Muddy Waters Mapping Using Machine Learning

Subjects: Remote Sensing

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The quality of drinking water is a critical factor for public health and the environment. Inland drinking water reservoirs are essential sources of freshwater supply for many communities around the world. However, these reservoirs are susceptible to various forms of contamination, including the presence of muddy water, which can pose significant challenges for water treatment facilities and lead to serious health risks for consumers. In addition, such reservoirs are also used for recreational purposes which supports the local economy.

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1. Introduction

Heavy rainfall and landslides are becoming more frequent extreme events due to climate change. Such events induce increased run-off, high-flow, flooding and erosion leading to increased sediment particles in the water. The erosion is especially high when soil is exposed in regions such as construction/mining sites, burned areas, or areas with poor agricultural/forestry practices, which in turn results in large volumes of sediment entering the water abruptly, constituting it as “muddy”. Hereafter, we will refer to highly turbid water that contains a significant amount of sediment independent of its origin, grain size or mineral compositions, among others, as “muddy”. Muddy water can have a series of not only negative implications such as on a lake ecosystem (e.g., altering the physicochemical regime) [1], human infrastructure (e.g., dams, water utilities hardware) and the local economy (e.g., when used for recreational purposes) [2][3], but also positive ones (e.g., enhancing soil fertility) [4] and for this reason its presence needs to be monitored.

2. Impact

A crucial factor for monitoring muddy water is its effect on human health. According to [5], there is a correlation between turbid water and gastrointestinal illnesses, at least when certain values are exceeded. In particular, Ref. [6] found increased hospital admissions of elderly people due to gastrointestinal illness following periods of high turbidity. In addition, an increase in microbial load has been documented during water turbidity peaks [7], and despite distribution systems implementing filtering mechanisms, part of the microorganisms may not be eliminated.

As aforementioned, the effects of highly turbid waters extend to the water ecosystem and the implications of sediment-laden waters on the aquatic fauna have been documented by a number of studies, such as [2][8][9][10][11].

According to them, the natural habitat of the water fauna is degraded, mainly due to sedimentation and turbidity, which is caused by pollutants resulting from human activities (agriculture, mining, etc.), that also affect human health through fish consumption. High silt concentration and long-sustained muddy waters can cause permanent damage to diversity, biomass, growth and reproduction rates. As the turbidity increases, the sunlight that reaches the bottom of the water bodies is decreased leading to less photosynthetic production, which affects herbivorous insects and fish, and alters the whole food web. Another critical factor is the high organic concentration coupled with muddy waters, as the oxygen levels are reduced while organic matter is accumulated. All the above factors pose a threat to aquatic fauna contributing to higher mortality rates.

Concerning the economic implications of mud in water bodies, the shortage in aquatic fauna is of great interest for human populations which depend on fishing activities. Heavy metals and pesticides being carried through water [2] can lead to high mortality rates and prohibition of fishing or consumption, negatively affecting the local economy. Another problem caused by the accumulation of mud is the blockage of streams [4] which can lead to flooding of nearby residential areas and farming lands, causing expensive damages and destruction of crops; thus, the local economy is highly impacted.

3. Detection with Remote Sensing

Monitoring and detecting muddy water in drinking water reservoirs is essential for the efficient management of water resources and the protection of public health [3] as already mentioned. Traditional methods of water quality monitoring, such as in situ sampling and laboratory analysis, are time-consuming, expensive, and limited in their spatial and temporal coverage. In recent years, satellite remote sensing has emerged as a powerful tool for monitoring water quality on a larger scale, offering several advantages over conventional methods. Satellite data can provide comprehensive, cost-effective, and more frequent information on water quality status in inland drinking water reservoirs. For this reason, the researchers focus on the exploitation of optical Sentinel-2 data to transform them into information and knowledge useful for the users. For further information on water quality parameter monitoring with optical satellites one can refer to the review [12].

