WaterLog: A New Spectral Index for Mapping Aquatic Surfaces in Urban Contexts

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1. Abstract

This paper proposes a new spectral index called waterLog, aiming to enhance the delineation and performance of water body mapping in urban areas using satellite imagery. To evaluate the effectiveness of the proposed index, we compare its performance in water surfaces (WSs) in different cities in South America with the results obtained by other well-known water indices in the literature (namely, NDWI, MNDWI, AWEIsh, and AWEInsh). We utilized composite images from the Sentinel satellite (2A and 2B), all acquired in June 2021, and in cities located south of the Tropic of Capricorn to obtain images with the highest incidence of shading. This strategy enhances confusion involving mapping water classes and shadows associated with urban infrastructures, thereby allowing for a better assessment of index effectiveness. In this scenario, the present study revealed that selecting the best single index for mapping all WSs is impossible, as their performances varied across the analyzed locations. Overall, the performance of the indexes - evaluated by partial ROC curve analysis and non-water misclassification points restriction - revealed quite similar results, especially considering waterLog, NDWI, and MNDWI. Despite the similarity, in the six areas analyzed, Waterlog outperformed in three. Additionally, when considering a single threshold for all the cities, waterLog showed the best result in mapping, reducing confusion involving water and shading. Such results, therefore, are interpreted as an essential contribution to water body mapping, considering its practical applications in environmental monitoring and water resource management in urbanized areas.

Keywords: water, spectral index, urban environment, image classification

2. Introduction

According to Shiklomanov and Rodda [1], about three-quarters of our planet is covered by water, of which 5% comprises the surfaces of rivers, lakes, and glaciers. Freshwater, including that found in subsurface sources, accounts for approximately 2.5% of the total volume of the hydrosphere [1]. Given its extensive coverage on the globe, aquatic surfaces (WSs) play a vital role in the functioning of the environment as a whole, directly and indirectly influencing climate mechanisms, the hydrological cycle, ecosystem interactions, and human activities [2], [3]. Thus, due to its significance with repercussions at different scales of approach, there is a growing demand to accurately quantify the temporal-spatial extents and variabilities of WSs through observations made by terrestrial resource satellites [4], [5], [6].

In the context of urban areas, mapping WSs serves numerous purposes, including supporting policies aimed at both water resource sustainability - such as water quality monitoring [7], [8], [9], and mitigating social and environmental impacts, such as floods caused by unplanned urban growth and climate change [10], [11]. To address these impacts, managers should focus on practices and actions that make cities more resilient [12], [13]. In addition to floods, WSs play a crucial role in mitigating temperature [14], [15], increasing air humidity levels [16], and influencing wind patterns [17] in their surroundings, serving as an essential local climate regulation ecosystem service [18]. On the other hand, WSs in urban areas also constitute significant sources of greenhouse gas emissions, contributing to global warming [19].

On a first approach, without delving into the environment's complexity, delineating WSs through remote sensing imagery seems to be easily achievable. This is because the spectral characteristics of water bodies themselves result in low reflectance of energy in the near-infrared (NIR) and shortwave infrared (SWIR) channels [20], appearing as dark tones in the image, which distinguishes them from emerged areas, appearing lighter [21]. However, the water column is composed of mixtures of organic and inorganic materials, so depending on the concentration of these materials, the spectral signature of water bodies can vary drastically, making correct identification challenging [21]. For example, lakes can be classified according to the presence of nutrients, ranging from oligotrophic to eutrophic, which, in the presence of light, can favor the development of phytoplankton and possibly algae [22], [23], as well as the spectral response variation concerning the concentration of suspended materials [24], [25].

Another important consideration is that the composition and extent of WSs are highly variable in space and time [5], [26], [27]. These variations depend on various factors, such as terrain characteristics - including rock types, soil, vegetation - and human activities - associated with agriculture and civil construction - which accelerate river systems' hydrodynamic and morphodynamic processes [28]. In addition to the conditions of the aquatic environment itself, mapping uncertainties can also stem from variations in solar illumination angles and sensor viewing angles [29], which can eventually interfere with confusion involving water and other classes with low energy reflection, such as paved roads and building shadows [30], [31], [32].

