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RESEARCH ARTICLE

Shoreline delineation service: using an earth observation data cube and sentinel 2 images for coastal monitoring

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Abstract

Coastal management has a critical role in estimating the coastal environmental and socio-economic dynamics, providing various vital regional and local services. Remote sensing earth observations are essential for detecting and monitoring shorelines. UAVs combined with satellite remote sensing address the shoreline delineation problems to detect the shoreline and identify the shoreline zones. The paper presents a shoreline delineation service utilizing UAV and Sentinel 2 images within a Data Cube environment for monitoring coastal areas. The BandRatio, McFeeters, MNDWI1, and MNDWI2 algorithms have been implemented in the service to analyze the accuracy of each algorithm by comparing satellite and UAV-derived shorelines. As a case study, the Lake Sevan shoreline delineation, as one of the most incredible freshwater lakes in Eurasia, has been studied using the service. MNDWI2 algorithm showed the best accuracy for Lake Sevan shoreline delineation.

Keywords Unmanned aerial vehicle · Satellite remote sensing · Sentinel-2 · Data cube · Shoreline · NDWI · MNDWI · Mixed pixels · Water extraction algorithms · Lake sevan

Introduction

Coastal management has a critical role in estimating the coastal environmental and socio-economic dynamics, such as shoreline analysis around the coastal area impacting the land-use changes (Kamphuis 2020). Shorelines provide various vital regional and local services, including tourism, recreation, fisheries, trade, and aesthetic and cultural value. Shoreline management services may guide management regulations and strategies to address the ecosystem's biophysical changes over time (Drakou et al. 2017; Rao et al. 2015).

Capturing and understanding the shoreline change behaviour in a coastal management context is critical for a range of scientific, engineering, and management questions. It is essential to delineate shoreline position and monitor the changes considering the human impact on the coastal zones. Shoreline changes prediction through erosion and accretion have vital implications for coastal communities and policymakers (Zhang et al. 2004). The natural processes and human activities drive the shoreline changes because of the dynamic nature of water bodies and the coastal land. Lake Sevan, the biggest freshwater lake in Armenia and South Caucasus, is chosen as a study area (Baghdasaryan et al. 1971). Since the beginning of the last century, as one of Armenia's most ecologically sensitive regions, this shoreline has been changing continuously with different intensities causing many ecological problems, such as eutrophication or activation of erosion processes (Pavlov et al. 2010).

Earth observations (EO) may play a significant role in coastal observation for detecting and monitoring coastlines (McCarthy et al. 2017). It can be complemented with Unmanned Aerial Vehicles (UAVs) currently involved in

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a wide range of remote sensing (RS) applications by providing high-resolution acquisitions (Zanutta et al. 2020). UAVs offer timely and cheaper data acquisition capacity. They can also offer additional multi-spectral information and facilitate data acquisition by avoiding the clouds perturbation, as they usually fly below clouds (McEvoy et al. 2016). Combined UAV and satellite RS may increase the shoreline delineation quality to detect the coastline and identify the coastline zones by applying geographic object-based image analysis high-resolution orthophotos (Boon et al. 2016). In the meantime, the spatial resolution of satellite imagery has significantly improved in the last decade, making it applicable for monitoring medium to large areas in length from a few kilometres to hundreds of kilometres (Lewis et al. 2016).

Currently, satellites and UAVs generate high-resolution and large-scale images, requiring efficient platforms to analyze this large and heterogenous volume of EO data. EO Data Cubes (DC) is a novel solution to store, manage, organize, and explore Big EO data to bridge the gap between Big Data analytical capabilities and users' expectations (Giuliani et al. 2017). EO DC address volume, velocity, and various Big Data challenges and provide access to extensive spatio-temporal data in an analysis-ready format.

The web-based services may provide a clear and simple yet very powerful and effective way to process high-resolution satellite and UAV images combining the benefits of EO DC. Consequently, the paper aims to present a Shoreline Delineation Service utilizing remote sensing imagery within the DC for monitoring water areas, which process UAV images to select the accurate shoreline delineation extraction algorithm from Sentinel 2. As a case study, the service has been validated to monitor Lake Sevan's shoreline as one of the most incredible freshwater lakes in Eurasia.

The paper is structured as follows. Section "Related work" presents several studies and services of shoreline delineation. Section "Shoreline delineation DC service" offers the shoreline delineation service and the methodology, while "The study area and experiments" describes the study area and the experimental results. Section "Conclusion" concludes the paper.