The presence of muddy water that acts as a contaminant in drinking water reservoirs can be explored by optical sensors and is mostly studied in open seas [13] and to a lesser extent in inland large water bodies (e.g., [14]). In particular, the focus is on parameter retrieval of water quality environmental proxies with respect to muddy waters, such as turbidity [15][16] or total suspended matter (TSM)/total suspended sediment (TSS) [17] rather than binary classification/detection (e.g., presence/absence) or multi-class classification (e.g., [18]). There is also research on the monitoring of spatiotemporal changes in TSM combined with retrieval [19]. In addition, turbidity monitoring and retrieval in inland waters such as rivers [20][21], and spatiotemporal monitoring and retrieval in estuaries [22] have been studied. One reason for the research focus being on parameters' (turbidity, TSM) retrieval is due to the huge local variations in physical processes in inland waters that make a global water quality estimator very difficult. Many of the mentioned studies focus only on local water bodies [13][17][19][20][21][22] and the results of the monitoring cannot be used globally. In addition, in some cases the spatial [13][14][15][17][18][19][22] and temporal [15][17] resolution is not sufficient for monitoring.

4. Atmospheric Corrections

A potential issue that is observed in the literature is the choice of atmospheric corrections. Atmospheric correction refers to the process of removing or compensating for the effects of the Earth's atmosphere on optical satellite or airborne data. When electromagnetic radiation passes through the atmosphere before reaching the Earth's surface, it interacts with various atmospheric components. These interactions can introduce errors and distortions in the data such as scattering and absorption, among others, making it challenging to accurately interpret and analyze the remote sensing imagery, thus making atmospheric correction a very important preprocessing step. Atmospheric correction algorithms can be divided into two categories, namely absolute and relative ones [23]. Absolute algorithms use several atmospheric and illumination parameters, as well as sensor viewing geometries to calculate the actual surface reflectance. On the other hand, relative algorithms make assumptions about the reflectance of specific objects (e.g., water bodies, desserts) or relationships between ground truths, resulting in a relative pixel value. There are several works dedicated to building benchmark datasets for classification or semantic segmentation where the respective authors do not always explicitly argue on the reasons behind choosing certain atmospheric correction algorithms [24] or not choosing any atmospheric correction algorithm at all [25]. However, there are other such datasets where the respective authors explain the absence of any atmospheric correction algorithm as an extra step in increasing the generalizability and skill of a deep learning model [26]. The above examples refer to land cover classification applications, although there are works such as [16] referring to water applications where the authors again do not provide any argumentation regarding the use of specific atmospheric correction algorithms. However, there are works such as [27] that are dedicated in the comparison among different atmospheric correction algorithms in the classification task, as well as others such as [28] that explicitly compare between absolute and relative atmospheric correction algorithms.

In the context of water quality parameter retrieval, the importance of choosing an accurate atmospheric correction algorithm has been well-established [29][30]. However, for the classification or semantic segmentation task, the impact of various atmospheric corrections algorithms is not entirely clear. According to the computer vision and image analysis theory, irrespective of the field of application, the image property of contrast between objects plays a crucial role in the distinction capability, which is evident by research that develops/assesses image enhancement methods focusing specifically on contrast [31][32][33][34]. As a result, the latter implies that for the semantic segmentation/classification/object detection tasks, the need for an atmospheric correction algorithm specialized in water is not needed. What would be most important is the contrast (or relative brightness) among different objects/classes for each spectral band, instead of the absolute pixel values or surface reflectance. Three ACs (polymer (https://www.hygeos.com/polymer, accessed on 24 August 2023), ACOLITE (https://odnature.naturalsciences.be/remsem/software-and-data/acolite, accessed on 24 August 2023) and C2RCC (https://c2rcc.org/, accessed on 24 August 2023)) were performed on L1C products, while the fourth AC (sen2cor (https://step.esa.int/main/snap-supported-plugins/sen2cor/, accessed on 24 August 2023)) was already applied on the L2A product. The spectral response of muddy waters and clean waters were investigated qualitatively. It is noticeable that in the case of sen2cor, polymer and ACOLITE ACs the relative difference of the spectral response between muddy and clean waters is similar, while this is not the case for C2RCC. In addition, not all ACs give all spectral bands as a corrected output which the researchers consider as a drawback especially in the case that we would like to include different land and cloud classes in the ML approach. Since this is a deep research problem on its own and based on the prior exploration the researchers showed above, the researchers selected the simplest AC algorithm—sen2cor—as applied in the L2A products.

