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MULTITEMPORAL ANALYSIS OF INLAND WATER BODIES IN THE CONTEXT OF WATER SECURITY: A COLOMBIAN CASE STUDY

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ABSTRACT

This paper presents an analysis of two inland water bodies, Salvajina Reservoir and Sonso's lagoon, located in the Upper Cauca River Basin, Colombia. Such analysis is carried out in the context of Water Security (WS) by considering their inherent problems to be monitored in a permanent manner (i.e., difficult access, insecurity) and taking advantage of Remote Sensing (RS) platforms. To do so, temporal mapping was done by: (i) automatically segmenting the inland water bodies; (ii) applying the Case 2 Regional Coast Color (C2RCC) algorithm to obtain an approximation to water quality parameters (e.g., chl-a, TSM); (iii) extracting statistical information such as area variation, radiometric index values, and mean values in parameters of water quality; and (iv) providing relevant information for decision makers in the context of WS. The analysis was done over Landsat-8 and Sentinel-2 images between 2014-2021 and 2020-2021, respectively. Planet images were used to validate the segmentation results.

Index Terms — *Water Security, temporal analysis, Segmentation, C2RCC, Remote Sensing*.

1. INTRODUCTION

Water Security (WS) can be defined as the provision of quantitatively and qualitatively acceptable water for health, production of goods and services and livelihoods, along with an acceptable level of risk for people and the environment. Despite the relevance of WS, it is not always considered due to different limitations. In fact, there exist several problems with water resources conservation (quantity and quality), affecting especially the Sustainable Development Goal (SDG) number six [1]. The SDG6 is related with ensuring availability and sustainable management of water and sanitation for all. A clear example of issues related to SDG6 and WS happens in the Upper Cauca River Basin (UCRB) in Colombia, where water is affected by several economic and daily basis activities [2]. Due to different conflicts, access to such inland water bodies is usually difficult, reducing the possibilities of properly monitoring them. A way to help reduce these problems is to properly map the inland water bodies by using efficient and low-cost tools such as the ones offered by remote sensing.

While several studies can be found in the literature related to both segmentation, to classify an image in 2 classes (i.e. water – non water - [3], [4], [5], [6]), and the implementation of algorithms such as Case 2 Regional Coast Colour (C2RCC) to analyze the composition of the water bodies and their variability over time ([7], [8], [9]), this work seeks at combining these methods in order to adapt to the challenging conditions of Colombian inland water bodies. This study presents the temporal analysis of Salvajina Reservoir (SR) and Sonso's Lagoon (SL) located in the UCRB and exploits some water quality parameters (e.g., chlorophyll-a (chl-a), total suspended matter (TSM), percentage of absorption of color dissolved organic matter (CDOM)) measured through the Sentinel Application Platform (SNAP) toolbox called C2RCC processor [10]. The proposed method further allows the extraction of statistical information, useful in the initial characterization for taking further decisions in the context of WS.

2. STUDY AREA

The proposed method was applied to two water bodies: SR and SL, located in the UCRB, Colombia (see Fig. 1). The SR, located in the department of Cauca, is a water body used for different purposes such as: (i) the Cauca River's flow, (ii) dilution of pollutants and (iii) production of electrical energy. The SR is an area of difficult access due to the armed conflict. The SL, located in Valle del Cauca, is a wetland, decreed as a Nature Reserve since 1978, that varies the distribution of its water mirror throughout the year due to aquatic plants. Each of these water bodies is a good example of areas with different contexts and with limited possibility of implementing an effective method to assess their WS in a direct way.

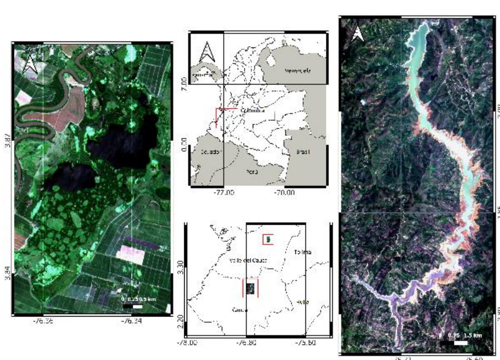


Fig. 1. Sonso's Lagoon, water surface ~1.3km^2 (SL - left) and Salvajina Reservoir, water surface ~ 15km^2 (SR - right).

