Marine and Coastal Zone changes over decade using Satellite Image Segmentation

Jyoti Madake
Vishwakarma Institute of Technology, Pune, 411037, Maharashtra, India
jyoti.madake@vit.edu

Abhijeet Padwal
Vishwakarma Institute of Technology, Pune, 411037, Maharashtra, India
abhijeet.padwal21@vit.edu

Yogesh Pande
Vishwakarma Institute of Technology, Pune, 411037, Maharashtra, India
yogesh.pande21@vit.edu

Parth Nevase
Vishwakarma Institute of Technology, Pune, 411037, Maharashtra, India
parth.nevase21@vit.edu

Abstract:* *This study explores the utilization of satellite image segmentation to monitor changes in marine and coastal zones over the span of a decade, focusing on the coastal regions of Maharashtra, India. Satellite remote sensing, with its high spatial and temporal resolution, offers a powerful tool for observing these critical environments. The research employs segmentation techniques such as K-means clustering to analyze multispectral satellite images from the Landsat 8 and Landsat 9 missions, covering the years 2013 to 2024. By using these algorithms, the study identifies significant changes in the coastal zone, including shifts in water and land areas and habitat mapping. The results, visualized through segmented images and graphical representations, provide insights into the dynamics of coastal ecosystems and serve as a guide for sustainable coastal zone management. This research offers valuable information for environmental monitoring, resource conservation, and marine spatial planning, facilitating informed decision-making in coastal and marine management.

Keywords—Coastal and Marine Zone Management, Satellite Image Segmentation, K-means Clustering, Mean Shift Algorithm

I. INTRODUCTION

The sustainability and health of Earth's marine and coastal environments, which support a wide variety of wildlife and supply vital nutrients necessary for human survival, are critical to maintaining the planet's ecological balance. Nonetheless, the growing threats brought about by environmental deterioration and human activity highlight the pressing need for efficient management strategies to protect these essential ecosystems. Because of its extensive coverage, high geographical resolution, and temporal consistency, satellite remote sensing has become an effective tool for monitoring and managing marine and coastal zones.

Image segmentation algorithms play a key role in the efficient management of coastal and maritime zones by utilizing the abundance of information found in satellite data. K-means clustering is one of these algorithms that has attracted a lot of attention as a well-liked unsupervised clustering technique. K-means effectively separates distinct areas of the picture according to their spectral properties by repeatedly dividing the image into K clusters based on spectral similarities and updating cluster centroids.

Mean shift segmentation, on the other hand, provides a non-parametric method of segmentation by dividing the picture into distinct, coherent sections and locating dense areas inside the feature space. Furthermore, region expanding segmentation offers a region-based approach by generating homogenous regions by repeatedly merging nearby pixels with comparable properties, beginning with seed points.

The purpose of this study is to investigate how segmentation techniques for satellite images, namely K-means clustering, may be used to manage coastal and marine environments. The research explore the fundamental ideas, benefits, and drawbacks of K-means clustering in the extraction of pertinent data, such as the identification of maritime hazards, habitat mapping, and coastline demarcation. The research want to offer insights and solutions for efficient management of coastal and marine habitats through a thorough examination of the potential and difficulties posed by K-means clustering.

The research hope to give decision-makers, academics, and practitioners working in marine and coastal resource management and conservation useful insights and tools through the integration of satellite image segmentation with other geospatial technologies and environmental data.

II. LITERATURE SURVEY

Coastal image classification using smartphone-based systems for Sargassum monitoring relies on deep learning techniques. These systems offer efficient solutions for processing low-cost imagery, aiding in beach management and environmental monitoring. Valentini and Balouin (2020) [1] demonstrate the effectiveness of convolutional neural networks (CNNs) with superpixel over-segmentation for accurate classification. Previous studies [2] [3] highlight the utility of video monitoring and satellite observations in coastal research, emphasizing the importance of automated techniques for timely detection and response to coastal hazards.

