Exploring Unsupervised Domain Adaptation Approaches for Water Parameters Estimation from Satellite Images

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Abstract: In this paper, we compare several domain adaptation approaches in classifying water quality in reservoirs using spectral data from satellite images to two optical parameters: turbidity and chlorophyll-a. This assessment adds a new possibility in monitoring these water quality parameters, in addition to the traditional in-situ investigation, which is expensive and time-consuming. The study acquired images from two data sources characterized by different geographic regions (USA and Brazil) and verified the inference quality of the model trained in the source domain on samples from the target domain. The experiments used two classifiers, OS-CVM and ANN, for domain adaptation methods based on instances, features, and depth. The results suggest domain adaptation is an efficient alternative when labeled data is scarce. Furthermore, we evaluate the need to handle imbalanced data, a characteristic of real-world problems like the data explored here. Based on promising accuracy results, we show that applying domain adaptation techniques in databases with little data, such as the Brazilian database, and without labeled data, is an efficient and low-cost alternative that can be useful in monitoring reservoirs in different regions.

1 INTRODUCTION

Big public and private companies are responsible for building large freshwater reservoirs to meet one or more human needs, including water supply, flood control, and power generation. Regardless of its use, water quality must be constantly monitored to ensure safe consumption. However, monitoring water quality in large reservoirs *in situ* involves many challenges, such as high costs, travel across large areas, and difficulty accessing specific locations. Monitoring water quality via remote sensing (RM) is a simple alternative to design and implement at a relatively low cost. Optical water quality parameters such as turbidity and chlorophyll can be determined by integrating machine learning (ML) algorithms and satellite imagery (Zhu et al., 2022; Li et al., 2022).

However, working with large volumes of labeled data is one of the biggest challenges. Therefore, the scientific community has sought alternatives to the problem of scarcity of labeled data to enable and expand the use of techniques in these challenging situations (Masud, 2012), (Li et al., 2020), (Oza et al., 2023). One of these techniques is Domain Adaptation (DA), a concept in ML that refers to the ability to apply a trained model in a specific context to a different context where data distributions may differ. DA can be employed in classification tasks such as classifying RM images (Tuia et al., 2016), (Zheng et al., 2022).

The scientific community discusses the evaluation of water quality parameters in satellite images through ML techniques (Wagle et al., 2020; Krishnaraj and Honnasiddaiah, 2022; Tian et al., 2023), employing temporal analysis approaches, parameter estimation through regression and anomaly detection methods. Other works investigated the application of DA in RM and other applications (Elshamli et al., 2017; Tuia et al., 2021; Luo and Ji, 2022). That said, a significant contribution of this article is a new study in the area, which applies DA techniques for assessing water quality in satellite images.

The hypothesis is: if the labeled data from the image database (USA) have different probability distributions but with the same characteristics of other reservoirs in other regions, such as the Três Marias reservoir, Minas Gerais, Brazil. Is it possible that they could be used to classify water quality parameters in such different regions? This work proposes a new methodology for classifying water quality parameters to answer this hypothesis. For that, two optical wa-

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ter quality parameters were chosen for the analysis: chlorophyll-a ($\mu g/L$) and turbidity (NTU), and seven DA techniques, MDD (Zhang et al., 2019), fMMD (Uguroglu and Carbonell, 2011), KMM (Huang et al., 2006), DANN (Ganin et al., 2016), WDGRL (Shen et al., 2018), CDAN (Long et al., 2018), KLIEP (Sugiyama et al., 2007) were tested in two classifiers: One Class Support Vector Machine (OCSVM) (Schölkopf et al., 1999) and Artificial Neural Networks (ANN) (Mahmon and Ya'acob, 2014).

The main contributions of this paper can be summarized based on three significant aspects: (i) We propose a new methodology to classify water quality parameters (turbidity and chlorophyll-a) in satellite images, adding DA techniques. The methodology uses two different classifiers to classify turbidity and chlorophyll-a values, OCSVM and ANN, and we will compare them to determine the methodology's applicability; (ii) The methodology used the American reservoir database to classify turbidity and chlorophyll-a values through DA and then apply DA to classify the Tres Marias data set. Promising experimental results should motivate the application of the methodology to different reservoirs regardless of geographic location; and, (iii) We have employed the SMOTE method to deal with the problem of imbalance between classes through the comparative analysis of the accuracy values with and without DA in both scenarios: using data balanced by the SMOTE method and unbalanced data.