Related work

Despite the simplicity of shoreline definition, it is challenging to detect it practically adequately (Boak and Turner 2005). The need to delineate shoreline position and assess its variation through space and time is significant given the long history of human settlement within or close to the coastal zone. Therefore, airborne, satellite, and UAV platforms are widely used to study shoreline delineation for different applications and study areas using various platforms and approaches. Several studies focus on specific water bodies and their shorelines. For instance, Gallop et al. (2015) studied long-term shoreline changes in southwestern Australia using aerial photographs. It was realized that over 96% of beaches straightened during the period. Empirical orthogonal function helped to explain 45% of the variability between transects of the beach. A study by Kotzee and Reyers (2016) focused on analyses of three municipalities affected by a flood in a specific area in South Africa. The principal component analysis was applied to explore disaster planning, mitigation, and subsequent potential occurrences or increased number of currencies of floods. A digital shoreline analysis system is proposed by Nandi et al. (2016) to calculate the rate of shoreline change in a monitored area.

The authors Bishop-Taylor et al. (2021) used three decades of Landsat imagery to map Australia's dynamic coastline at mean sea level and implemented sub-pixel waterline extraction to characterize accuracy and sensitivity to indices and spectra (Bishop-Taylor et al. 2019). The suggested sub-pixel shoreline extraction method has a low computational overhead as an open-source tool. Another study considers a long-term study of shoreline changes extracted from satellite data using normalized indices for delineation and quantified via Digital Shoreline Analysis System toolbox (Hovsepyan et al. 2019).

Several studies focus on applying satellite images and geospatial techniques for coastal zone management and monitoring. The study (Nassar et al. 2019) evaluates the coastal changes in the North Sinai coast, offering a decision algorithm using satellite images. Mirza Razi Imam Baig et al.?s study (Baig et al. 2020) has been conducted along the coast of Andhra Pradesh, India, using multi-temporal satellite images of several years. Linear regression and endpoint rate, and weighted linear regression are used for calculating shoreline change rate. Instead of Landsat data, thermal infrared images received provided by aerial vehicles have been used to monitor manually Long Island in New York (Tamborski et al. 2015).

Several studies directly focused on small water bodies by utilizing UAVs to detect changes in shorelines. For instance, paper (Čermáková et al. 2016) deals with UAV utilization to monitor small water areas and studies in particular shorelines changes. It is suggested to use UAVs in RS applications in combination with different methods, algorithms, and procedures (Pajares 2015), for instance, to drive accurate morpho-sedimentary investigations at very high resolution (Mury et al. 2019). Also, there are studies aimed to use UAV-derived data for environmental monitoring of the coastal areas of lakes with changing water to detect the shoreline and reveal the sources of the coastal erosion of shores and monitor the destructive shoreline processes (Medvedev et al. 2020).

With developments in remote sensing and analysis technology, along with advances in numerical modeling, there became probable that more datasets with sufficient spatial and temporal coverage to allow for the understanding of short-term and long-term variability coastline of water bodies. All studies mentioned above are not linked with the DCs or don't use HPC resources for large-scale simulations. Therefore, their ability to handle large-scale data is limited. Our approach is entirely comprehensive, getting benefits from the processing of UAVs and satellite images within one service, hiding the difficulties to get, process, analyze and visualize the data within the DC. The suggested service aims to seamless management and processing of large-scale data for the shoreline delineation.

Shoreline delineation DC service

The shoreline delineation DC service detects the provided region's shoreline in a selected date range from EO data. The service consists of frontend and backend components (see Fig. 1). As an underlying infrastructure, the service relies on the resources of Armenia's research cloud computing ecosystem (Astsatryan et al. 2021b; Shoukourian et al. 2013). Simulation time of the service varies from a few seconds to a few minutes, depending on the complexity of the query and the study area dimensions.

The web-based user frontend (http://datacube.sci.am), relying on the interactive computing open-source Jupyter framework, executes Python scripts to generate plots for satellite images (White et al. 2016). Python-based applications are carried out within the Jupyter notebook to bundle code and results.

The core of the data repository is the Armenian Data Cube containing American Landsat and European Copernicus Sentinel missions Analysis Ready Data (ARD) over Armenia since 2016, which includes nine Landsat (171031, 170031,169031, 171032, 170032, 169032, 168032, 169033, 168033) and eleven Sentinel-2 (38TLL, 38TML, 38TNL, 38TLK, 38TMK, 38TNK, 38SMJ, 38SNJ, 38SPJ, 38SNH, 38SPH) scenes (Asmaryan et al. 2019). In addition to the satellite images, the data repository provides internal access to UAV images currently covering the shorelines of Lake Sevan. The Armenian Data Cube uses the power of the Open Data Cube (ODC) analytical framework (http://www.opendatacube.org) to address the societal and scientific challenges, giving a better picture of the land resources and changes (Strobl et al. 2017). At its core, the ODC comprises Python libraries and a PostgreSQL database that helps work with geospatial raster data. The ODC seeks to increase the value and impact of global EO satellite data by providing an open and freely accessible exploitation architecture. Satellite and UAV images provide secure monitoring for environmental issues with global coverage and geospatial consistency. The data repository module receives a query to get the satellite and UAV images that correspond to the requested region and period. The satellite images are provided to the data extraction module, while UAV images feed the data validation module.