[4] Coastline detection from satellite imagery is crucial for understanding coastal dynamics. Recent studies have emphasized the need for automated methodologies due to limited availability of labelled data. This study introduces the Sentinel-2 Water Edges Dataset (SWED), providing a benchmark for coastline extraction models. Various CNN models are evaluated, with the Sobel-edge loss function showing promise for detecting fine-scale features [5] [6]

[7] Coastal monitoring is vital for sustainable management, yet data acquisition is challenging. This study evaluates machine learning (ML) algorithms for automatic shoreline monitoring using high-resolution satellite images. Object-based image analysis (OBIA) outperforms pixel-based methods, with Random Forest (RF) on multiresolution segmentation (MRS) yielding the best accuracy. The approach offers a reliable tool for managing coastal erosion [8] [9]

[10] Aquaculture area extraction from coastal waters is crucial for various management tasks. Zhang et al. [11] proposed a method based on Gaofen-2 satellite imagery to extract aquaculture areas in turbid coastal waters, achieving high accuracies even in high turbidity conditions. Various methods have been explored for this purpose, including visual interpretation [12], ratio index analysis [13], and object-based analysis [14]. Challenges include dynamic turbidity and similarity of spectral characteristics. Remote sensing techniques offer promising solutions [15]

[16] Coastal marine debris detection and density mapping using very high-resolution satellite imagery is a critical endeavor in assessing and mitigating the impact of marine pollution. Sasaki et al. [17] present a comprehensive study utilizing in-situ clean-up data in conjunction with high-resolution satellite images to estimate and categorize debris along the beaches of southern Japan. They employ machine learning techniques, specifically leveraging Shannon’s entropy computed from WorldView 2 and 3 imagery, to effectively detect and map coastal debris, correlating well with ground truth data. This innovative approach assigns debris concentration to individual satellite image pixels, enabling visualization of debris distribution even in areas lacking ground truth data. The study underscores the urgency of addressing marine debris pollution, emphasizing its detrimental effects on marine ecosystems and coastal activities. Previous research highlights the widespread nature of marine debris pollution [18] its adverse impact on marine life and human activities [19] and the challenges in accurately detecting and characterizing debris using remote sensing techniques. The integration of machine learning with high-resolution satellite imagery represents a promising strategy in advancing marine debris monitoring and management efforts.

[20] The literature review on marine aquaculture and spatial planning encompasses several key themes. First, it highlights the importance of marine aquaculture in meeting the growing demand for seafood while alleviating pressure on terrestrial agriculture [21] [22]. Second, it discusses the challenges in monitoring marine aquaculture using traditional statistical methods, emphasizing the need for remote sensing technology to provide accurate spatial data [23] [24]. Third, it underscores the significance of marine spatial planning in effectively managing marine development, controlling aquaculture expansion, and protecting sensitive ecosystems [25]. Finally, it addresses the environmental impacts of marine aquaculture, including pollution and ecosystem disruption, necessitating careful planning and regulation. Overall, the review emphasizes the importance of integrating remote sensing technology, marine spatial planning, and environmental considerations to sustainably manage marine aquaculture. The article [26] explores K-Means Clustering, a key algorithm for data analysis. It covers its mathematical basis, steps, choosing 'K', strengths, weaknesses, real-world applications, and includes a Python implementation. It emphasizes K-Means' role in data-driven decision-making across domains. The paper introduces the concept of stability for segmentation algorithms in processing large remote sensing images. It evaluates the stability of four algorithms and proposes modifications to enhance the stability of the mean-shift algorithm. Stable algorithms ensure consistent results across different image subsets, crucial for remote sensing and image analysis applications. Mean shift is a non-parametric clustering algorithm used for finding peaks in data density. It iteratively shifts a kernel over data points towards areas of higher density until convergence. It automatically determines the number of clusters and adapts the kernel bandwidth during the process. Mean shift segmentation, a variant, partitions images into coherent regions by shifting kernels towards dense regions. It's widely used in computer vision for tasks like object tracking and image segmentation.

III. METHODOLOGY

Fig 1. Workflow of proposed research

A simple segmentation pipeline with three key phases is shown in Figure 1. First, input is given in the form of preprocessed photos. Next, the input images undergo segmentation. Ultimately, output is produced in the form of segmented pictures with labels. This procedure makes it easier to divide images into different areas according to comparable pixels, which might help with further analysis or visualization.

3.1 Dataset

The Landsat 8 and Landsat 9 missions provided multispectral satellite images for the dataset utilized in this study, which was centred on the Indian state of Maharashtra. The data offers a thorough summary of changes to the coastal zone during a ten-year period, from 2013 to 2024. *The EarthExplorer* platform of the United States Geological Survey (USGS) provided every image, guaranteeing accuracy and uniformity. The photographs in the collection were taken without clouds to preserve image quality and reduce atmospheric influence.