2 BACKGROUND AND RELATED WORK

This study used and evaluated different DA techniques to solve the problem of classifying water quality parameters in reservoirs using RM image data. This section briefly summarizes the DA notation and its primary division.

We use D_s to denote the source domain and D_t to denote the target domain. The samples in the set and their corresponding labeling in D_s are given by $X_s = \{x_1^s, ..., x_{n_s}^s\}$ and $Y_s = \{y_1, y_2, ..., y_{n_s}\}$ with $x_i^s \in R^D$ and $y_i^s \in \{1, 2, ..., C\}$, where n_s is the number of labeled samples, D is the dimensionality and C is the number of classes. In this work, the problem of classifying turbidity and chlorophyll-a parameters falls under unsupervised DA, in which there is no labeling in the target domain. The target domain will have an unlabeled database $X_t = \{x_1^t, ..., x_{n_t}^t\}$ where n_t is the number of target samples (Peng et al., 2022).

Since the probability distribution between the source domain and target domain is different, the label space of the source domain and the label space of the target domain are also different. The idea is to create a new representation space with the features of the data that belong to the source class and that, at the same time, exist in the target class. In this way, a classifier will be trained on the labeled source data so that it can later be safely applied to the unlabeled target data. DA methods can be divided into traditional shallow methods and, more recently, deep DA methods. Traditional methods can be based on instances, features (both used in this work), and classifiers to minimize distances between domains. Deep DA methods use CNN, autoencoder, or adversarial to reduce the gap between domains (Wambugu et al., 2021), (Peng et al., 2022). Table 1 summarizes the works with the DA methods characterized by traditional and deep DA methods observed in RM problems.

Table 1: A brief summary of the existing works on DA methods for the Classification of Remote Sensing Data.

Author	Application	Method
(Zhang et al., 2022),	Road segm.	Deep DA
(Ji et al., 2021)	Land Cover Class.	Deep DA
(Liu and Qin, 2020)	Land Cover Class.	Feature-based
(Yan et al., 2022)	Various	Feature-based
(Yan et al., 2018)	Scene class.	Instance-based
(Liu and Li, 2014)	Land Use class.	Instance-based

The instance-based DA methods handle shifts between data distributions, minimizing target risk using the source's labeled data. In this type of adjustment, only the marginal distributions of the source or target samples are considered to align the distribution of the domains. In the feature-based approaches the basic idea is to transform source and target data into a feature space, mapping so that the data distribution is similar. In other words, the method learns a transformation that extracts the representation of invariant features across domains. Then, the method minimizes the gap between domains in the new representation space in an optimization procedure while preserving the underlying structure of the original data. In this case, adaptation is performed by the joint extraction of features, typically based on subspace and transformation. The deep learning DA adds adaptation layers to an original deep network architecture to perform source-target transformation or adopts an adversarial learning strategy to minimize cross-domain discrepancy (Farahani et al., 2021), (Peng et al., 2022).

3 MATERIALS AND METHODS

Figure 1 describes the developed methodology. The basic idea is to assign labels to the data from the structured databases (USA and Três Marias) according to the binary classification criteria defined for the turbidity and chlorophyll-a parameters. Using Google Earth Engine services, this labeled data is merged with the reflectance values of the satellite image pixels (Figure 1 - 1). Next, the values are filtered to avoid negative data quality due to spectral noise, clouds, and shadows (Figure 1 - 2). Then, the database is divided into the source domain and target domain according to the criteria established for each experiment (Figure 1 - 3). It is essential to mention that the target domain does not use labeled data. So, our experiments are classified as unsupervised, where the source domain has labeling data and the target domain does not. An optional step is added to handle the imbalanced data issue (Figure 1 - 4). Subsequently, the two classifiers, OCSVM and ANN, are trained without DA and with the 7 DA methods (Figure 1 - 5). Finally, the result of each experiment is compared to analyze the applicability of the methodology (Figure 1 - 6).

3.1 Database

The structured database used in this research represents the dependent variables (which will be predicted/estimated). The parameters explored were turbidity and chlorophyll-a: (A) In situ campaigns (Três Marias, Brazil, shown in Figure 2a). The in situ water sample collection points are red in Figure 2a. Water quality parameters were sampled through in situ campaigns carried out between 2019 and 2022, in periods of flood and drought, distributed along the Três Marias Reservoir—sampling objects: physical-chemical parameters of surface water. (B) United States of America (illustrated in Figure 2b and 2c) - The US National Water Quality Monitoring Program provides a long-term historical basis of physicochemical parameters of water quality[1].