The data extraction module extracts the satellite images in NetCDF format from the data repository via ODC API query by indicating the area of interest and the date filters. The extracted information, which contains information

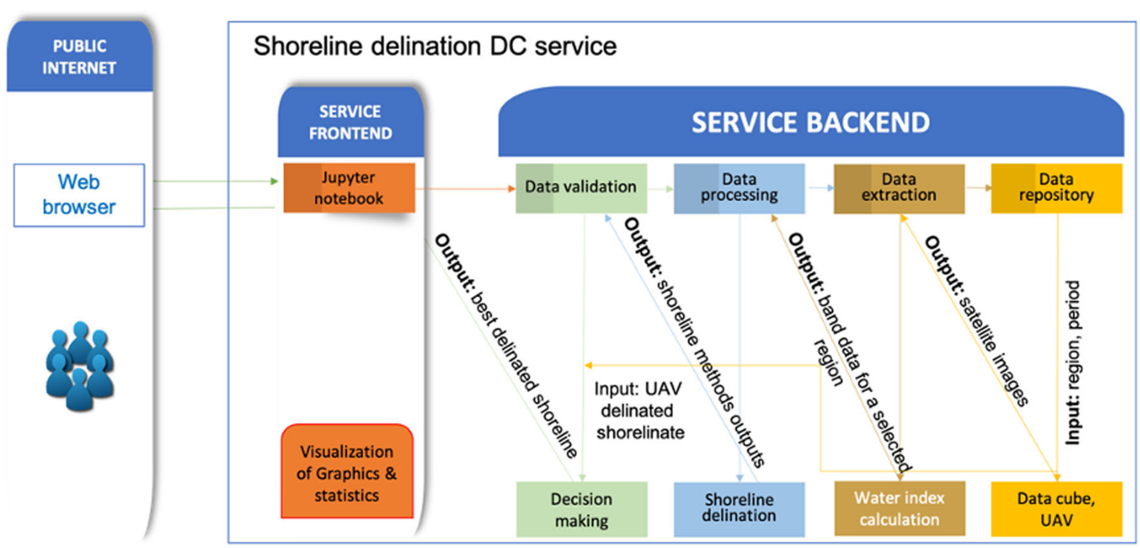

Fig. 1 The architecture of the shoreline delineation service

about different spectral bands, is critical to calculating water indices. For instance, the GREEN, RED, BLUE, NIR, SWIR1, and SWIR2 bands are extracted for Sentinel 2. McFeeters (1996), NDWI (Normalized Difference Water Index), NDWI1, NDWI2 (Pan et al. 2020), and MSAVI (modified soil adjusted vegetation index) (Zhao et al. 2009) band-ratio methods have been implemented to take advantage of the differences in the reflectance of different wavelengths of light. For instance, the NDWI is a satellite-derived index from the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) channels. The SWIR reflectance reflects changes in vegetation water content and the spongy mesophyll structure in vegetation canopies. In contrast, the NIR reflectance is affected by internal leaf structure and leaf dry matter content but not by water content. The NIR combination with the SWIR removes variations induced by