Monitoring and measuring coastal changes throughout the Maharashtra coastline is the main goal of this dataset. It makes it possible to analyse accretion, erosion, and other human-caused effects in great detail. The data offers a strong foundation for examining changes in coastal zones by supporting various methodologies such as change detection, land cover categorization, and mapping of coastlines. Furthermore, the fact that the dataset is publicly available guarantees replication and permits additional study and verification.

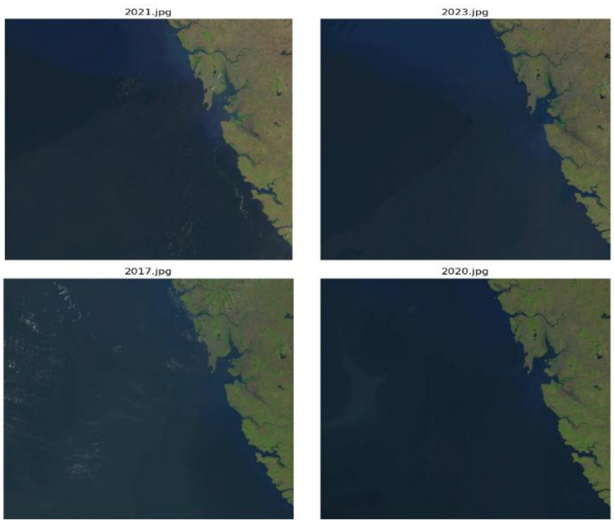

Fig 2. Sample Images from Dataset.

The given fig 2. describes the randomly generated images from the dataset. The images clearly show the marine and coastline zone. Furthermore, the suggested study provides a thorough investigation that uses the mean shift and k-means algorithms to categorize photos and assess whether locations are suitable for solar power installations. Our technique takes into account several elements, including land use patterns, topography features, and sunshine exposure, with the goal of offering valuable insights that are essential for making educated decisions in sustainable energy planning.

3.2 K-Means Clustering

The research used K-means clustering, a popular technique for dividing data points into discrete groups. The technique first initialized the cluster centroids in the feature space at random. The closest centroid was then allocated to each data point, which in this case represented a pixel, resulting in the formation of first clusters. The centroids were then adjusted repeatedly until convergence was reached by calculating the mean of the data points given to each cluster. After convergence, the resultant clusters were examined closely to identify places that would be good candidates for solar installation. These determinations were usually made based on brightness or geographical distribution.

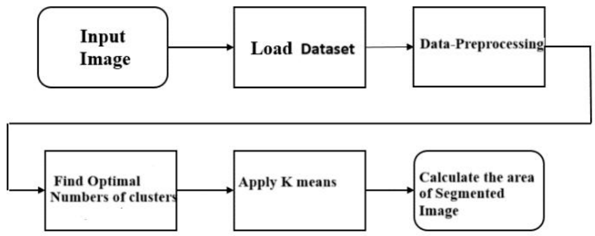

Fig 3. Block diagram of k-means clustering

The K-means algorithm can be represented by the following steps .

Randomly initialize K cluster centroids in the feature space.

Assignment: Assign each data point (pixel) to the nearest centroid, forming initial clusters.

Update Centroids: Recalculate the centroids by computing the mean of data points in each cluster.

Repeat: Iterate steps 2 and 3 until convergence criteria are met (e.g., centroids do not change significantly).

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} \left| |x - \mu_i| \right|^2 \quad (1)$$

Where,

J is the objective function representing the sum of squared distances of data points to their respective cluster centroids.

K is the number of clusters.

C_i is the set of data points assigned to cluster i.

μ_i is the centroid of cluster i.

The areas of the divided regions that indicate appropriate locations for solar installation were computed. The best places to install solar panels were then graphically represented by a binary mask, with darker sections denoting these areas. This binary mask made it easier to see the regions that had been identified, which helped with the decision-making process for where to put solar equipment. All things considered, K-means clustering was an essential instrument for grouping picture pixels into clusters, which made it possible to locate and identify appropriate locations for solar energy installations in accordance with preset standards.