3. PROPOSED METHODOLOGY FOR COLOMBIAN INLAND WATER BODIES ANALYSIS

The proposed methods make use of the standard steps to analyze inland water bodies (see Fig. 2): (i) selection of proper dataset; (ii) segmentation of each inland water body, according to their particular characteristics; (iii) extraction of water quality information and (iv) extraction of statistical information relevant for decision making in the context of WS.

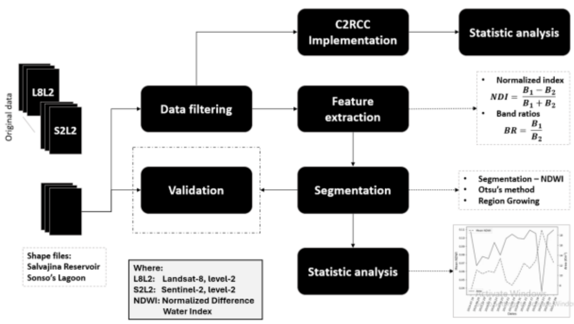


Fig. 2. Block scheme with the proposed methodology.

3.1. DATASET SELECTION/FILTERING

While performing temporal analysis of any land cover type, having a high temporal resolution is of great relevance. Free access satellite images, such as Landsat-8 (L8 - NASA) and Sentinel-2 (S2 - ESA), usually provide these characteristics and were therefore considered for carrying out the different analysis of this study. The use of two different satellites is due to the water bodies sizes, being the SR larger than SL. SR can be mapped with a 30m spatial resolution, whereas it becomes difficult to do the same for SL, and thus 10m spatial resolution is used. The studied period considered for this study goes from 2014-2021 for SR and 2020-2021 for SL.

Table 1. Available images and cloud coverage percentage for characterizing SR and SL.

Cloud coverage area of interest, SR - Landsat 8		Cloud coverage area of interest, SL - Sentinel 2	
Acquisition date	**Cloud coverage (%)**	**Acquisition date**	**Cloud coverage (%)**
19/07/2014	0.14	7/01/2020	0.00
20/06/2015	0.04	17/01/2020	0.00
29/12/2015	0.0004	6/02/2020	0.00
15/02/2016	1.76	2/03/2020	0.55
22/06/2016	0.00	22/03/2020	0.00
24/05/2017	12.47	15/06/2020	0.00
22/04/2017	6.41	16/01/2021	2.90
25/08/2016	0.00	31/01/2021	0.00
31/08/2018	3.95	1/05/2021	8.69
22/01/2019	1.22	20/07/2021	0.00
17/07/2019	0.00		
18/08/2019	0.00		
23/10/2020	0.00		
19/05/2021	0.04		
6/07/2021	0.03		

Google Earth Engine (GEE) platform was used to access the data, since it allows to cut the entire tile or path/row of L8 and S2 images and to download only the Area of Interest (AOI). Data was further filtered out by keeping only cloud free images over the water bodies and with the lowest percentage of clouds over the correspondingly defined AOI. Table 1 shows the detailed list of images used for the analysis.

3.2. FEATURE EXTRACTION AND INLAND WATER BODIES SEGMENTATION

Once data has been filtered out and downloaded, the next steps are those of extracting different features (radiometric indices and band ratios), that help to better highlight water bodies, and finally segment the images into 2 classes: water and non-water. Several satellite remote sensing methods such as image classification, linear un-mixing, single-band thresholding and water index are available in literature to study water bodies [3], [4]. Albeit there exist others normalized indices to detect water bodies (such as the Modified NDWI) their results depend strongly on the color, content and depth of the investigated water body[11]. For these reasons, the NDWI was used in this research as one of the main features to analyzed the SR and SL. With a proper feature extracted, we can proceed to segment the water bodies. This can be done by different approaches, but the three most used in literature were applied to the NDWI images obtained for each water body, and compared to select the best performing one:

- **Otsu's thresholding**: corresponds to the linear discriminant criteria that assumes that image consists of only object (foreground) and background, and the heterogeneity of the background is ignored. It segments the image into two light and dark regions T_0 and T_1, where region T_0 is a set of intensity levels from *0* to *t* and T_1 is from *t* to *z*. Where *t* is the threshold value and *z* is the image maximum gray level;
- **Region Growing (RG)**: consists in segmenting an image from a set of seeds. Each of these seeds could be a single pixel or a group of pixels, and they can be specified manually by a human operator or by pre-processing steps. These seeds grow and form regions according to the specific connectivity and thresholds fixed [5];
- **Segmentation by applying the physical meaning of the NDWI**, that is: fix a manual threshold that separates the positive and negative values of the index [4].

