IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium | 979-8-3503-2010-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/IGARSS52108.2023.10282717

RAPID MAPPING OF WATERBODY VARIATIONS IN THE CENTRAL RIFT VALLEY, ETHIOPIA, USING THE DIGITAL EARTH AFRICA OPEN DATA CUBE

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ABSTRACT

Mapping waterbodies variations through time is only possible thanks to the use of in-situ hydrometric sensors or remotely sensed data. Few areas around the world count with a functional in-situ sensor's network, but all areas can be observed with satellite imagery. Several previous studies have mapped waterbodies by means of optical satellite imagery. Combining both optical and radar data is an alternative to avoid high cloud coverage or low data availability. This work presents a workflow for mapping waterbodies variations of lakes, spatially and temporally, located in the Central Rift Valley, Ethiopia by considering Landsat-based analysis-ready data alongside Sentinel-1/2 imagery, and comparing automatic thresholding methods. The workflow is simple, yet effective, and makes use of the Digital Earth Africa Open Data Cube, for the very first time in Ethiopia to accelerate time-series processing with the potential to extend this analysis to a national scale, addressing water security challenges.

Index Terms— Digital Earth Africa, Open Data Cube, remote sensing, Sentinel-1 and 2, Ethiopia

1. INTRODUCTION

A lack of long-term in-situ hydrometric records constitutes a major challenge in Ethiopia, adversely affecting the sustainable management of water resources [1]. Damaged gauges, uncertainty and suboptimal quality of recorded data, missing data records, arise due to lack of maintenance and infrastructure, limiting the understanding of water scarcity and the accurate estimation of water storage of inland waterbodies [2]. Furthermore, over the last four decades a considerable decrease in the size of the main large Ethiopian waterbodies has been observed, particularly in the Central Rift Valley (CRV) basin (Figure 1.). The area of Lake Abijata has shrunk significantly [3] and Lake Ziway's water level has decreased [4, 5]. This is caused by increasing population growth, irrepressible industrial and agricultural activities, unregulated water abstraction, land use land cover changes, and extreme climate variability [5, 6]. Monitoring the spatio-temporal variations of those waterbodies is therefore crucial to measure water scarcity and support stakeholders to effectively manage water access, which is important for livelihoods and agricultural activities across the entire country of Ethiopia.

Figure 1: Central Rift Valley sub-basin in Ethiopia including the main towns, rivers and lakes.

With the advancement of high performance cloud-based computing platforms (e.g. [7]) and open Earth Data Cubes such as Digital Earth (DE) Australia [8] and DE Africa [9], it is now possible to access and analyse time-series of Earth Observations derived from freely-available optical and radar satellite imagery without the need to download high volumes of data and/or install commercial software for post-processing [8]. Moreover, open Earth Data Cubes provide Analysis-Ready satellite Data (ARD) (e.g. Landsat-based water observations from space (WOfS); [10, 11]), as well as satellite imagery that have been geometrically and radiometrically corrected, including for actual surface

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reflectance [8], which is useful for rapid mapping applications. Relevant previous studies have investigated the use of open DE Australia for mapping water surface extent changes since 1987 using Landsat [12], developing a supervised classification workflow using radar satellite imagery to extract waterbodies [13] and delineating Australia's coastline over 28 years using Landsat imagery [14]. However, only one recent study [9] demonstrated the advantages of using the DE Africa open Data Cube and its Sandbox (a python-based cloud-computing environment [7]), via a single example of mapping wetlands with Sentinel-1 along the Buba river in the Lagoas de Cufada Natural Park, Guinea-Bissau [9]. The DE Africa Sandbox is a relatively recent cloud-computing platform (established in 2020 [7]), and has not yet been fully explored for the entire continent of Africa, and has never before been used in Ethiopia to address water security related challenges.

The presented study maps and monitors the spatio-temporal variations of waterbodies and inform the management of the scarce water resources in the CRV sub-basin. It focuses on extracting the water surface extent of Lake Abijata over the last five years. This study leverages the built-in functions of the DE Africa Sandbox cloud-computing environment, the WOfS ARD, and Sentinel-1 and 2 products to rapidly generate a time-series of water surface area observations to aid further understanding of lake change dynamics.

2. METHODOLOGICAL WORKFLOW

The methodological workflow consists of eight steps, processed in the DE Africa Sandbox python environment, as follows:

1. Create a maximum water extent;
2. Remove speckle noise only on Sentinel-1;
3. Calculate water indices;
4. Define automatic threshold;
5. Create monthly time-series;
6. Apply the threshold to extract only water pixels;
7. Validate with benchmark datasets and calculate evaluation metrics Intersection over Union (IoU), precision, recall and F1-score;
8. Calculate the waterbody surface area [km^2].

