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ESTIMATION OF ANNUAL TROPHIC STATE INDEX DISTRIBUTION OF A TROPICAL RESERVOIR USING LANDSAT IMAGERY TIME SERIES

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ABSTRACT

The eutrophication of reservoirs significantly impacts human health and environmental security. However, *in situ* water quality monitoring can be expensive once it includes equipment and human resources. An effective proxy for water quality is the Trophic State Index (TSI) Chlorophyll-*a* (chl-*a*) based. Remote sensing techniques have helped the authorities and scientific community to map TSI worldwide. Then, this study aimed to develop a remote sensing-based TSI algorithm and estimate the TSI spatiotemporal distribution in a reservoir in Brazil. The chl-*a* concentration was used as a proxy to TSI and classified into three classes: OligoMeso, EutroSuper, and Hyper. The calibrated algorithm was applied to the Jaguari-Jacareí reservoir to obtain TSI between 2013 and 2022. Classification results achieved an overall accuracy of 75% for a validation dataset. Although the general pattern of the TSI in the reservoir is majority OligoMeso, the results indicate two patterns established according to dry and wet seasons.

***Key words* —** Water quality, Inland waters, Landsat-8, Modelling, Random Forest.

1. INTRODUCTION

The world demand for water has always been one of the main concerns of world climate conferences [1]. Although Brazil has the most significant volume of freshwater in the world [2], increasingly intense land use and land cover changes may directly affect the quality of available water [3,4]. One of the most critical indicators of water quality is its eutrophication level, which increases with anthropogenic inputs into aquatic systems, nutrient inputs being a major concern. The leading indicators of the trophic state are the concentrations of phosphorus, nitrogen, and chlorophyll-a [5]. The Trophic State Index (TSI) [6,7] is an effective indicator of inland water quality because it is a stable parameter in time [8]. Chl-a is a highly coted method since it represents an integrated response to both nutrients [9]. However, collecting samples along reservoirs is time and cost consuming, needing other approaches to reduce the cost. Satellite remote sensing may provide an alternative way to retrieve TSI at higher spatiotemporal resolution [10,11]. The Operational Land Imager (OLI), onboard Landsat-8 platform, has been used since its launch, in 2013, to derive inland and ocean water quality products [12]. Thus, this paper aims to assess the spatial and temporal variability of TSI in a reservoir in Southeast Brazil by using Landsat-8/OLI images by a TSI algorithm.

2. MATERIAL AND METHODS

2.1. Study area

The study area comprised the Jaguari-Jacareí reservoir (Fig. 1), the main suppliers of the Cantareira reservoirs system, which is responsible for supplying 8.8 million people in the metropolitan area of São Paulo. The Jaguari-Jacareí reservoir has a total capacity of 808.12 hm³ and 1,027/203 km² of contribution area [13]. The Jacareí reservoir is in a downstream position to the Jaguari. The Jaguari-Jacareí reservoir was one of the most affected reservoirs by the historical drought during 2013/2014 in São Paulo State (Brazil) [14]. Detailed information about the reservoir is descripted in Domingues (2019) [15].

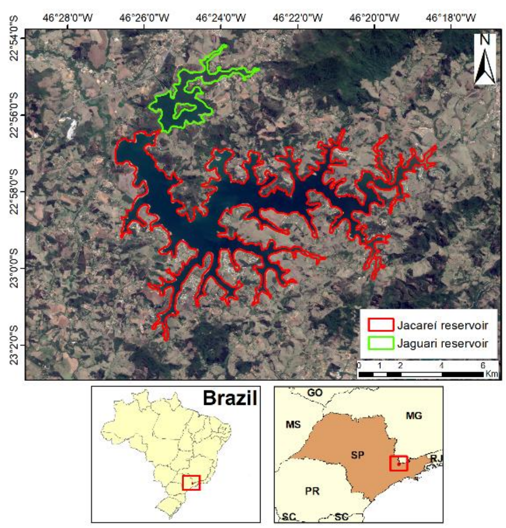

Figure 1. The Jaguari-Jacareí reservoir, São Paulo, Brazil (MSI RGB-432 composition on September 18, 2022).

2.2. *In situ* and satellite remote sensing datasets

The *in situ* dataset used for model development comprises 346 samples for chl-*a* concentration and remote sensing reflectance (Rrs) collected in seven reservoirs: Billings, Funil, Ibitinga, Itaipu, Nova Avanhadava, Promissão and Três Marias; all of them located in Southeast Brazil, collected during 2005 and 2021 [16]. The TSI were grouped into three classes described in [17] (Table 1), according to chl-*a* concentration, and each class was well represented (Fig. 2). For model validation, *in situ* chl-*a* concentration data was provided by *Companhia Ambiental de São Paulo* (CETESB).

Classes	Chlorophyll-*a* concentration (mg/m³)
1 - OligoMeso	chl-*a* ≤ 11.03
2 - EutroSuper	11.03 < chl-*a* ≤ 69.05
3- Hyper	chl-*a* > 69.05

Table 1 - Chlorophyll-based classification of Trophic State Index (TSI) for reservoirs in São Paulo.