5. Annotation in Semantic Segmentation

To implement the data annotation for semantic segmentation, there are a number of approaches that one can follow independent of the field of application. For instance, the most simple, laborious and time-consuming is the manual pixel-level annotation, where one could assign a label to any pixel by hand. Another less laborious and time-consuming approach is polygon annotation, where one draws polygons and assigns a class to all pixels overlapping the polygon. In addition, there could be semi-automatic approaches such as using a simple but efficient machine learning algorithm or spectral indices and ratios. However, despite that they are easily reusable and less time-consuming, they may lack quality or need supervision and manual corrections and expert knowledge, as is the case for the rest of the approaches.

There are a number of spectral indices which are used extensively in optical satellite data to extract various land cover types, such as vegetation, water bodies, etc., or simply as proxies for land cover types. They basically exploit a number of spectral bands which in turn hide information about land cover. These bands have the properties of highlighting or suppressing specific image features. By combining two or more of these bands, one can generate spectral indices which disclose significant information from an image. The researchers put a focus on the so-called normalized difference indices, as their values span in the range from −1 to 1 and different value ranges within this range reveal different characteristics. Using normalized difference indices in the annotation process results in the method that falls under the category of semi-automatic annotation techniques, because pixel clustering involves the decision upon threshold values and photointerpretation of an expert to create the masks. To achieve the goal of annotation, the researchers combined two normalized difference spectral indices: the Modified Normalized Water Index (MNDWI) [35] and the Normalized Turbidity Index (NDTI) [36]. The MNDWI is a modified version of NDWI [37] and is better at suppressing the background noise of built-up areas, which is useful for urban and suburban areas of study. The index uses the Middle Infrared (MIR) band that substitutes Near-Infrared (NIR) and the Green band, and is defined as:

$$\frac{Green - SWIR}{Green + SWIR}$$

while the NDTI is defined as:

$$\frac{Red - Green}{Red + Green}$$

The computations of each index are performed in a pixel-wise sense. As a first step, the researchers set a threshold to both MNDWI and NDTI (depending on each region), then the researchers subtract the values of the MNDWI mask from those of the NDTI mask. The last step is to assign the value 0 to the regions that are not muddy, so whatever is not muddy, that is 1, becomes 0. Thus, the researchers arrive at two classes: muddy water and non-muddy water. Following the annotation, the researchers investigated the average values of spectral signatures per AOI per polygon in order to assess the quality of the annotation.

The results obtained using the method of index combination are gratifying, but there are some problems or limitations arising. To begin with, where snow is present, the researchers encounter additional noise. Additionally, the same applies for the case of clouds. This makes the use of manual cleaning of these parts mandatory, as no threshold value combination can remove them. This unfortunately applies for the noise in general, making it unavoidable to use manual labor. Except for that, the other caveat is the subjective nature of the method, as it relies on one’s photointerpretation skills. The expert photointerpretation relies on the researcher’s previous knowledge on muddy waters. Of course, the results of the expert are not 100% accurate as they are based on satellite images, but also edge cases such as single ambiguous pixels cannot be assigned values easily, so there is some uncertainty. Assuming that a validation/comparison on the expert’s choices could be made, then in situ or drone measurements should have been provided on each specific AOI, at the same time of the satellite passing. However, very often, this is not feasible as it requires many resources (human, financial, timing etc.) and coordination. Therefore, since validation of the expert’s selection is unfeasible, the researchers consider it as one of the least unsuitable approaches. Furthermore, the threshold values depend on each separate region, making it impossible to extract an optimal value combination to apply to the whole dataset, as the differences in composition and photo capturing conditions vary for each region. This limitation prevents us from creating a fully automated annotation technique. Finally, another limitation that applies to all techniques is the satellite’s spatial resolution. Although a 10 m × 10 m resolution is high, it limits the results of all methods. To proceed with the manual cleanup using QGIS, the researchers converted the raster results to vectors. The final two classes are then distinguished. The first one is the muddy water class, with pixel values of 1. The second class includes the bare soil, clean water, vegetation, snow, clouds, algae, etc., and is named as non-muddy, with pixel values of 0.