The maximum water extent, extracted from the annual WOfS ARD [11], corresponds to those image pixels with the highest temporal frequency of pre-classification as wet using Landsat imagery between 1984 and 2022. It is assumed that wet observations correspond to a waterbody when a pixel is wet at least 20% of the time during a year [11]. The extracted maximum water extent was converted into a polygon, with its geometric extent served as the region of interest for the presented workflow. In particular, the maximum and minimum water extents of Lake Abijata observed in 1984 and 2019 respectively. Figure 2 shows the estimated difference of the water extent between 1984 and 2019 with a 108 km^2 dramatic decrease of the size of the lake based on the WOfS ARD. Such decrease could be attributed to land use land cover changes in the CRV [5] and to water extraction for industrial activities [15].

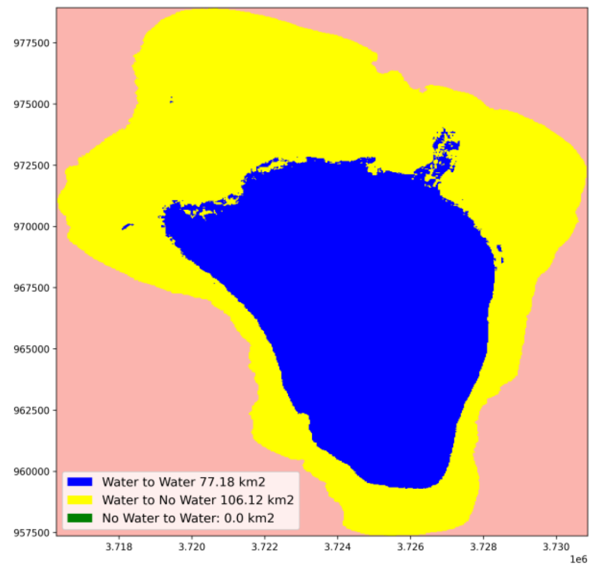

Figure 2: Calculated water extent change of Lake Abijata between 1984 and 2019 from WOfS ARD.

Within the maximum water extent, Sentinel-1/2 products, already radiometrically and geometrically corrected, were retrieved for the monitoring period 01/2018-01/2023. Specifically for the Sentinel-2 imagery a pixel quality filtering mask was applied to select cloud free datasets. The Sentinel-1 water index (SWI) was calculated according to [16], as follows:

$$SWI = 0.1747\cdot\beta_{vv}+0.0082\cdot\beta_{vh}\cdot\beta_{vv}+0.0023\cdot\beta_{vv}^2 - 0.0015\cdot\beta_{vh}^2 + 0.1904 \quad (1)$$

where β_{vh} and β_{vv} refer to the backscatter coefficients in VH and VV polarisations respectively, converted from Sentinel-1 digital number (DN) as follows:

$$\beta = 10 \cdot \log_{10}(DN) \quad (2)$$

The Sentinel-2 modified normalized water index (MDWI; [17]) was also calculated as follows:

$$MNDWI = (\rho_{Green} - \rho_{SWIR}) / (\rho_{Green} + \rho_{SWIR}) \quad (3)$$

where ρ_{Green} represents the reflectance of the green B3 band and the ρ_{SWIR} represents the reflectance of the shortwave infrared B11 band of Sentinel-2. To ensure a consistent Sentinel-1 and 2 time-series, imagery was resampled to a

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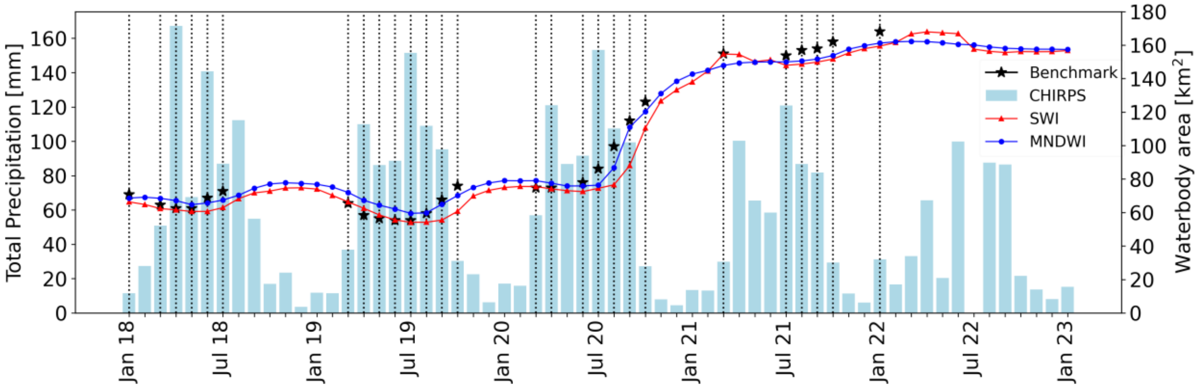

Figure 3: Monthly time-series of waterbody surface area of Lake Abijata, estimated with Sentinel-1 (SWI) and 2 (MDWI) imagery over the last 5 years. The 27 dashed lines correspond to the dates of the delineated benchmark lake shorelines. Calculated surface area from benchmark datasets shown in black star.