One of the most used methods to map WSs is by generating index images, where different spectral bands are combined to enhance water bodies and increase their distinction from other land classes. A spectral index is generated through mathematical operations involving ratios, differences, normalization, multiplication, and others using physical values or digital numbers from two or more bands [33]. The first spectral index constructed for water, the Normalized Difference Water Index (NDWI), was proposed by McFeeters [34], who combined spectral bands from green visible light and NIR to enhance water while simultaneously eliminating the presence of soil and terrestrial vegetation. Subsequently, Xu [35] proposed a modification to NDWI by replacing the NIR band with the SWIR-1 band. This modified NDWI (MNDWI) is more suitable for enhancing and extracting water information in regions with a background dominated by built-up land areas because it reduces noise from built-up areas over NDWI. Since then, several other indices have been proposed in the literature and compared to assess their performance in different scenarios worldwide. Among them, we can mention the Automated Water Extraction Indexes - $AWEI_{nsh}$ and $AWEI_{sh}$ [30], the Simple Water Index – SWI - [36], the Multi-spectral Water Index - MuWI-C and MuWI-Rc - [37], and the Automated Water Extraction Model in Complex Environment – AWECE - [38].

Despite the variety of spectral indices aimed at enhancing water bodies, there is still no consensus on the best index developed to date for mapping WSs. Some studies have proposed adopting strategies that combine different spectral indexes to improve the potential for water information extraction and reduce classification errors [32], [33], [39], [40]. Jiang et al. [39], for example, used a combination of information extracted from vegetation indices such as NDVI [41], built-up area index NDBI [42], and MNDWI to delineate water surfaces through a transformation of the RGB-HSI color space. Subsequently, they created a second HSI image combining the blue and NIR bands and NDVI to remove shadows classified as water.

Therefore, given the numerous challenges still present in mapping WSs, the present study aims to present a new proposal for a spectral index focused on water body mapping, considering the confusions commonly encountered, especially water, low-energy reflecting urban materials, and other artifacts such as buildings shadows. Our index, named waterLog, is compared with other existing water indices in the literature to demonstrate its effectiveness for different scenarios in South America.

3. Method

3.1. Satellite images

For the proposition and analysis of the waterLog index, we used multispectral images from the Sentinel 2A and 2B satellites calibrated to surface reflectance (Table 1). Geographical cutouts containing WSs and tall buildings located in the cities of São Paulo, Curitiba, Florianopolis, Porto Alegre (Brazil), Buenos Aires (Argentina), and Viña del Mar (Chile) were selected. All cities are located south of the Tropic of Capricorn (-23.27°), which favors the occurrence of significant shadow presence in the images. We chose images without clouds acquired all in June (with azimuth and zenith angles ranging from 28.8 to 30.8 and from 53.2 to 64.1, respectively), the month of the winter solstice in the Southern Hemisphere when shadows from tall buildings are more pronounced. If more than one image was recorded in the month, we selected the image visually showing the highest tide level to achieve greater water surface detection.

Table 1 – Images used in the study and acquisition parameters.

City/Country	Centroid of the selected areas	Satellite	Date	Mean solar angle	
				Azimuth	Zenithal
São Paulo / Brazil	-46.67702, -23.58752	Sentinel-2B	06/05/2021	30.8	53.2
Curitiba / Brazil	-49.29172, -25.43496	Sentinel-2A	06/13/2021	30.5	55.6
Florianópolis / Brazil	-48.55586, -27.59260	Sentinel-2A	06/13/2021	28.8	56.7
Porto Alegre / Brazil	-51.22097, -30.03500	Sentinel-2A	06/13/2021	30.6	60.3
Buenos Aires / Argentina	-58.44039, -34.55563	Sentinel-2B	06/17/2021	28.9	64.1
Viña del Mar / Chile	-71.54578, -33.01574	Sentinel-2A	06/07/2021	29.7	62.0

3.2. Proposed index

To increase the separability between pixels corresponding to WSs and non-water surfaces and thus improve the performance of systematic water body mapping, we propose a new index called waterLog in this study. This proposition is an adaptation of the well-known MNDWI index [35], where we use the shortwave infrared 1 (SWIR1) bands and insert a logarithmic scale in the green channel band and an adjustment factor n. The formula is:

$$waterLog = \frac{\ln(Green) \cdot n - SWIR1}{\ln(Green) \cdot n + SWIR1}$$

Where:

$Green$ is the green band.