6. Model Development

For the model development, the researchers selected a Random Forest (RF) which is considered a powerful ML model and has been used in remote sensing extensively. It is recommended especially in tabular data formats, such as in the researchers' case, not images or time series (despite that, there is also research on these types of data). Therefore, starting the model development workflow, the researchers selected 166,738 pixels in total which belong to all aforementioned AOIs, after undersampling the negative (non-muddy water) class in order to achieve a class balance between muddy and non-muddy water classes which is crucial for the ML model development. In turn, those were randomly split into training and test sets with 133,390 and 33,348 pixels, respectively. In the training samples the researchers included several classes relevant to land such as bare soil, green vegetation, brown vegetation, different crops, bare rocks, as well as clean water and clouds. After selecting the training and test sets, the researchers perform an optimization based on Grid Search to derive the best possible hyperparameters for the RF model. The hyperparameters the researchers try to find optimal values for are (a) number of trees (b) tree depth and (c) class balance. To find the optimal numbers, the researchers performed a five-fold cross validation with 5 repeats based on the F1-score classification metric, which resulted in 7425 total model fits.

7. Results

Concerning the model evaluation after optimizing it, in order to further assess the results, the researchers first examined the feature importances that are derived from the RF model which are inherently produced, and secondly the researchers applied the optimized model to other AOIs. This way the researchers are able to assess the true performance of the model in the so-called unseen cases, which are data that have not been used in the training procedure. The unseen data include the test set also for which the researchers derived several accuracy metrics along with the training set, such as Accuracy, Recall, Precision, F1-score and Receiver Operating Characteristic-Area Under Curve (ROC-AUC). All metrics achieved a performance of over 98%. After applying the RF model to cases with similar muddy water characteristics such as in Prokopos (Greece), the researchers notice an adequate performance. However, this does not seem to be the case when the researchers apply the model in regions with shallow waters and high chlorophyll content, where an overestimation can be observed. Therefore, the researchers conclude there might be cases that the model would overestimate and probably underestimate in muddy water types that exist and have not been included in the training dataset from other AOIs and events. Regarding the feature importances, the researchers notice the biggest contributions from $B11$, $B12$, $B4$, $B8$, and $B5$ bands. Especially, the contribution from $B11$ and $B12$ can be attributed to the presence of several land classes and clouds in the training dataset.

8. Prospect and Usability

The proposed approach of muddy water mapping which is based on semantic segmentation does not aim to substitute the the typical water quality parameter retrieval approaches. In an operational setting and depending on the purpose of use, it can have the advantages of low latency of product generation (e.g., no need for specialized time-consuming atmospheric correction), it can be sensor-independent and a model could be easily updated by exploiting transfer learning (assuming deep learning-based model usage). In the case of the RF approach and the non-variable enough dataset, the model can be retrained on a new AOI in order to deliver valid products to an end-user. Thus, such a product/service can be integrated in water management and decision support systems, as is the case for the proposed approach of the current work as a pilot (https://portal-wqems.opsi.lecce.it, accessed on 24 August 2023). An end-user may only need the information of whether such an extreme event occurs or not, the geometrical features and extent, and an indirect visual estimation of sediment content (derived by the prediction probabilities) which are essential for the emergency response. From a research perspective, unknown regions and water bodies of muddy water presence can be identified around the world (assuming a highly variable training dataset).

9. Suggestions

The potential that came with open and free Copernicus data is undeniable. Copernicus satellite missions such as Sentinel-2 and Sentinel-3 can provide both high spatial and temporal resolutions, although not at the same time, since Sentinel-3 comes with almost daily measurements but low spatial resolutions (∼300 m) (https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-3-olci/resolutions/spatial, accessed on 24 August 2023) while Sentinel-2 comes with high spatial but lower temporal resolution. In addition, recent years have shown an emerging interest in the adaptation of deep learning (and especially CNN-based) approaches for the downscaling task by sensor fusion (e.g., [38]). Therefore, the researchers suggest that the monitoring of muddy waters in the context of this work could be improved by the wider adaptation and fusion of Sentinel-2 and Sentinel-3 missions, and the development of deep learning downscaling approaches to generate water quality products of high both temporal and spatial resolution.

10. Conclusions

In conclusion, this research focuses on the mapping/detection of muddy waters through a machine learning-based semantic segmentation approach for inland drinking water reservoirs with a spatial resolution of 10 m using Sentinel-2 satellite data. The task at hand is fairly new and requires further research, especially in the part of generating annotations and a more variable training dataset. The model the researchers developed is a Random Forest model used on data in a tabular format; based on the training dataset the researchers used, it performs fairly well. This means that there is room for improvement from the proper dataset generation side which would offer maximal generalization capabilities. With increasing complexity there is demand for more complex models, thus, the researchers foresee a future utilization of image-based deep learning approaches such as CNNs.

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