3.3 Mean Shift

In the literature, a variety of segmentation techniques have been used to process remote sensing photos.. A complete review of those algorithms is beyond the scope of this paper. The mean-shift algorithm has received a lot of attention from the remote sensing community. Variants such as variable-bandwidth mean shift, medoid shift, and quick shift have also been investigated in this context. It has been found to perform well with various remote sensing data ranging from medium to very high resolution and in various applications. Its multivariate nature, as the simplicity of the filtering step, and the availability of various implementations, among which one is from the authors themselves are some of the keys to this popularity. The research has already been done using this algorithm for various works, and the need to resolve its instabilities and to allow for scalability to real remote sensing data has been driven by our applications. Mean shift is a procedure for locating the maxima—the modes—of a density function given discrete data sampled from that function. This is an iterative method, and the research start with an initial estimate x. A kernel function $K(x_i - x)$ is is employed to determine the weight of nearby point for updating the mean. Typically, a Gaussian kernel is used, where

$$K(x_i - x)= e^{-c||x_i-x||^2} \quad (2)$$

The weighted mean of the density within the kernel's window is calculated using the formula:

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i-x)xi}{\sum_{x_i \in N(x)} K(x_i-x)} \quad (3)$$

Here, $N(x)$ represents the neighbourhood of x, consisting of points where $K(x_i - x) \neq 0$.
The difference $m(x) - x$ is termed the mean shift. The algorithm updates the estimate by setting $m(x)$, and this process repeats until $m(x)$ converges.

Detailed Working Algorithm:

The mean shift algorithm starts with an initialization phase in which each data point is given a mean shift vector, which is initially set to zero. The program then calculates the mean shift vector for each data point, which shows the direction and amplitude of the data distribution's local mode. The data points are guided by these mean shift vectors into denser regions, which may represent cluster centres. The data points are updated by moving them along their corresponding mean shift vectors after this computation. The algorithm's pace of convergence may be managed by adjusting the step size parameter, which determines the extent of this shift. Until the convergence requirements are satisfied, this procedure of calculating mean shift vectors and updating data points is repeated. When the shift magnitude drops below a predetermined threshold, or when the mean shift vectors are stable, convergence can be identified. When convergence is reached, data points that converge to the same mode or peak in the data distribution are used to identify clusters. The mean shift clustering procedure is completed when data points converge to the same mode and are regarded as belonging to the same cluster.
The mean shift algorithm is particularly effective in identifying dense regions in the feature space, making it suitable for tasks like image segmentation, where coherent regions need to be identified without assuming specific cluster shapes or sizes. Its adaptability to varying data distributions and ability to handle irregularly shaped clusters make it a powerful tool in data analysis and pattern recognition tasks.

IV. RESULT AND DISCUSSION

Data about land and sea areas seen in a series of photos from 2013 to 2024 are shown in this table.

Image	Year	Water Area	Land Area
0	2013	805185	194815
1	2014	805360	194640
2	2015	798084	201916
3	2016	796436	203564
4	2017	790362	209638
5	2018	800463	199537
6	2019	785942	214058
7	2020	798963	201037
8	2021	789416	210584
9	2022	789578	210422
10	2023	806145	193855
11	2024	805360	194640

Table 1.1

Table1.1 explains the "Water Area" column shows the entire area submerged under water in square units, while the "Land Area" column shows the total area above land, likewise in square units. For instance, in the 2013 image, the land area is 194,815 square units, while the water area is 805,185 square units. The statistics for the years that followed also show differences in the covering of land and sea. Interestingly, there are variations in these measures across the years, which may indicate alterations in the surrounding circumstances or the features of the image. Overall, this table offers insightful information on the spatial distribution of land and water areas shown in the photo series, information that may be used to land management, urban planning, and environmental monitoring.

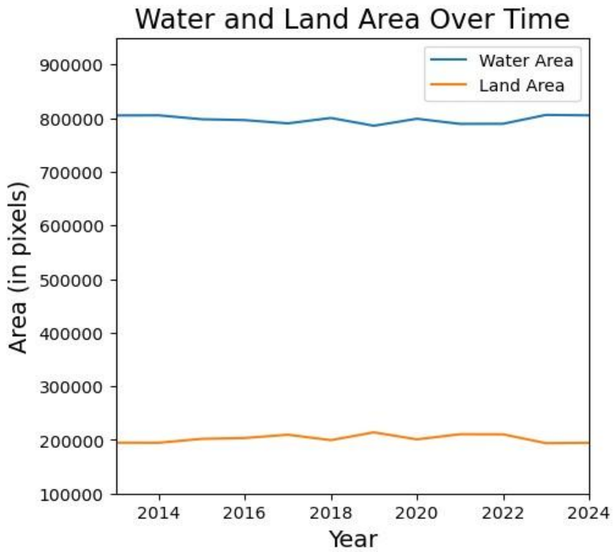

Fig 4. Graphical representation of changes over decade

The plotted graph in Fig 4. shows how the land and ocean areas have changed between 2013 to 2024. The area is shown in square units on the y-axis, while the years are shown on the x-axis. Each line in the line plot represents a different land or water area, showing how these areas fluctuate throughout time. The graph provides important insights into environmental dynamics and changes in land use patterns by graphically illustrating trends and variations in the water and land coverage captured in the series of photos. With its detailed overview of the geographical changes in the research region, this graphical representation improves comprehension of the data provided in the table.