$SWIR1$ is the shortwave infrared 1 band.

$\ln$ is the natural logarithm to be applied to the green band.

n is a positive multiplicative adjustment factor.

As multispectral images from Sentinel were used in the study, and the bands have variations in spatial resolution (between 10 and 60 m) according to different intervals of the electromagnetic spectrum, we adopted as reference the resolution recorded in the wavelength band of green, which has 10 m on the ground. Therefore, the SWIR1 band, which has 20 m, was resampled to 10 m to match the pixel size of the two bands used to calculate the waterLog index.

In various water bodies, the variability of reflectance in the green band has been reported by Knaeps et al. [43], Uudeberg et al. [44], and Soomets et al. [22]. In our proposal, the logarithmic scale works by reducing the amplitude of the green band reflectance values, while the adjustment factor n is employed for the following purposes: 1) to rescale the threshold value close to zero, making the interpretation of the waterLog index more intuitive, as values above and below zero would correspond to water and non-water bodies, respectively; for this case, we assume n = 150 or values close to it; 2) alternatively, n = 100 or close to this value can be helpful to approximate waterLog values to other spectral indices, such as MNDWI, to facilitate comparative analyses between indices. As in our evaluation, comparative analyses were conducted (as detailed in sections 3.3 and 3.4 of this article) to verify the effectiveness of waterLog; we adopted the parameter n = 100 as a benchmark.

3.3. Evaluation of the proposed index

3.3.1. Comparison with other spectral indices

As previously mentioned, the effectiveness of the waterLog index was checked by comparing its performance in discriminating WSs from non-water Surfaces with the performances obtained with other well-known indexes in the literature (Table 2). Thus, we compared the effectiveness of waterLog with the indices NDWI, MNDWI, $AWEI_{sh}$, and $AWEI_{nsh}$.

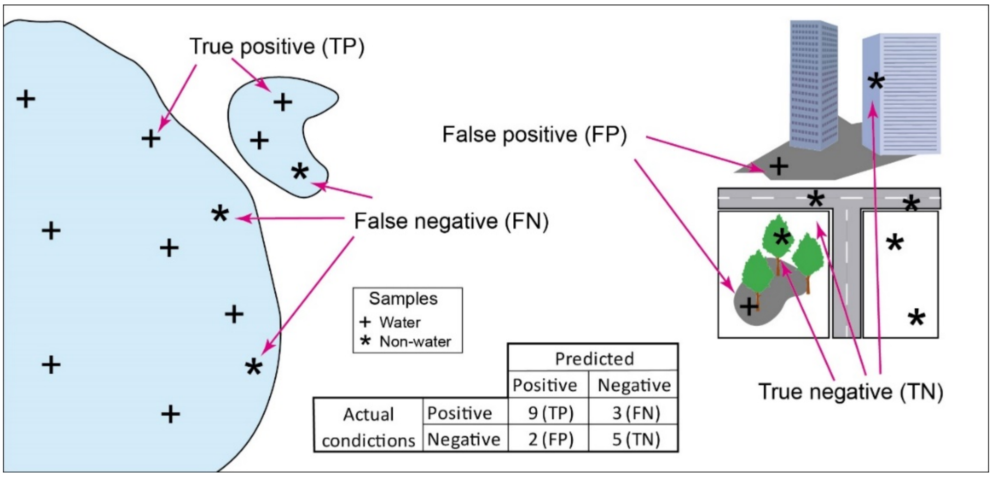
Table 2 – Indices used in the evaluation of WSs mapping.