It was necessary to define standard measurement units for each evaluated water quality parameter: µg/l for chlorophyll-a and NTU for turbidity.

3.2 RM Data Acquisition

Spectral data from the Sentinel-2 satellite were used to develop the methodology. The applied data underwent atmospheric correction (surface reflectance) and orthorectification processes, and the spectral bands were resampled (when necessary) to a spatial resolution of 20 m. This resolution was defined because it presented a lower level of interference/noise during the statistical analysis of the reflectance of pixel values. In order to mitigate harmful data quality aspects arising from spectral noise, clouds, and shadows, a combination of filters, indices, and auxiliary properties of the satellite image was applied: cloud detection masks (MSK CLDPRB and QA60); snow/ice masks (MSK SNWPRB); pixel classification, SCL (Scene Classification); Normalized Difference Water Index (NDWI); Snow Detection Index, Non-Binary Snow Index for Multi-Component Surfaces (NBSI)[2].

An algorithm in Python, CaptGeo, was developed to extract the reflectance values of pixels from the spectral bands of satellite images. The algorithm computes and extracts pixel values from the Google Earth Engine cloud platform. The application receives as input data a structured file with the measurements of a parameter (turbidity, chlorophyll-a) and their respective geographic coordinates, from which the location and reflectance value of the pixel correspond to each one of the spectral bands available in the satellite image. After processing, a structured file with the turbidity and chlorophyll-a data and the values of the spectral bands referring to each geographic coordinate corresponds to the data that will be used as input in the ML models.

3.3 Experimental Results

Google Colab was used to implement the methodology, with the Python 3.6 programming language and the Scikit-learn and Adapt libraries (de Mathelin et al., 2021), (Pedregosa et al., 2011), (Bisong, 2019). The metrics considered to evaluate the results obtained in adapting the domain were accuracy and balanced accuracy. The neural network used has two intermediate layers with ten neurons each. The output layer is a sigmoid function; it will set class 0 or 1 depending on the threshold. Initially, the US database was chosen to classify turbidity and chlorophyll-a values. For this, the database was divided into two groups: longitudes at 96.9915° W (named here by first division - FD, illustrated in Figure 2b) and the second latitude at 36.9915° N (named now second division - SD, showing in Figure 2c). We obtained the two databases, FD and SD, based on the longitude and latitude values. In this way, testing two antagonistic scenarios/environments with different biomes was possible.

Both datasets FD and SD were divided again to create the source domain and target domain; the two classifiers (OCSVM and ANN) were used for training the source domain, and the target domain was used for testing, without using labeling data. The binary

[1]Resource access: https://www.waterqualitydata.us/.

[2]For a detailed explanation of the bands, the number of pixels, and the filters used, please consult our previous work in paper (Souza et al., 2023)

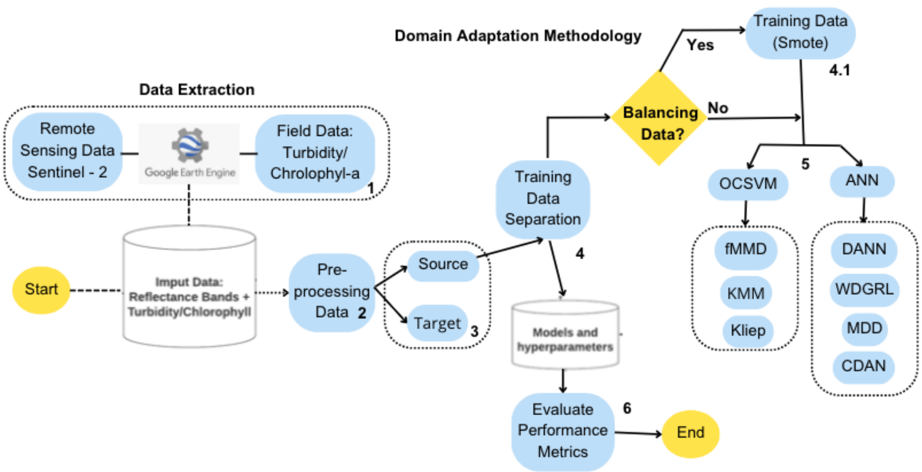
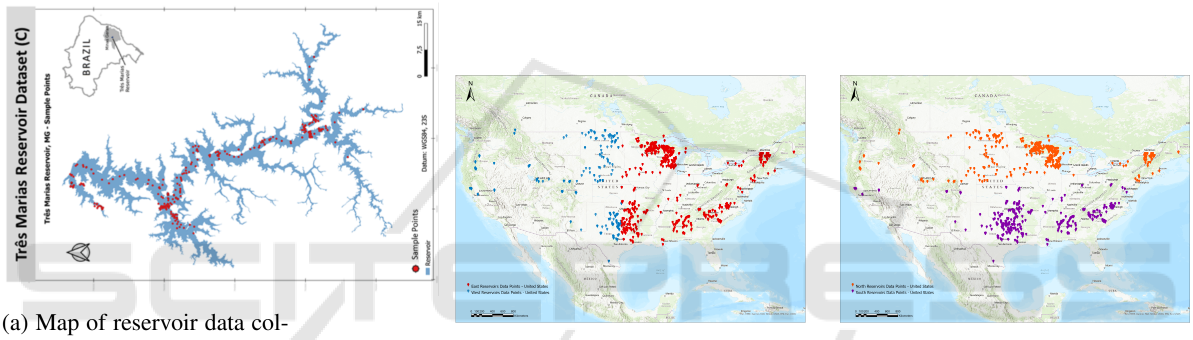