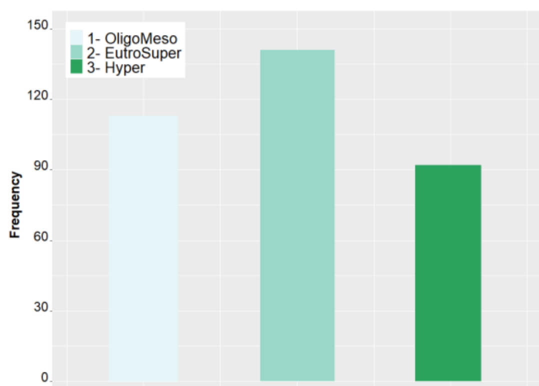

Figure 2. Data frequency for each TSI class based on 346 *in-situ* samples.

The *in situ* measured Rrs (ranging from 400-900 nm) were used to simulate the OLI/Landsat-8 bands considering their respective spectral response function for the development of the model. OLI provides multispectral data with nine optical spectral bands, ranging from visible to shortwave infrared (SWIR), with a spatial resolution of 30 m, radiometric resolution of 12-bits, and a 16-days revisit period.

2.3. TSI model

A Random Forest (RF) machine learning algorithm, one of the well-known supervised classifiers [18], was used to predict TSI on the Jaguari-Jacareí reservoir over time. The classifier takes a dataset as input and, by aleatory resample it with reposition (bootstrapping), creates *n* different decision trees, which votes for the output class. The RF classifier proved to be one of the most accurate machine learning approaches and useful for retrieving water quality parameters [7].

Thirteen features were used as input data for RF model: four bands simulated from OLI (blue, green, red, and NIR), three Simple Band Ratios (red/green, NIR/green, NIR/red), three Normalized Index (red-green/red+green, NIR-green/NIR+green, NIR-red/ NIR+red) and three Spectral Slope (red-green/(665-560), NIR-green/(865-560), NIR-red/(865-665)) [9]. A Monte Carlo (MC) simulation was performed (1,000 iterations) over our *in situ* dataset to evaluated the accuracy of the TSI model. The MC randomly divided the dataset in training (80%) and validation sets (20%), generating different models through iterations. This research selected the best model according to the best global accuracy.

2.4. Validation and application to satellite data

A total of eight samples of chl-a concentration were obtained on the Jaguari-Jacareí reservoir from CETESB [19] between the 2013 and 2022 years, considering a window of ±2 days in relation to the OLI/Landsat-8 overpass, considering cloud free pixels. It was assumed that, since TSI is a more stable parameter, this time lag will not be sufficient to change the reservoir's condition. These data were related to the Landsat/OLI Rrs to validate the TSI machine learning calibrated using the LabISA database.

For time series analysis, 71 OLI surface reflectance scenes were obtained from Landsat Collection 2 Level 2, between 2013 and 2022, except 2015. OLI scenes for 2015 were overlooked because of the limited number of pixels for the entire reservoir because of the peak of drought [20]. The level of the reservoir reached the lowest historical value (< 10%), and in that condition, the estimates would present a bias due to the low representativity of the total area.

3. RESULTS AND DISCUSSION

The confusion matrix and precision metrics of the model for both *in situ* and CETESB data validation (Figure 3) have resulted in an accuracy of 91% and 75%, respectively.

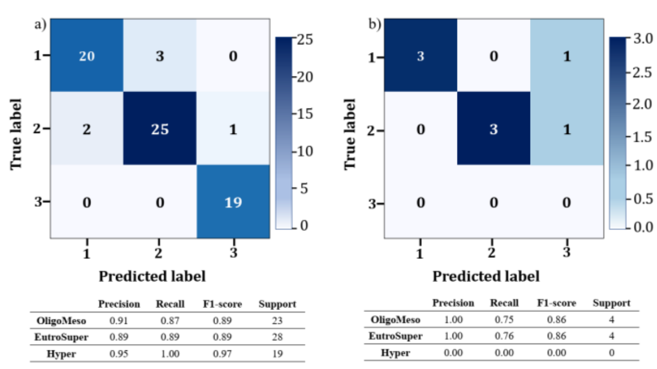

Figure 3. Classification confusion matrix validation of the model for (a) *in situ* and (b) CETESB datasets.

All classes were well-modelled, even for the class which represents the lowest values of chl-*a* concentration (OligoMeso: < 11.03 mg/m³). There were no samples of class 3 (Hyper) on the CETESB dataset, which is why no classification on the matrix was done.

The annual mean of TSI along the reservoir displays a seasonal pattern according to the wet (summer) or dry (winter) seasons in Southeast Brazil (Figure 4). The higher TSI level in February may be explained by the high summer air temperature and nutrients inputs due to precipitation, which provide an ideal condition for the phytoplankton growth [21]. In addition, the rain may carry a considerable amount of nutrients to the water bodies, including phosphorus and nitrogen. Moreover, the high levels of surface solar radiation, common in the summer, have direct relationships with chl-a [22].