Índice	**Autor**	**Características**
$waterLog = \frac{\ln(Green) \cdot n - Swir1}{\ln(Green) \cdot n + Swir1}$	Our proposal	The values range from -1 to +1. When n = 150, the threshold for separating water and non-water surfaces is close to 0.
$NDWI = \frac{green - Nir}{green + Nir}$	McFeeters [34]	The values range from -1 to +1, with a threshold for separating water and non-water surfaces close to 0.
$MNDWI = \frac{green - Swir1}{green + Swir1}$	Xu [35]	The values range from -1 to +1, with a threshold for separating water and non-water surfaces close to 0.
$AWEI_{sh} = blue + 2.5 \cdot green - 1.5 \cdot (Nir + Swir1) - 0.25 \cdot Swir2$	Feyisa et al. [30]	In the study area, the values ranged from -10,052.5 to 19,856.
$AWEI_{nsh} = 4 \cdot (green - Swir1) - (0.25 \cdot Nir + 2.75 \cdot Swir2)$		In the study area, the values ranged from -37,391.5 to 14,946.

3.3.2. Reference samples

Reference samples were collected to support the performance analysis obtained with the various indices. Samples representing WSs and Non-Water Surfaces were carefully selected in a supervised manner based on the visual interpretation of the images (Table 1). Highresolution images from Google Earth were also used to aid in identifying different targets. One hundred twenty-three thousand five hundred samples (1 sample corresponds to 1 point) were selected, respecting the minimum spatial sample distance of one pixel to avoid spatial sample duplication. From this sample universe, 18,500 samples (~15%) correspond to WSs (represented by sea, rivers, reservoirs, and lakes - polluted or not, etc.). In contrast, the remaining 105,000 points (~85%) represent Non-Water Surfaces (represented by different types of vegetation, buildings, exposed soil, and sand strips on the ground), which may or may not be shaded. Figure 1 illustrates the sample selection process and the possible hits and errors contained in the mapping, represented by True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Figure 1 – Sampling scheme adopted in the study, with samples of Water Surfaces (WSs) and Non-Water Surfaces and the possible hits and errors (TP, TN, FP, and FN) that may be encountered in the mapping.



It is important to note that strips on the ground comprising the edges of water bodies were avoided in the sampling due to the seasonal variability of water level heights and the spectral mixture between aquatic and non-aquatic elements, which could make the analysis more complicated. This is also one of the reasons why we chose to select Sentinel images acquired during higher tide periods. After this step, the values of the corresponding pixels of the waterLog, NDWI, MNDWI, $AWEI_{sh}$, and $AWEI_{nsh}$ indices were extracted for each selected sample.

3.4. Data analysis

Considering the quantities of hits and errors obtained with the samples (see Figure 1), four statistical analyses were performed to check the efficiency of the indices in separating WSs and Non-Water Surfaces (Table 3). The first one considered the area under a segment of the Receiver Operating Characteristic curve (pROC), where the False Positive Rate (FPR) is less than or equal to 0.02, thus considering a maximum error of 2%. The comparison of pROC area values between the indices indicates the efficiency of one classifier, in relation to the other, in discriminating WSs in the considered slicing intervals.

In the second analysis, TPR_{max} was considered for FPR = 0, corresponding to the length of the ROC curve touching the TPR axis and indicating the hit rate with zero commission errors. In this case, the FNR corresponds to the complementary value of this TPRmax, which in turn corresponds to omission errors for FPR = 0. Thus, the shorter the length of the ROC curve touching the TPR axis, the higher the omission error.

In the third analysis, we compared the omission errors of the spectral indices, considering that in the model, 20 points located in non-aquatic surfaces were mistakenly classified as water (FP). For this, we established thresholds considering the twentieth-highest value of each index from points located in non-aquatic surfaces. It is important to note that the number of 20 samples was arbitrarily defined, and the behavior of FN errors was evaluated solely by changing the quantity of FP.