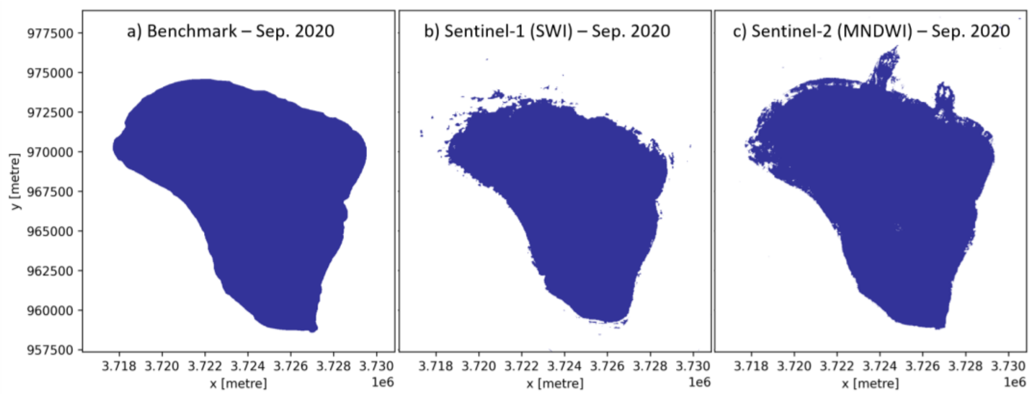

Figure 4: September 2020 waterbody resulted from a) benchmark data, b) SWI and c) MNDWI proposed workflow.

20 m spatial resolution. To define optimal automatic thresholds for the monthly time-series, two methods were examined: a) the Li [18]; and the Otsu's method [19]. Both methods were tested separately for Sentinel-1 and 2 average monthly imagery. The thresholds were then applied and speckle noise was removed. Results were validated against benchmark datasets that were delineated by photointerpretation around the lake's shoreline using very high spatial resolution Planet imagery [20] for 27 individual dates.

3. RESULTS AND CONCLUSIONS

The five-year image-series initially consisted of 147 and 363 Sentinel-1 and 2 images respectively, which were then aggregated in a median monthly time-series. Threshold values defined with the Li method were within the range of 0.44- 1.52 and -0.09-0.06 for Sentinel-1 and 2 time-series respectively. Regarding the Otsu's method, the threshold values were within the range of 0.94-1.88 and -0.02-0.18 for Sentinel-1 and 2 time-series respectively. Even though threshold values were different per each monthly image, evaluation against the delineated benchmark lake shorelines showed relatively small discrepancies. For Sentinel-1 and 2 the differences between the evaluation metrics were all smaller than 0.23 and 0.07 respectively for the two methods. Finally, the Otsu's method was chosen for further analysis.

The calculated surface area of Lake Abijata, over the last five years is shown in Figure 3. A relatively good fit is observed between the two time-series, also reflected by the evaluation metrics. Among all metrics, IoU provided the lowest values of 0.78 in September 2020 and 0.79 in April 2019 for Sentinel-1 and 2 respectively. Waterbody outputs for September 2020 are shown in Figure 4. Sentinel-2 MNDWI captured wet regions around the rivers' flow, not included in Sentinel-1 SWI output. During the 2020 and 2021 monsoon periods, both Sentinel-1/2 results underestimated the lake's actual surface area. However, Sentinel-1 provided a better fit during the 2018 and 2019 dry seasons than Sentinel-2 outputs (Figure 3). Furthermore, differences between Sentinel-1/2 during March-June 2022 are also observed (Figure 3). Benchmark datasets for the remaining months in 2022 will be generated, to further understand these discrepancies. A significant increase in

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surface water area is observed after July 2020 while a significant decrease in rainfall is observed in the years 2021 and 2022 compared to the previous years, according to the CHIRPS (Rainfall Estimates from Rain Gauge and Satellite Observations [21]) precipitation datasets (Figure 3). However, to further investigate the observed discrepancies publicly-available water level datasets will be included into the analysis.

The presented work has demonstrated the advantage of implementing the DE Africa services for rapid mapping of waterbodies, using a conventional remote sensing methodological workflow to complement scarce hydrometric in-situ datasets, and fill data gaps. Results can also serve as input features for a more advanced deep learning segmentation method. After further assessing the performance of the workflow for the Lake Abijata, it will be implemented in all waterbodies of the CRV to provide a holistic overview of the spatio-temporal water surface area variations, providing a fundamental basis to water-resource management authorities in the CRV, Ethiopia.

4. ACKNOWLEDGMENTS

This work was supported by the Water Security and Sustainable Development Hub funded by the UK Research and Innovation's Global Challenges Research Fund (GCRF) [grant number: ES/S008179/1]. The authors would like to thank Planet Labs Inc. for providing the images used (for validation) in this study under the "Education and Research Program".

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