Figure 1: Overview of the proposed Domain Adaptation pipeline.



(a) Map of reservoir data collected from the Três Marias, Brazil.

(b) USA map of reservoir data divided by FD.

(c) USA map of reservoir data divided by SD.

Figure 2: Brazil and USA reservoir datasets.

classification was divided based on a value defined from a series of studies related to legal standards established within the scope of water resources management [3]. The binary division was established as follows: i) Turbidity - Class 0, values below 25 and Class 1, values above 25 NTU; ii) Chlorophyll-1 - Class 0, values below 11.03 and Class 1, values above 11.03 $\mu g/L$. In this work, binary classification proved to be more accurate, according to the results discussed in the following subsection. Furthermore, for thresholds below 25 NTU, the separation of pixels becomes more complex as the reflectance values become increasingly similar; therefore, it was observed that the band variation is sensitive to multiclass classification.

After the results of the experiments observed in the US database, new experiments were designed for the Brazilian database. The fundamental question to be answered is the applicability of DA methods in classifying water quality parameters in reservoirs with a labeled database to other reservoirs with little or no labeled data. The experiments below seek to answer this question, especially for geographic differences.

3.3.1 United States Subdivision

Table 2 describes the latlong division of the United States, the sample number of Source and Target Domain, and the sample numbers according to the class division for turbidity and chlorophyll-a values.

Table 3[4] describes the balanced accuracy values for 25 NTU (Nephelometric Turbidity Units) and 11.03 $\mu g/L$ divided by regions according to the mentioned above. The first classifier tested in this case was the OCSVM without DA. Then, the same classifier was used to train the database with the three different DA methods (KLIEP, KMM - instance-based,

[3] https://www.epa.gov/dwreginfo/drinking-water-regulations; https://www.irishstatutebook.ie/eli/2014/si/122/

[4] The red color in the table indicates that the classification without DA obtained higher accuracy values than using DA (negative transfer). The green color indicates that the classification with DA obtained a higher accuracy value than without DA (positive transfer).

Table 2: United States longitude and latitude divisions - turbidity and chlorophyll-a values.

Parameter	Long/Lat	Source	Target	Class 0	Class 1	NTU/$\mu g/L$
Turbidity	FD	1637	225	1533	104	25
Turbidity	SD	1347	515	1243	104	25
Chlorophyll-a	FD	4029	465	2517	1512	11.03
Chlorophyll-a	SD	2186	2308	1277	909	11.03

and fMMD - feature-based). The balanced accuracy values described in Table 3 show that DA improved accuracy for all experiments. We can observe that the Kmm, and fMMD methods stand out when classifying the turbidity parameter. The Kernel Mean Matching - KMM method is an instance-based sample bias correction that minimizes the maximum mean discrepancy (MMD) between the source and target domains. The algorithm corrects for the difference between the input source and target distributions by preweighting the source instances to minimize the difference between the training/test point means in a Reproduction Kernel Hilbert Space (RKHS) (Huang et al., 2006). The fMMD method is feature-based, using input features to minimize the maximum mean discrepancy (MMD) between the source and target data.