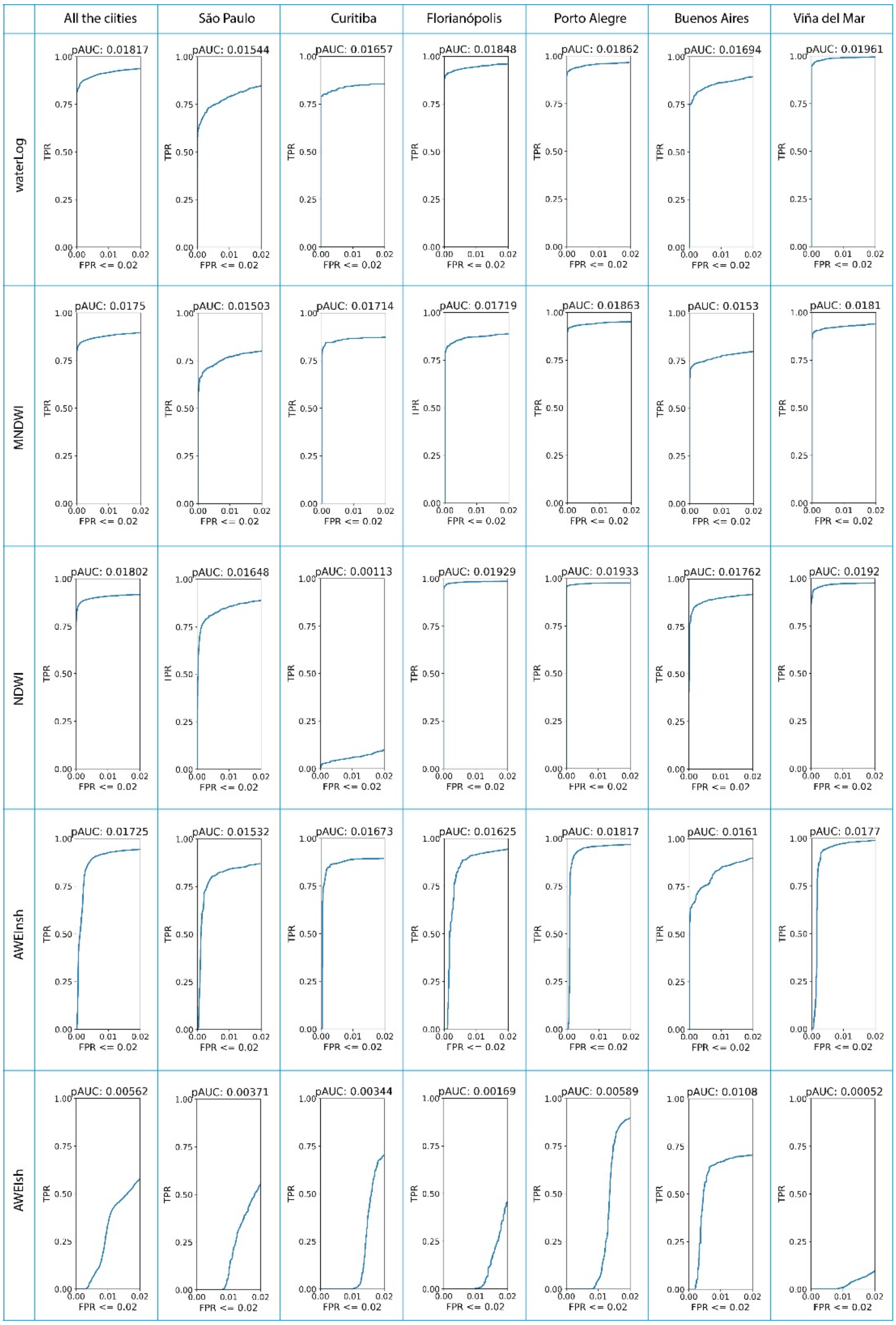
Table 3 – The analyses used for comparing spectral indices.

Analysis	**Interpretation**	**Formula**
The area under the partial ROC curve	The larger the area, the better the index performs in differentiating between WSs and Non-Water Surfaces.	$$pAUC = \int_0^x TPR(fpr)d_{fpr}$$ Where: $TPR(fpr)$: corresponding to a specific FPR. d_{fpr}: small change in the FPR threshold. x: upper limit of FPR.
Threshold established by the highest value of the index in Non-Water Surfaces	The larger the length of the ROC curve tangent to the TPR axis and the lower the FNR value for zero false positives, the greater the WSs mapped.	$$T > x_{0_{max}}$$ Where: x_0 is the highest index value in non-water surfaces.
Threshold established by the twentieth highest value of the index in WSs.	The smaller the FNR, the greater the WSs mapped, considering 20 points classified as FP.	$$T > x'_{0_{20}}$$ Where: $x'_{0_{20}}$ is the twentieth index value in non-water surfaces.