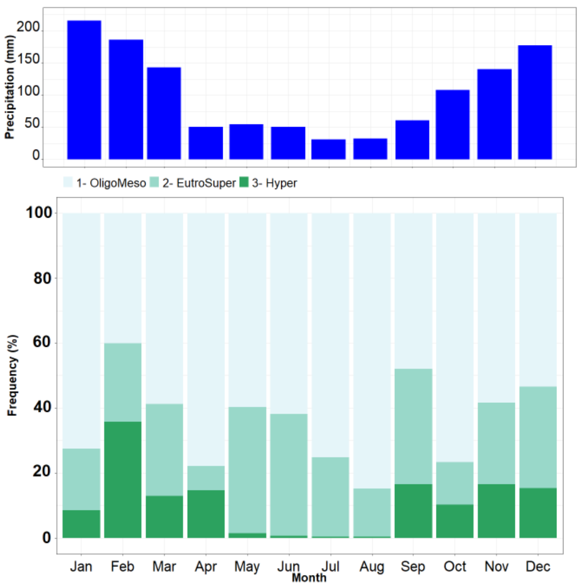

Figure 4. The yearly mean of precipitation (top) and the monthly occurrence percentage of the satellite-derived Trophic State Index classes (below) in the Jaguari-Jacareí reservoir between 2013 and 2022.

The spatial distribution of TSI in the reservoir (Figure 5) highlights the difference between the seasons and shows a difference between the reservoirs as well, mainly during the wet season. Therefore, two scenes representing dry (July, Figure 5a) and wet (February, Figure 5b) were selected to demonstrate that behavior. The accumulated precipitation during February and July was 141.2 mm and 9.2 mm, respectively. During the dry season, it is possible to notice a more homogeneous distribution represented by the OligoMeso class, while in February (wet season), the other classes (EutroSuper and Hyper) are also significantly present. The low downstream flow in February in the Jacareí reservoir could be a factor that contributes to a higher water residence time, and this condition favors algae blooms.

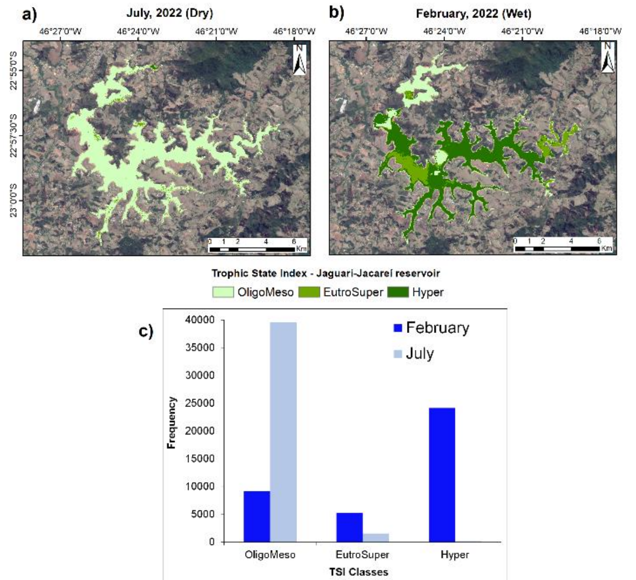

Figure 5. Spatial distribution of TSI in the Jaguari-Jacareí reservoir for (a) dry and (b) wet seasons, and (c) the frequency (number of pixels) of TSI classes for each image.

Some variables may affect the environmental conditions in the water column, such as precipitation, wind speed, and water-flow [8,20]. In this case, the precipitation and downstream flow may be the main variables related to TSI variable in the reservoir studied (Table 2).

	Vol (%)	Natural flow (m³/s)	Downstream flow (m³/s)
February	41.2	35.4	0.5
July	40.8	6.2	1.2

Table 2. Mean of the hydrodynamics conditions in the Jaguari-Jacareí reservoir during February and July, 2022.

4. CONCLUSIONS

Water availability concerns not only the quantity and access to it but also the quality of it. Monitoring the variability of the water quality in reservoirs may be expensive, mainly in huge countries like Brazil. Remote sensing techniques and modeling can provide an effective way to retrieve information about a lot of water-bodies quality at the same time, at a low cost. The Trophic State Index has been used as an efficient water quality indicator worldwide, which is why it is important to develop models that can be applied to several different environmental conditions. Previous *in situ* datasets can be used for training and validation of the algorithms in order to obtain spectral response patterns for given TSI. In this paper, the best model was applied to Landsat-8 images, and three trophic state classes between 2013 and 2022 were estimated. The results demonstrated that the model with grouped classes of TSI can explain the reservoir trophic state spatial-temporally with an accuracy of 75%. This efficient classification can provide valuable spatial and temporal information on the conditions of the Brazilian reservoirs for policy makers to support inland water sustainable management. Additionally, this work is an initial effort to understand how climatic and hydrological forcings may have altered the behavior of the TSI in this reservoir in recent decades.

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