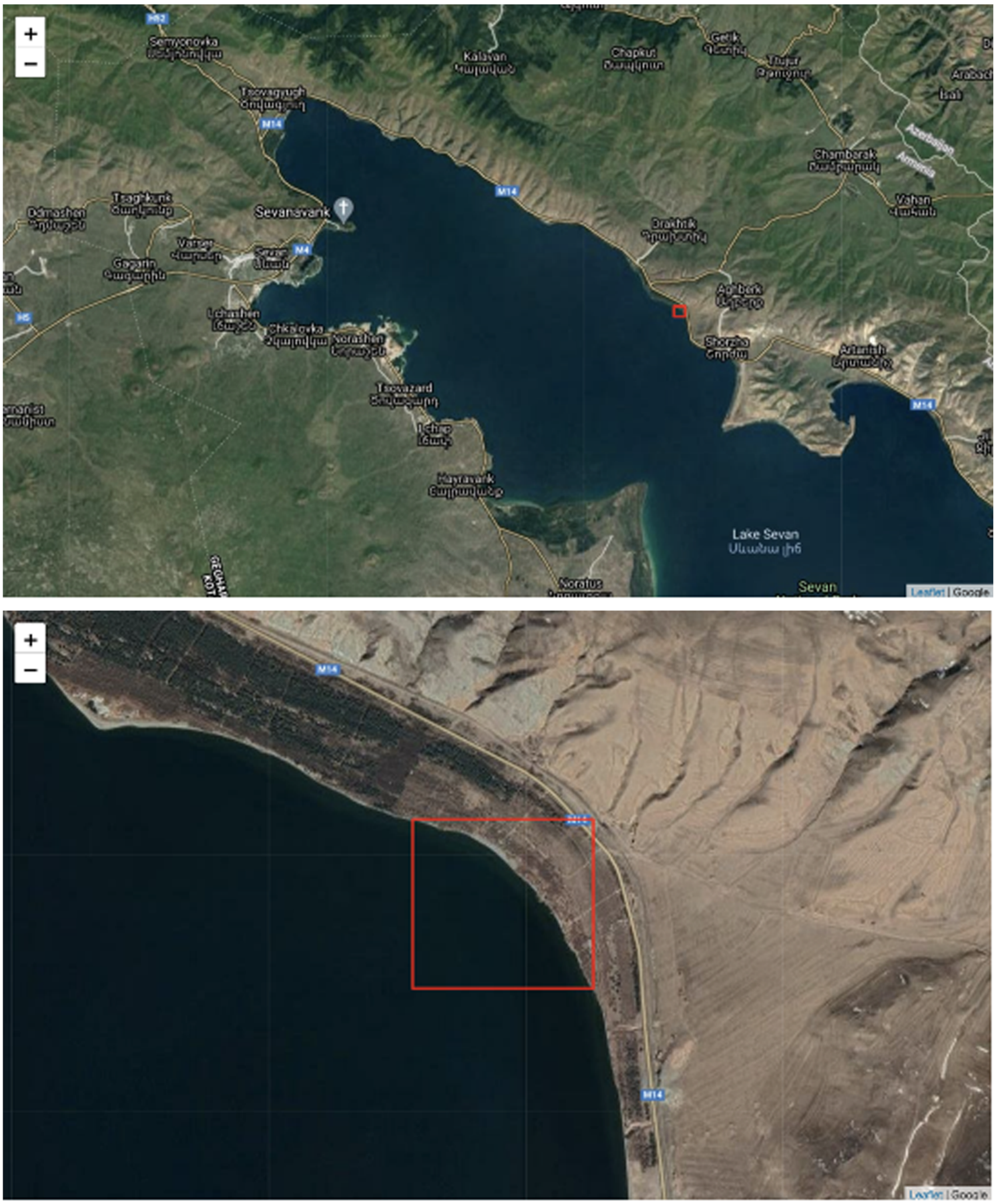

Fig. 2 Study area: lake Sevan (top), Draxtik region (bottom)

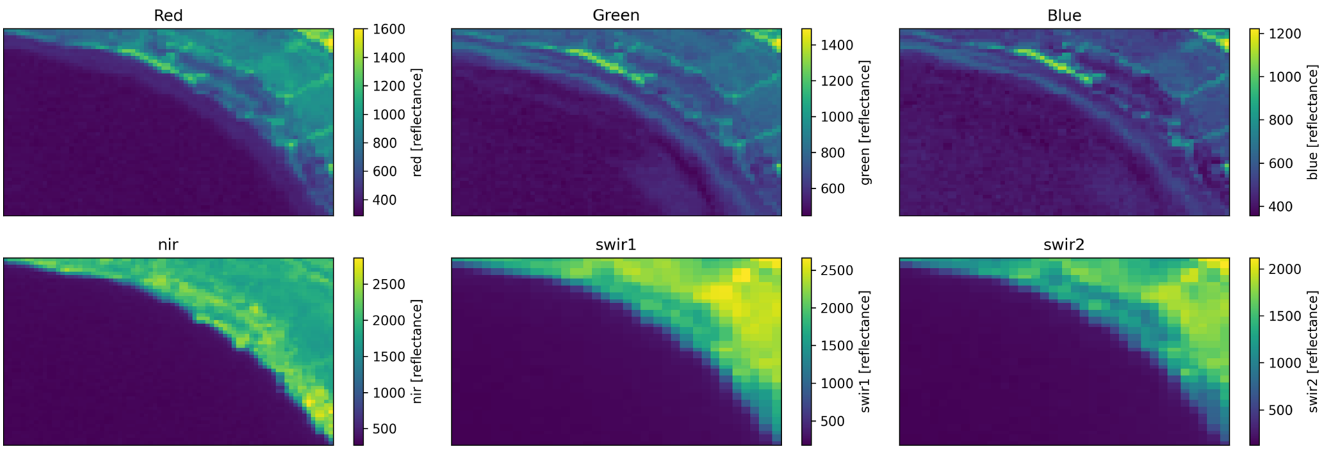

Fig. 3 Sentinel 2 bands (Sep. 15, 2018)

internal leaf structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content (Ceccato et al. 2001). The module output is a band data for a selected region, represented as three matrices where each one corresponds to the RGB image components (R-RED, G-GREEN, B-BLUE).