The selection of the best performing algorithm is done by means of the metric Intersection over Union (IoU), which is the size of the intersection divided by the size of the union. In this case, segmentation results are compared with ground truth data obtained by photointerpretation and by using Planet data at 3m spatial resolution. Two to three images, for each water body, were delineated by considering acquisition dates like those shown in Table 1 for L8 and S2.

3.3. WATER QUALITY PARAMETERS EXTRACTION BY C2RCC IMPLEMENTATION

The C2RCC (see Fig. 3) was considered for water quality parameters extraction given its wide use and the fulfillment of initial conditions in the analyzed water bodies. In other words, the water has low levels of reflectance and the signal measured from the satellite is determined in more than 90% by the signal of the atmosphere [12]. The robustness of C2RCC, in addition to its large database, allows the calculation of water quality variables with reliability[13]. This model uses images processed at the top of the atmosphere (TOA), and internally, the C2RCC performs the necessary corrections to surface reflectance. Given that in-situ data were not available, validation was carried out by following information and news found in literature.

Fig. 3. Block scheme – C2RCC implementation.

3.4. STATISTICAL INFORMATION EXTRACTION FOR DECISION MAKING

The statistical analysis consists of characterizing the studied water bodies by extracting mainly the mean values of water quality parameters (i.e. TSM), area variation over time and mean values of NDWI radiometric index. This is done to carry out a temporal analysis of the SR and SL and extract possible correlations between variables that indicate water quality and spatial variation over time. Such variables are indicators of water conditions relevant in terms of WS.

4. RESULTS

This work proposed a temporal analysis of inland water bodies located in two different areas of Colombia. The method is based on the spatio-temporal segmentation of the water bodies and was validated by means of IoU. An average an overall accuracy of 87% for SR and a ranging overall accuracy of 32%-72% for the SL (see Table 2 and Fig. 4) were obtained. The range offered for SL is due to the variability of the water mirror across the year, as explained in section 2. The three methods performed satisfactorily, but the RG outperformed all of them.

Table 2. IoU for the three segmentation methods in SR and SL.

IoU - Salvajina Reservoir				
Validation Dates (Planet images)	**Comparison Dates**	**IoU - Bin Otsu (%)**	**IoU - Bin NDWI (%)**	**IoU - Bin RG (%)**
2/02/2016	15/02/2016	83.99	83.69	84.70
18/08/2019	18/08/2019	87.89	91.53	91.22
4/07/2021	6/07/2021	90.49	89.01	90.86
Average		87.46	88.07	88.93
IoU - Sonso's Lagoon				
Validation Dates (Planet images)	**Comparation Dates**	**IoU - Bin Otsu (%)**	**IoU - Bin NDWI (%)**	**IoU - Bin RG (Without river) (%)**
7/01/2020	7/01/2020	29.29	77.40	80.57
6/02/2020	6/02/2020	16.28	38.57	50.85
1/05/2021	1/05/2021	52.59	70.96	85.70
Average		32.72	62.31	72.37

Once the water bodies are segmented, the C2RCC is applied to derive water quality parameters that allow us to perform a statistical analysis relevant for decision makers. Using the C2RCC model available in SNAP, it was possible to obtain values in relation to TSM, chl-a and CDOM (see Fig. 5 for an example in SR) for both SR and SL, obtaining the spatial representation of the content of each parameter on different dates. Such temporal analysis allowed to find that there is a possible correlation between the mean values of chl-a and TSM in SR and SL. An inverse correlation can be also found between the values of the NDWI and the area variation of the SR, this is because of the reflectance values of the water, deeper water has the general color reflected as blue while shallow water has higher reflectance in the green and red band that could be due to the bottom effect [4], highlighting the low water level in SR on 2020/10/23 (see Fig. 6 for details). Something similar happens with the SL, but the inverse correlation cannot be seen as directly, perhaps because of aquatic plants on the water surface. Due to space limitation, only one date of the SR results is shown (Fig. 5), and it is possible to notice how the changes in chl-a concentration, TSM concentration and CDOM absorption coefficient are visualized throughout the SR, having values between (0-50) mg/m^3 for chl-a, (0-60) g/m^3 for TSM and 0,96-1,00 for coefficient of absorption of CDOM. These results are obtained without in-situ data but are a good approximation of the state of the water body.