Table 3 also describes the classification by RNA without DA and by RNA and four DA methods (DANN, WDGRL, MDD, and CDAN). The highlight of these experiments was the WDGRL method that works on adversarial neural network architectures. The discriminator approximates the Wasserstein distance between the encoded source and target distributions based on WGAN (Wasserstein Adversarial Generative Network) (Arjovsky et al., 2017). For the chlorophyll-a results (Table 3 on the right), we can highlight the values obtained by KMM with OCSVM, DANN, and CDAN with ANN. The DANN method aims to find a new representation of the input features in which any discriminator network cannot distinguish the source and target data. This new representation is learned by a network of encoders in an adversarial manner. A task network is learned in the coded space parallel to the encoder and discriminator networks. In the CDAN method, the discriminator is conditioned on the prediction of the task network for source and target data. Thus, the focus is on the source-destination correspondence between instances belonging to the same (de Mathelin et al., 2021) class. For both OSCVM and ANN, the results suggest that applying DA to classify the chlorophyll parameter is more appropriate, thus ensuring a better response from the classifier with unbalanced data and without labeling in the target domain.

The table 4 describes the balanced precision values per class using the Synthetic Minority Oversampling (SMOTE) technique (Chawla et al., 2002). Smote synthesizes new samples based on existing samples; therefore, the new data generated, closer to the real data, promotes balance in the class. The accuracy values described in Table 4 show that applying DA has the highest accuracy compared to classification without DA. Only in two scenarios using the ANN classifier can we observe the presence of negative transfer for turbidity and chlorophyll-a. Negative transfer occurs when the application of DA techniques impairs classifier performance. Still, it is possible to highlight the accuracy values of the TrAdaBoost, KMM, and KLIEP methods in the classification by OSCVM DANN and CDAN again for ANN. The KLIEP method, also an instance-based method, corrects for the difference between the input distributions of the source and target domains through a reweighting of the source instances that minimizes the Kullback-Leibler divergence between the source and target distributions (Wen et al., 2015).

So far, results indicate an advantage when applying DA to both classifiers to classify turbidity and chlorophyll-a values in reservoirs, surpassing the accuracy value without DA in most experiments. However, for balanced data by Smote, deep-based methods obtained negative transfer in two scenarios. For the rest of the experiments, it was possible to observe that the KMM and fMMD method got promising results in most OSCVM experiments, followed by DANN and CDAN by ANN.

3.3.2 Três Marias Reservoir

The following experiments used the complete US database as the source domain (without dividing it by longitude and latitude) and, database from the Três Marias reservoir, Minas Gerais, Brazil, was used as the target domain. An illustration of chlorophyll-a data in 2 dimensions is shown in Figure 3a before the DA method application. Source data is shown in blue (USA), and target data is shown in red (Três Marias). Figure 3b illustrates the distribution of features after applying the instance-based method. Figure 3c after applying the feature-based method and Figure 3d after applying the deep-based DA method. Interestingly, the distribution resulting from the deep method is similar to that from the feature-based. This is because deep-base methods also use strategies that in-

Table 3: Turbidity and Chlorophyll-a - USA division - Unbalanced Data - Balanced Accuracy.

Method	Parameter	FD	SD	Parameter	FD	SD
OCSVM	Turbidity	0.695206	0.637180	Chlorophyll-a	0.770352	0.713083
Kliep		0.676338	0.657131		0.762072	0.719558
KMM		0.752523	0.656824		0.788668	0.709516
fMMD		0.704640	0.711570		0.752960	0.695959
ANN		0.717694	0.702136		0.792831	0.809472
DANN		0.676338	0.718839		0.812211	0.830679
WDGRL		0.771391	0.715593		0.812165	0.807481
MDD		0.661090	0.657131		0.774838	0.823180
CDAN		0.654563	0.697807		0.803469	0.837994

Table 4: Turbidity and Chlorophyll-a - USA division - Balanced Data by SMOTE - Accuracy.

Method	Parameter	FD	SD	Parameter	FD	SD
OCSVM	Turbidity	0.831111	0.895146	Chlorophyll-a	0.752688	0.729203
Kliep		0.848889	0.916505		0.726882	0.709272
KMM		0.871111	0.904854		0.765591	0.790295
fMMD		0.822222	0.897087		0.769892	0.744367
ANN		0.826667	0.842718		0.817204	0.830589
DANN		0.848889	0.834951		0.804301	0.816724
WDGRL		0.813333	0.831068		0.800000	0.810225
MDD		0.831111	0.833010		0.804301	0.818891
CDAN		0.844444	0.819417		0.808602	0.832322