The data processing module aims to detect the shoreline from satellite bands received from the data extraction module based on clustering, noise removing, and edge detection methods. Threshold, edge, cluster, and neural network-based image segmentation techniques are widely used to identify the high similarities and contrast of pixels by dividing an image into several discrete regions. The clustering methods are among the most efficient segmentation methods, such as K-means clustering or Fuzzy C -means (Sinaga and Yang 2020). First, the K-means clustering method is applied in the module to parcel each observation into the land segment and water clusters to find the shoreline between these two types. Every observation belongs to the cluster with the closest mean, filling in as a cluster prototype. In case the noise is presented in the band data, the boundary detection process is a challenge because it corrupts the image by disturbing the pixel values. Therefore, after the segmentation, a Gaussian blur is applied for blurring an image by a Gaussian function, which smooths the data to remove noise (Flusser et al. 2015). Then, an edge detection method may recognize and segment the band data's edges on discontinuous gray points. The Canny Edge detection multi-stage algorithm (Canny 1986) is applied in the module. The Canny operator chooses the edge points by threshold approach, having a critical influence on the edge detection results. After using the K-mean segmentation, Gaussian blur, and Canny Edge detection methods described above, each shoreline result is masked with the corresponding initial image.

Finally, the data validation module gets the shoreline delineations of satellite images using different band-ratio water delineation methods and UAV images' shorelines