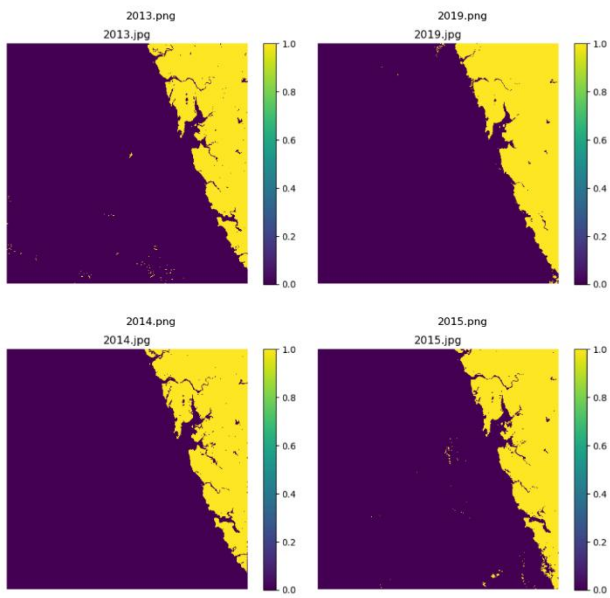

Fig 5. Segmented Images of Coastal zone

Fig 5. consists of four segmented images arranged in a 2x2 grid. Each segmented image likely represents a classification of land cover or features within the coastal zone. Different colors likely correspond to different categories (e.g., water and land). It shows changes in the coastal zone over a period of four years (2013, 2014, 2015, 2019).

V. CONCLUSION

This research highlights the vital role of satellite image segmentation techniques, particularly K-means clustering, in effective marine and coastal zone management. The integration of remote sensing technology, machine learning algorithms, and object-based image analysis enhances accuracy and efficiency in tasks such as shoreline detection, habitat mapping, and coastal delineation. By leveraging these advanced methodologies, The research contribute to the development of sustainable environmental management strategies, essential for preserving marine ecosystems and supporting informed decision-making in coastal resource conservation.

VII. REFERENCES

[1] Valentini, N., & Balouin, Y. (2020). Smartphone-Based Camera System for Coastal Image Segmentation and Sargassum Monitoring. Journal of Marine Science and Engineering, 8(1), 23.

[2] Osorio, A. F., et al. (2019). Virtual BUOY: A video-based approach for measuring near-shore wave peak period. Computers & Geosciences, 133, 104302.

[3] Wang, M., & Hu, C. (2016). Mapping and quantifying Sargassum distribution and coverage in the Central West Atlantic using MODIS observations. Remote Sensing of Environment, 183, 350–367.

[4] Seale, Catherine, Thomas Redfern, Paul Chatfield, Chunbo Luo, and Kari Dempsey. "Coastline detection in satellite imagery: A deep learning approach on new benchmark data." Remote Sensing of Environment 278 (2022): 113044.

[5] Bishop-Taylor, Robbi, Stephen Sagar, Leo Lymburner, and Robin J. Beaman. "Between the tides: Modelling the elevation of Australia's exposed intertidal zone at continental scale." Estuarine, Coastal and Shelf Science 223 (2019): 115-128.

[6] Clevert, Djork-Arné, Thomas Unterthiner, and Sepp Hochreiter. "Fast and accurate deep network learning by exponential linear units (elus)." arXiv preprint arXiv:1511.07289 (2015).

[7] Bengoufa, Soumia, Simona Niculescu, Mustapha Kamel Mihoubi, Rabah Belkessa, Ali Rami, Walid Rabehi, and Katia Abbad. "Machine learning and shoreline monitoring using

optical satellite images: case study of the Mostaganem shoreline, Algeria." Journal of applied remote sensing 15, no. 2 (2021): 026509-026509.