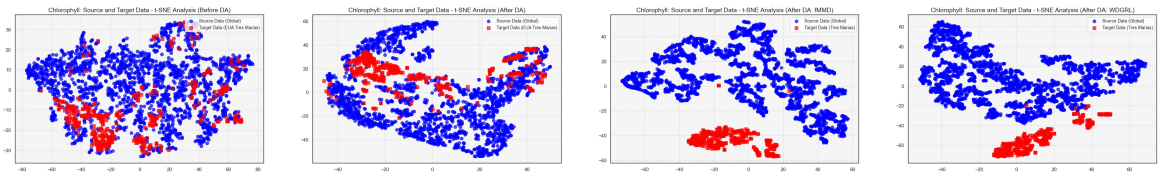
vestigate standard features with similar behavior concerning the task in the source and target domains. Then, generating a new feature representation to correct the difference between the source and target distributions. In Figure 3b, however, based on instances, it is possible to notice the attempt to reweight the data to correct the difference between the source and target distributions.

Table 5 describes the balanced accuracy values for Turbidity classification using the US source and Três Marias target domains. We can observe in Table 5 the good results of the balanced accuracy, mainly considering the KMM and fMMD methods. This result was expected, as these method have already shown promising results in the previous experiments, as mentioned earlier. These values prove the advantage of using DA to classify turbidity in different reservoirs, even in distant geographical positions.

Table 5 also describes the balanced precision values for the classification of chlorophyll-a considering the limit of 11.03 $\mu g/L$. This limit value was chosen based on the literature information described previously. The accuracy values of the KMM, fMMD, and WDRGL methods suggest that using DA for the Três Marias database with little data available is better than without DA. We also improved the classifier's response for the classification of chlorophyll-a. Therefore, by analyzing all the experiments carried out, it is possible to answer the question of the applicability of DA in data from labeled global reservoirs to other reservoirs without labels. In particular, we can consider the results obtained using AD in databases with little data promising. This is the case with the Três Marias database, which has scarce labeling data attesting to the model's applicability. A simple algorithm can be implemented and made available to Brazilian reservoir managers. The idea is to create an algorithm to classify turbidity and chlorophyll-a values, automatically choosing the one with the highest accuracy values. This ensures that the algorithm always selects the method with the highest accuracy values for each classification, whether turbidity or chlorophyll-a.

Table 5: Turbidity (T) and Chlorophyll-a (C) - Três Maria's Target - Balanced Accuracy.

Method	Parameter	25	Parameter	**11.03**
OCSVM	T	0.7312	C	0.5963
KLIEP	T	0.5588	C	0.5342
KMM	T	0.7325	C	0.6310
fMMD	T	0.7620	C	0.6234
ANN	T	0.8208	C	0.7515
DANN	T	0.8488	C	0.6932
WDGRL	T	0.8194	C	0.7581
MDD	T	0.6149	C	0.7378
CDAN	T	0.8181	C	0.6960



(a) Before DA. (b) Instance based. (c) Feature based. (d) Deep based.

Figure 3: Chlorophyll-a data distribution by t-SNE Analysis.

4 CONCLUSION

This study presented the performance of seven domain adaptation techniques (Kliep, KMM, fMMD, DANN, WDGRL, MDD, and CDAN) in classifying water quality in reservoirs using spectral data from satellite images to two optical parameters: turbidity and chlorophyll-a. We used the US database as the target domain to classify turbidity and chlorophyll values from the Três Marias database, which has little and unlabeled data. The hypothesis analyzed was whether labeled data from the image database (USA) with different probability distributions but with the same characteristics from other reservoirs in other regions (Brazil) could be used to classify water quality parameters in reservoirs using DA. To this end, we use two classifiers, OSCVM and ANN, and data augmentation by the SMOTE method to solve the class imbalance problem.

We observed that in most of the DA techniques tested, the individual performance of each one was good enough in at least one scenario. Trad-aBoost, KMM, and fMMD show promising and regular results for most experiments using the OCSVM classifier. They were followed by CDAN, DAN, and WDGRL using the RNA classifier. However, the RNA classifier presents the problem of negative transfer in some cases. Still, our experimental results indicate that using DA to classify turbidity and chlorophyll-a parameters in reservoirs is a promising solution. With this, we show that using large trained databases to classify databases with unlabeled and sparse data with the help of DA is possible. Monitoring water quality in large reservoirs could benefit from using remote sensing images as an efficient and low-cost alternative that will contribute to in situ monitoring in regions with little data or difficulty obtaining.

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