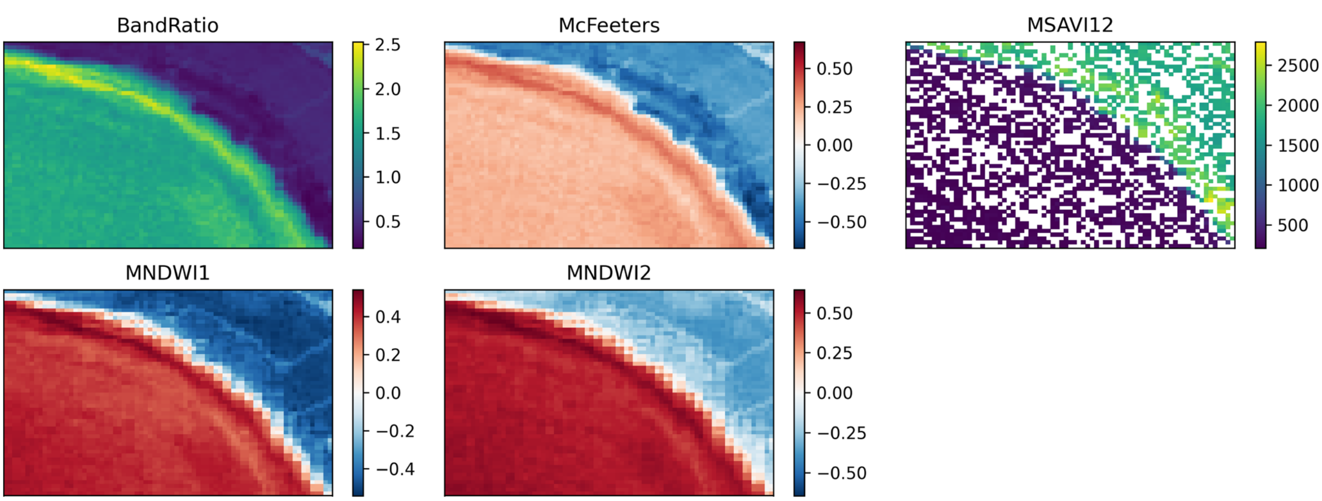

Fig. 4 Visualization of water indexes

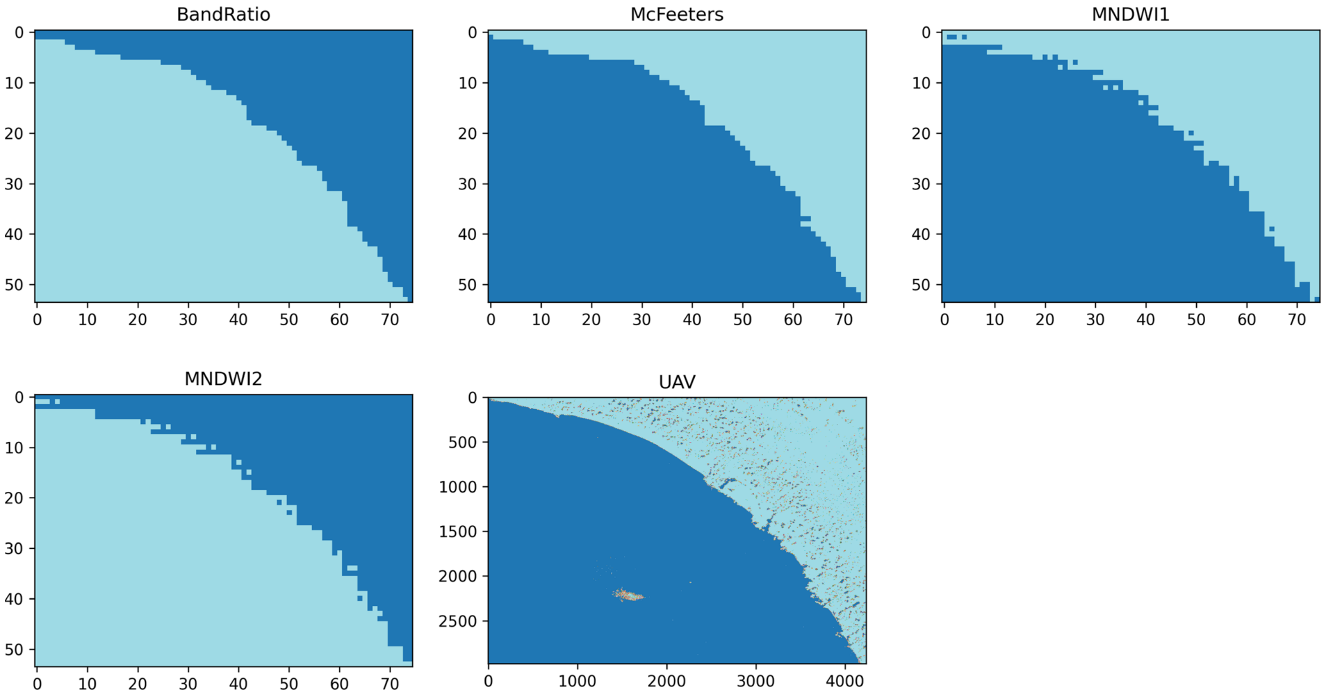

Fig. 5 Visualization of K-Means clustering method

from the data repository module. First, the Euclidian distances between nearest points are calculated, then the Root Mean Square Error (RMSE) is calculated for the whole line with pair of UAV shoreline results to validate by comparing algorithm results with UAV images, taken as observational data, and calculation of the RMSE. RMSE is the standard deviation for the prediction errors. Residuals measure how far from the regression line data points are. RMSE is a measure of how to spread out these residuals are. Therefore the RMSE euclidean distance is the critical evaluation metric to evaluate the service using different water index calculations.