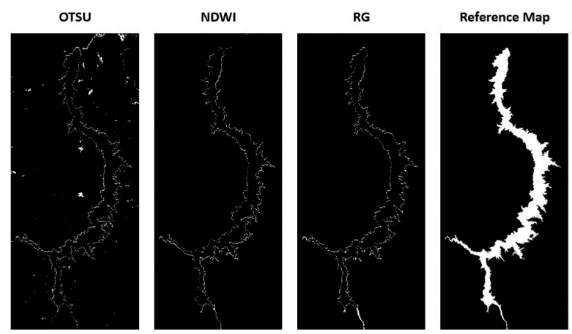
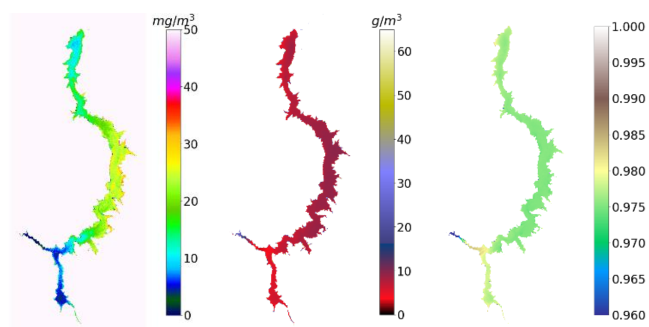


Fig. 4. Difference segmentation results obtained by each method for SR – 18/08/2019



(a) (b) (c)

Fig. 5. Water quality parameters SR – 18/08/2019. (a) chl-a, (b) TSM and (c) absorption coefficient - CDOM.

Regarding the validation of the results obtained, it is done through a comparison with the literature. Works that use similar methodologies over water bodies which may have similar characteristics to SR and SL, are considered for comparison. Some of the articles found are present in [7], [8], [14] and [15]. It is remarkable that as for [14], with their results in the Suez Canal, this work does not intend to indicate the absolute values of TSM, chl-a or absorption coefficient of CDOM, but their relative changes in time, highlighting that the C2RCC has been validated for different sensors, with good results for optically complex waters and that neural networks had been trained for extreme inherent optical properties ranges [15]. Such results, in addition to those obtained through segmentation, allow us to have an insight towards the WS in SR and SL since it is possible to have a wider view of the state of these water bodies in a dynamic manner. The temporal variable is important, since the amount of water in inland water bodies is constantly changing given the impacts on human activities, such as production activities, that vary from upstream to downstream.

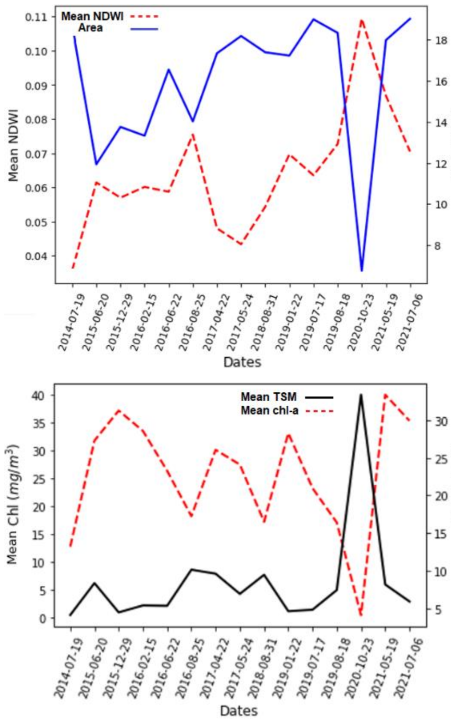


Fig. 6. Characterization of SR w.r.t. NDWI index and water body area (top) and water quality parameters (bottom).

5. CONCLUSIONS

This work presented a methodology for temporal segmentation and characterization of inland water bodies in the UCRB and an approximation to water quality parameters extraction through C2RCC. To achieve this goal, free access tools and data were used. Temporal segmentation was applied over the NDWI, and results were compared to validation data made by photointerpretation from Planet images. The results showed that it is possible to monitor spatial and temporal variation of SR and SL, being an important metric when studying phenomena such as floods, climate variability, and the measures related with WS. As future work, considering combined segmentation methods such as RG and segmentation by physical meaning of the NDWI (or other radiometric indices) could be useful to further increase the robustness of the method in separating water and non-water, as well as in-situ data to validate the results of the parameters estimated with C2RCC. Weather conditions information could also be considered as a complement for decision making.

6. AKCNOWLEDGEMENT

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