image 3: (a) original image (b) decorrelated image (c) segmented image (d) outlines of the original image

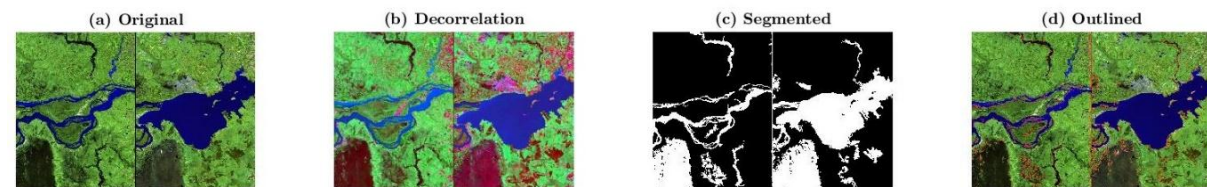


Figure 7 Image segmentation for satellite image 4: (a) original image (b) decorrelated image (c) segmented image (d) outlines of the original image

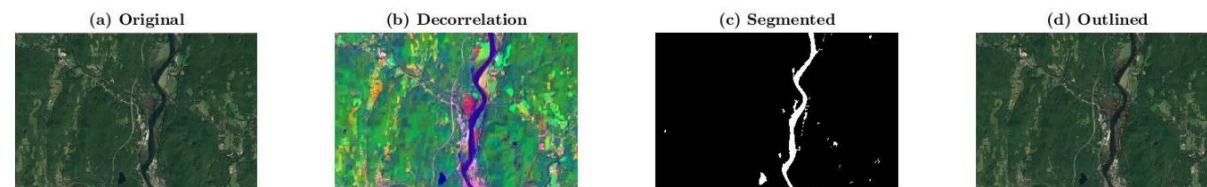


Figure 8 (a) Original satellite image (b) decorrelated image (c) segmented image (d) outlines of the original image

4. Conclusion and future work

In this paper, we presented our initial idea using various color models based on image processing methodology to detect rivers from satellite images. The methodology was tested on a set of images collected for the Connecticut River in the state of Connecticut taken at a height of 14,000-15,000 meters. The decorrelation process adopted to enhance the color in the images helped to enhance the quality of the images and make it easier to segment the images. A different level of segmentation was adopted for better detection of rivers. This research could serve as a groundwork for future research on developing water resource management, which is crucial for future generations. We suggest that this methodology could be enhanced by using meta-heuristic search techniques to better tune the segmentation filters to segment the rivers. Also, in further work, we will focus on the following trends: a more powerful segmentation approach to obtaining more accurate segments of the rivers, an enhancement model that is sufficiently adequate for the images, and a mechanism for extracting artificial and non-artificial objects of the rivers. These future directions can enhance the performance level of the proposed image segmentation method and promote work adequacy.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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