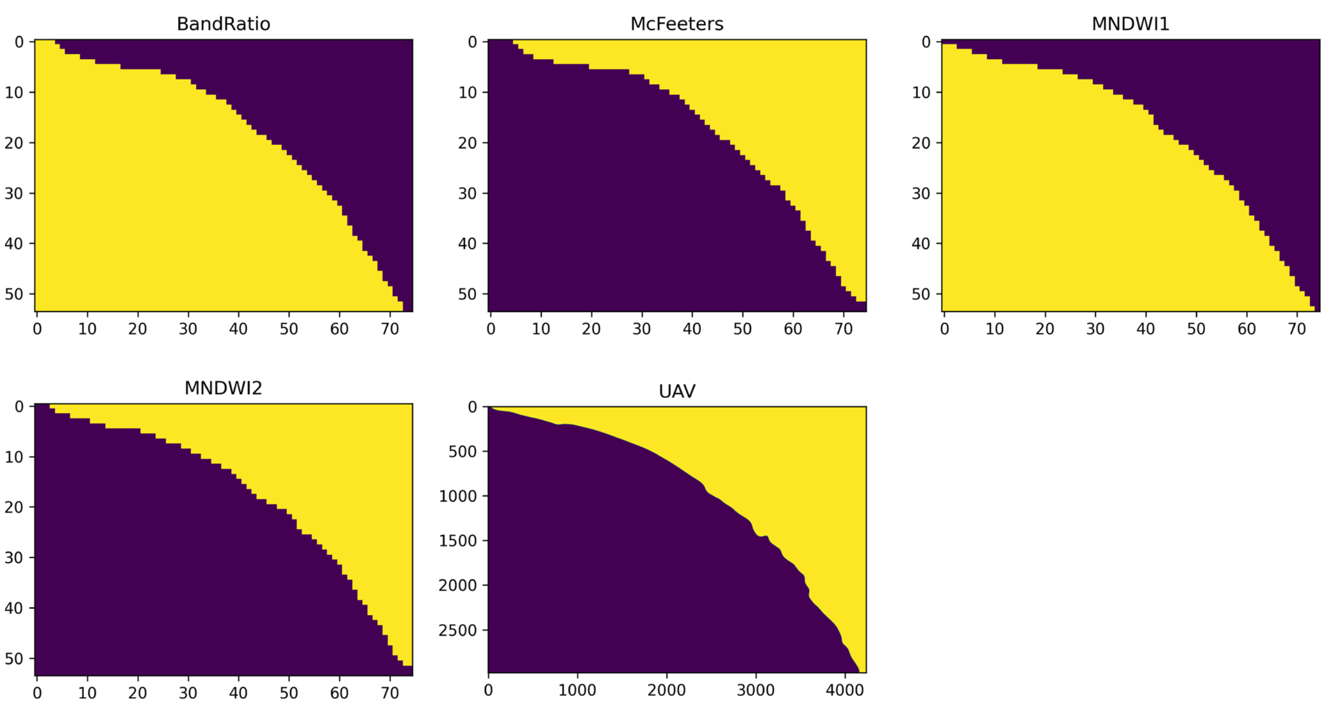

Fig. 6 Visualisation of Gausssian blur

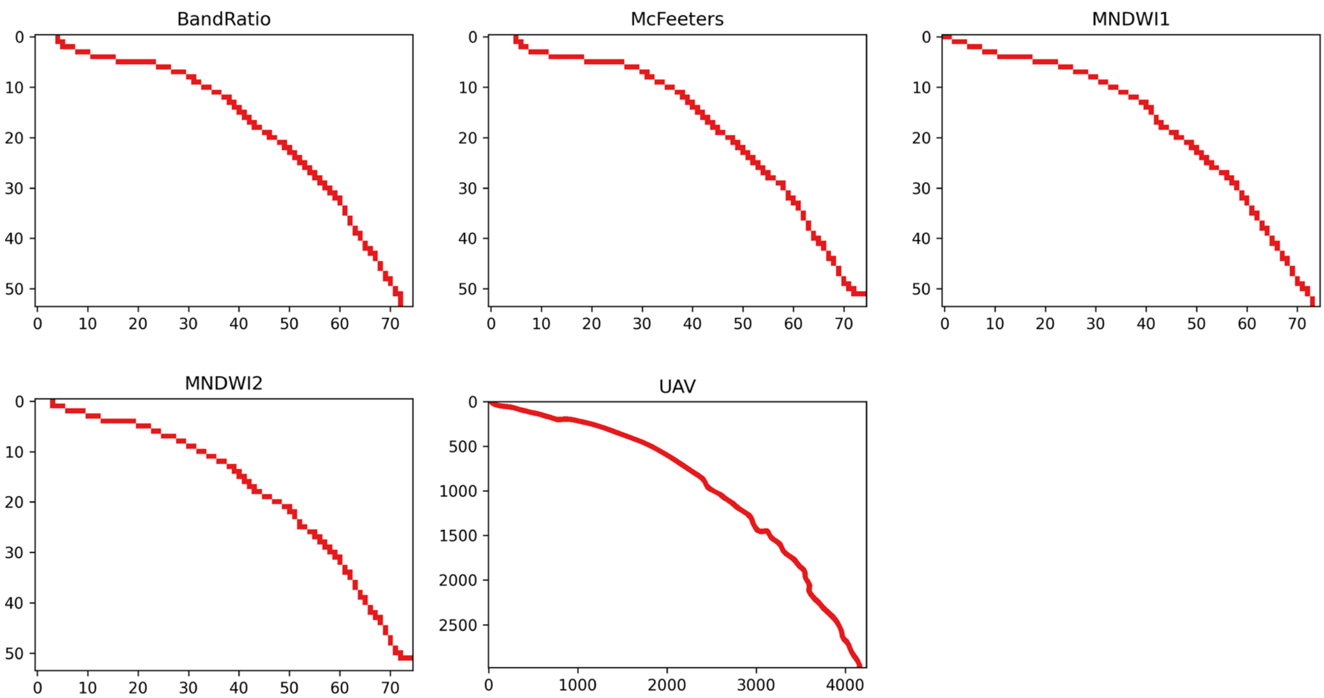

Fig. 7 Visualization of shoreline delineation

The study area and experiments

The service has been evaluated for different study areas and periods. In the article, we discuss the Draxtik part of Sevan lake located between points (40.5177, 45.2368) and (40.5233, 45.2445) (see Fig. 2) for September 14, 2018. Besides the visual representation, the service provides RMSE calculations of the Euclidean distance between all shoreline points of UAV and satellite images for specific dates and areas from UAV pictures to study and calculate the actual mean error. The mean error is essential to monitor shoreline changes by using satellite images.

The Jupyter notebook calls the data repository module to get the satellite and UAV images corresponding to the Draxtik part of Sevan for September 14, 2018. The satellite images are provided to the data extraction module, while UAV images to the data validation module. The data extraction module extracts the satellite images for the nearest date from the data repository using the DC API (see Fig. 3) with GREEN, RED, BLUE, NIR, SWIR1, and SWIR2 bands. Afterwards, the bands are used for Band ratio, McFeeters, MSAVI12, MNDWI1, MNDWI2 water indices calculations to delineate the water and land parts (see Fig. 4).

In the next step, the data processing module detects the shoreline separately using K-means, Gaussian blur, and Canny Edge detection techniques (see Figs. 5, 6, and 7).