[8] Ioc-Unesco, I. M. O., and UNDP FAO. "A blueprint for ocean and coastal sustainability." Paris. Report no (2011).

[9] Gens, Rudiger. "Remote sensing of coastlines: detection, extraction and monitoring." International Journal of Remote Sensing 31, no. 7 (2010): 1819-1836.

[10] Zhang, Xiaoyu, Shuchang Ma, Cheng Su, Yongheng Shang, Tinggang Wang, and Jianwei Yin. "Coastal oyster aquaculture area extraction and nutrient loading estimation using a GF-2 satellite image." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 13 (2020): 4934-4946.

[11] FOODS, MICROBIOLOGICAL HAZARDS IN. "Food and agriculture organization of the United Nations." A framework for land evaluation. Soils Bulletin 32 (2002).

[12] Yang, Yingbao, Nan Jiang, Liqiong Yin, and B. Hu. "RS-based dynamic monitoring of lake area and enclosure culture in East Taihu Lake." J Lake Sci 17, no. 2 (2005): 133.

[13] Ma, Yanjuan, Dongling Zhao, Ruimei Wang, and Wei Su. "Offshore aquatic farming areas extraction method based on ASTER data." Transactions of the Chinese Society of Agricultural Engineering 26, no. 1 (2010): 120-124.

[14] Xu, S., L. Xia, H. Peng, and X. Li. "Remote sensing extraction of mariculture models based on object-oriented." Geomat. Spat. Inf. Technol 41 (2018): 110-112.

[15] Jiaxing, C. H. E. N., Xiaoyu Zhang, and Guorong Huang. "Diffuse attenuation coefficient inversion for the Yangtze Estuary and its adjacent sea areas on the GOCI images and application in the preevaluation of airborne laser bathymetry." In 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), pp. 1-6. IEEE, 2019.

[16] Sasaki, Kenichi, Tatsuyuki Sekine, Louis-Jerome Burtz, and William J. Emery. "Coastal marine debris detection and density mapping with very high resolution satellite imagery." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 15 (2022): 6391-6401.

[17] Keller, Aimee A., Erica L. Fruh, Melanie M. Johnson, Victor Simon, and Catherine McGourty. "Distribution and abundance of anthropogenic marine debris along the shelf and slope of the US West Coast." Marine pollution bulletin 60, no. 5 (2010): 692-700.

[18] Thiel, Martin, I. A. Hinojosa, L. Miranda, J. F. Pantoja, M. M. Rivadeneira, and N. Vásquez. "Anthropogenic marine debris in the coastal environment: a multi-year comparison between coastal waters and local shores." Marine pollution bulletin 71, no. 1-2 (2013): 307-316.

[19] Sheavly, S. B., and K. M. Register. "Marine debris & plastics: environmental concerns, sources, impacts and solutions." Journal of Polymers and the Environment 15 (2007): 301-305.

[20] Wang, Jun, Xiaomei Yang, Zhihua Wang, Dazhuan Ge, and Junmei Kang. "Monitoring Marine Aquaculture and Implications for Marine Spatial Planning—An Example from Shandong Province, China." Remote Sensing 14, no. 3 (2022): 732.

[21] Jay, Stephen. "Built at sea: Marine management and the construction of marine spatial planning." The Town Planning Review (2010): 173-191.

[22] Kidd, Sue, and Dave Shaw. "Reconceptualising territoriality and spatial planning: insights from the sea." Planning Theory & Practice 14, no. 2 (2013): 180-197.

[23] Ottinger, Marco, Kersten Clauss, and Claudia Kuenzer. "Opportunities and challenges for the estimation of aquaculture production based on earth observation data." Remote Sensing 10, no. 7 (2018): 1076.

[24] Wang, Zhihua, Xiaomei Yang, Yueming Liu, and Chen Lu. "Extraction of coastal raft cultivation area with heterogeneous water background by thresholding object-based visually salient NDVI from high spatial resolution imagery." Remote Sensing Letters 9, no. 9 (2018): 839-846.

[25] Johnson, Ayana Elizabeth, William James McClintock, Ogden Burton, Wayde Burton, Andrew Estep, Kathryn Mengerink, Read Porter, and Stephanie Tate. "Marine spatial planning in Barbuda: A social, ecological, geographic, and legal case study." Marine policy 113 (2020): 103793.

[26]Pavankumar, unveiling patterns: a dive into k- means clustering; medium blog.2023