4. Results

As observed in Figure 2 and Table 4, the waterLog, MNDWI, NDWI, and AWEInsh indices exhibited very similar values of the area under the pROC curve (FPR <= 0.02) for virtually all analyzed locations, ranging from 0.01530 to 0.01961, except for Curitiba, where NDWI had a value of 0.00113. The worst results were found with the $AWEI_{sh}$ index, which got values well below the other indices, ranging from 0.00052 to 0.01080. The Length of the pRoc Curve tangent to the TPR axis corresponds to the proportion of hits considering the absence of FP. As observed, the pROC curve of $AWEI_{nsh}$ was very close to the TPR axis in Curitiba, Porto Alegre, and Buenos Aires but did not touch it, indicating the inability to correctly classify any water samples without considering the presence of commission errors (FP inclusion), considering the samples used. The pROC curve of $AWEI_{sh}$ was further away from the TPR axis.

Figure 2 – Partial ROC curve up to 0.2 FPR indicating the cities with the best performances by index.



Unlike the metric of the Area under the pROC Curve, the values found for the Length of the pROC Curve tangent to the TPR axis were more dispersed, with larger amplitudes (ranging from 0 - 0.94839). It was expected that the variability of the results obtained with spectral indices would increase with a higher restriction of the error rate. It was also noted that the hits were higher for locations with more water samples collected in maritime and estuarine environments, as with Florianopolis, Porto Alegre, and Viña del Mar. The waterLog index obtained the best results in three out of the six locations, namely Curitiba, Buenos Aires, and Viña del Mar, besides the best overall result considering all the cities included in the analysis.

Finally, the last two columns of Table 4 show that the decrease in the miss rate is associated with an increase in FP errors. This behavior was observed in all analyzed indices except for the $AWEI_{sh}$ index, where no variations were found in any of the analyzed cities, resulting in the erroneous classification of all water samples. The best performances were found with the waterLog, MNDWI, and NDWI indices, which showed lower miss rate values despite variations within each location and among locations. We can observe that choosing a single index as the best was impossible due to the mentioned fluctuations. However, considering the six cities included, the waterLog achieved the best performance in three (Curitiba, Buenos Aires, and Viña del Mar) and the overall result (All the cities).

Table 4 – Areas under the ROC curve and misclassification water points. Spectral indices with the best performances of each analysis are highlighted in bold.

Region	**Water class**	**Index**	**The area under pRoc Curve (FPR <= 0,02)**	**Length of pRoc Curve tangent to TPR axis (FPR = 0,00)**	**Miss rate (%)**	
					Zero false positive points	20 false positive points
					Limiar: $> x_{0_{max}}$	Limiar: $> x'_{0_{20}}$
All the cities		waterLog	0.01817	**0.75710**	**24.29**	**18.13**
		MNDWI	0.01750	0.75284	24.72	18.74
		NDWI	0.01802	0.55384	44.60	18.54
		$AWEI_{nsh}$	0.01725	0	100.00	99.70
		$AWEI_{sh}$	0.00562	0	100.00	100
São Paulo	polluted river, artificial ponds	waterLog	0.01544	0.42318	57.68	35.68
		MNDWI	0.01503	**0.55534**	**44.47**	33.98
		NDWI	0.01648	0.24609	75.39	**32.16**
		$AWEI_{nsh}$	0.01532	0	100.00	78.26
		$AWEI_{sh}$	0.00371	0	100.00	100
Curitiba	clearwater river, artificial pond with algae	waterLog	0.01657	**0.79060**	**20.94**	19.76
		MNDWI	0.01714	0.77564	22.44	**15.60**
		NDWI	0.00113	0	100.00	97.22
		$AWEI_{nsh}$	0.01673	0	100.00	19.44
		$AWEI_{sh}$	0.00344	0	100.00	100
Florianópolis	sea, artificial pond	waterLog	0.01848	0.88056	11.94	8.53
		MNDWI	0.01719	0.78815	21.18	16.59
		NDWI	0.01929	**0.94839**	**5.16**	**2.51**
		$AWEI_{nsh}$	0.01625	0	100.00	48.56
		$AWEI_{sh}$	0.00169	0	100.00	100
Porto Alegre	river, artificial ponds, and water treatment plant	waterLog	0.01862	0.79712	10.29	7.74
		MNDWI	0.01863	0.89799	10.20	7.93
		NDWI	0.01933	**0.93418**	**6.58**	**3.68**
		$AWEI_{nsh}$	0.01817	0	100.00	77.66
		$AWEI_{sh}$	0.00589	0	100.00	100
Buenos Aires	river mouth, artificial ponds	waterLog	0.01694	**0.74225**	**25.78**	22.28
		MNDWI	0.01530	0.66061	33.94	27.27
		NDWI	0.01762	0.40499	59.50	**16.68**
		$AWEI_{nsh}$	0.01610	0	100.00	34.12
		$AWEI_{sh}$	0.01080	0	100.00	100
Viña del Mar	sea and reservoir	waterLog	0.01961	**0.94808**	**5.19**	**3.18**
		MNDWI	0.01810	0.86126	13.87	9.58