Finally, the data validation module gets the UAV images' shorelines (see Fig. 8) from the data repository module to compare with the delineated satellite images. The channels are extracted from the UAV tiff file using the rasterio library. This study's UAV image has a spatial resolution of 30cm, which is applied as the observational data for algorithm validation. Each point from the water index

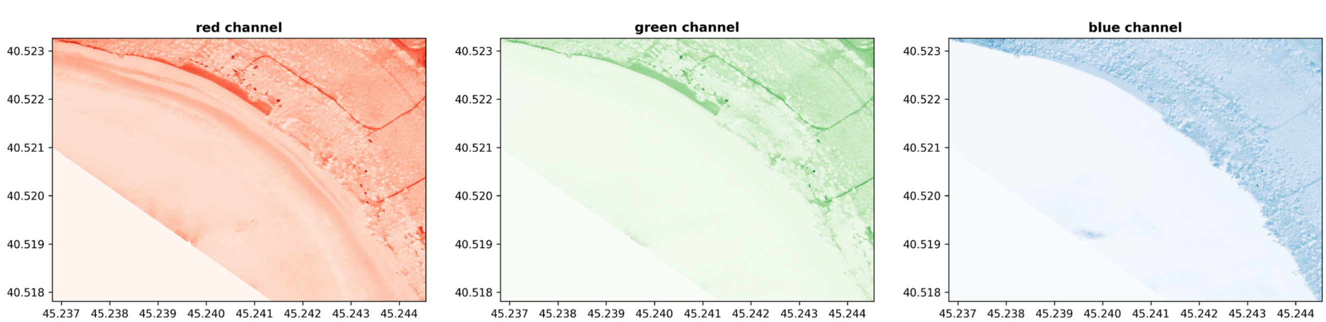

Fig. 8 UAV image bands (Draxtik)

Table 1 RMSE between shorelines extracted from UAV and Sentinel 2 images

Water index method	RMSE value (m)
BandRatio	10.14
McFeeters	11.93
MNDWI1	7.28
MNDWI2	7.63

contains the latitude and longitude coordinates, finding the nearest point from UAV. Then the Euclidean distance between all shoreline points is calculated (see Table 1).

The comparison shows that BandRatio, McFeeters, MNDWI1 and MNDWI2 indices give appropriate results. As we can see for this specific date the better result is given by MNDWI1. The service provides a visualization module to monitor the dynamics of shoreline for the different years (see Fig. 9).

Conclusion

EO DC is a new paradigm to store, manage, and process Big EO data by providing access to extensive spatio-temporal data in an analysis-ready format. A new approach, a shoreline delineation entirely comprehensive service, is suggested combining UAV processing with satellite images within the DC. The recommended service may address many issues related to the region's water shoreline, which is acceptable, especially for countries providing DCs. The current research aims at locating the water coastlines of the specified region in the selected date range from the Sentinel 2 satellite. The Jupyter notebook-based service consists of data repository, extraction, processing, and validation modules using Band ratio, McFeeters, MSAVI12, MNDWI1, MNDWI2) coastline delineation algorithms.

As a case study, the service has been validated to monitor the Draxtik part of Lake Sevan by calculating RMSE between shorelines extracted from Sentinel 2 and UAV images. The best outcome, i.e., the smallest RMSE, was obtained using the algorithm MSAVI12, RMSE=7.28 m.

We consider the work satisfactory because we present the service's capabilities using only one simple example. Still, our goal is to make a smart, universal, use application service and provide it to a wide range of users. To this end, we will continue to work on further improving the service and creating a service portfolio by combining it with other developed services, like the air temperature forecasting service using an artificial neural network for Ararat valley (Astsatryan et al. 2021a) or an interoperable cloud-based service for NDVI time series analysis (Astsatryan et al. 2015).

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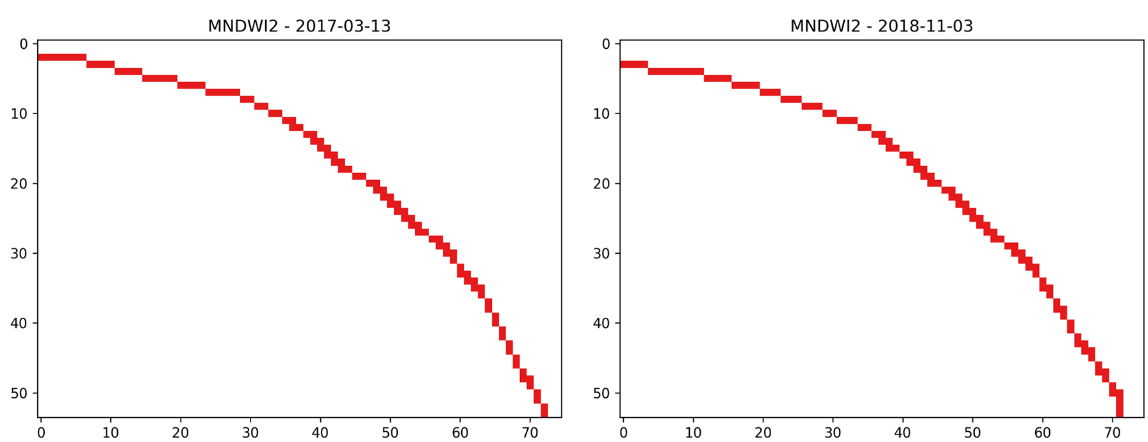

Fig. 9 Visualization of shorelines extracted for the different dates in 2017 and 2018

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