		NDWI	0.01920	0.86540	13.46	5.58
		$AWEI_{nsh}$	0.01770	0	100.00	84.38
		$AWEI_{sh}$	0.00052	0	100.00	100

5. Discussion

This research highlighted the complexity of mapping water surfaces (WSs) in urban contexts, where shadows, buildings, and dark materials with spectral characteristics similar to water (such as asphalt) introduce considerable errors in the classification process. Confusions involving shadow and water are common in studies mapping urban areas using satellite images, being well-documented in the literature [29], [32], [33], [37], [45], [46], [47].

The results presented in this study demonstrated that the percentage of samples correctly classified over WSs varies from one index to another. Zhou et al. [48] also detected in studies carried out in the Poyang Lake Basin (southeast China) where the performances of the indices in mapping water bodies also varied according to the satellite images used when comparing different indices constructed with Landsat-7/8 and Sentinel-2 satellite images.

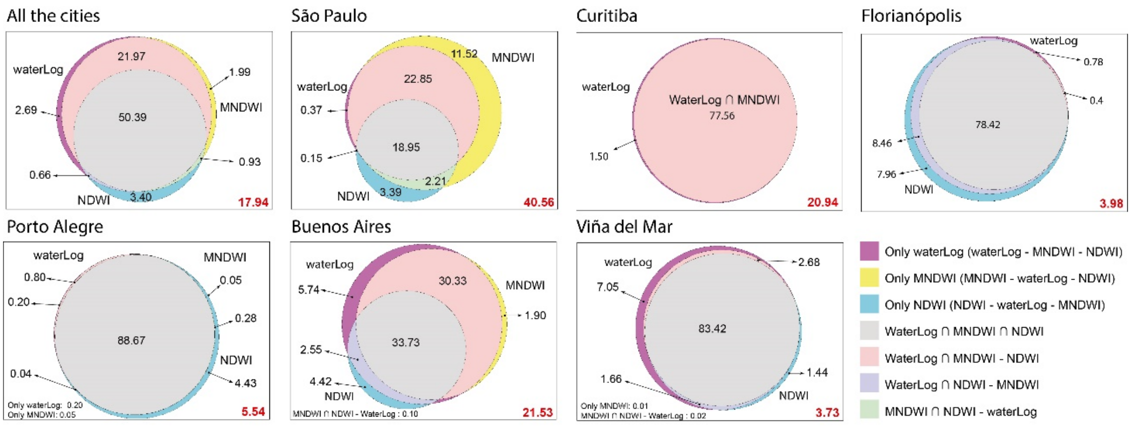
In our study, the waterLog, MNDWI and NDWI indices achieved the best performances in the analyses of the pROC curves and miss rates, with their performances varying according to the locations. Although the $AWEI_{sh}$ index is considered efficient for delineating WSs in environments with shadow occurrence [30], [33], [49], here it was not efficient, presenting along with $AWEI_{nsh}$ the worst results in the overall analysis. Such results are compatible with studies by [46], which report that such indices may not yield the expected results in areas with mountain and building shadows due to the noise generated by the shadow in classification, which leads to higher commission errors.

Although the waterLog, MNDWI, and NDWI indices presented the best results in the analyses, it was really not possible to definitely choose a single index as superior. To allow a more robust conclusion regarding which index is the best, it would be necessary to expand the variability of environments considered in the analysis so that samples with more excellent "global representation" were considered, and this was not the focus of this study, since the comparison is performed more as a baseline to evaluate the effectiveness of the waterLog index proposal.

Considering the context in which the analyses were performed, the MNDWI had better results in polluted water environments. The NDWI, in turn, was better in marine and estuarine environments. The waterLog achieved better results in maritime environments, river mouths (with suspended sediments), and lagoons with aquatic vegetation. Because the waterLog was more adherent to the diversity of environments, in the overall result, considering all cities, its performance was also superior to the other indices. These results corroborate with the studies of Sun et al. [50] and Li et al. [51] that compared the performance of different water indices in China (Shaanxi and Upper Yellow River, respectively) with the aim of mapping water bodies and both studies highlighted the importance of considering the complementarity of the indices to improve mapping performance. Thus, according to Li et al. [51], while the MNDWI is better for mapping water bodies in urban areas, the AWEIsh is better in areas with vegetation presence. Sun et al. [50] emphasized that the NDWI and MNDWI complement each other, and therefore, both should be used to extract different types of water features.

Following the reasoning of index complementarity, Figure 3 shows the percentage of water points correctly classified considering the waterLog, NDWI, and MNDWI indices. The diagram shows the intersection, the union (all circles), and the differences of each set. The intersection of all sets (represented by gray color) indicates the proportion of samples correctly classified as water by all indices. The intersection of only two indices means the third index doesn't classify the water (represented by salmon, lilac, and light green colors). Finally, the difference of one set in relation to the others indicates the correct classification by only one of the indices (represented by subtractive primary colors - magenta, yellow, and cyan).

Figure 3 – Venn Diagram with the percentage of sample points classified as water for the WaterLog, MNDWI, and NDWI indices. The values highlighted in red in the graphs represent sample points incorrectly classified as water (False Negative Rate - FNR). The union of all sets equals 100 - FNR. Thus: All Cities = 82.06%; São Paulo = 59.44%; Curitiba = 79.06%; Florianópolis = 96.02%; Porto Alegre = 94.46%; Buenos Aires = 78.47%; Viña Del Mar = 96.27%.



As shown (Figure 3), considering the union of the three indices (waterLog, NDWI, and MNDWI), the classification results considerably increased the TPR for FPR = 0. Thus, the highest TPR rates were found in Viña del Mar (96.27%), Florianópolis (96.02%), and Porto Alegre (94.46%). Furthermore, the contribution of waterLog was observed for all locations. In Viña del Mar, Buenos Aires, and Curitiba, the contribution of waterLog is more significant, with an increase of 7.05%, 5.74%, and 1.5% in the mapping, respectively. This result reinforces our finding that waterLog performs better for coastal environments with or without sediments and lagoons with aquatic vegetation.

6. Conclusion

This study contributes to the field of aquatic surface mapping, presenting elements that can guide the development of more effective mapping and monitoring methodologies essential for sustainable water resource management and developing policies for climate change mitigation and adaptation. The proposed spectral water index, waterLog, proved to be very promising compared to other well-known spectral indices in the literature (NDWI, MNDWI, $AWEI_{sh}$, and $AWEI_{nsh}$). In the tests conducted (ROC curve and miss rate), the waterLog index achieved performance compatible with NDWI and MNDWI. In the six cities analyzed (São Paulo, Curitiba, Florianópolis, Porto Alegre, Buenos Aires, and Viña del Mar), waterLog yielded the best result in three of them (Curitiba, Buenos Aires, and Viña del Mar), as well as the overall result (All the cities). When analyzing the behavior of each index (waterLog, NDWI, and MNDWI) in the Venn diagram, waterLog was highly effective in correctly classifying water points omitted by the other indices. The most significant contributions of waterLog in improving classifications were observed in coastal environments - on water surfaces with or without suspended sediments - and lagoons with aquatic vegetation. WaterLog can be analyzed individually, integrated with other spectral indices, or even used as an additional band for classification using artificial intelligence to incorporate improvements in mapping.

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