MUDDAT: A SENTINEL-2 IMAGE-BASED MUDDY WATER BENCHMARK DATASET FOR ENVIRONMENTAL MONITORING.

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1. INTRODUCTION

Climate change contributes to a rise in the frequency of extreme events such as heavy rainfalls, which in turn increase floods, landslides and soil erosion. As a result, a heavy load of sediment particles reaches water bodies such as lakes, through rivers, constituting them as muddy. Sediment-laden water occurrence is amplified even more by human activities such as bad agricultural/forestry practices or burned areas, as well as (illegal) waste disposal originating from (bad) industrial practices.

The presence of muddy waters in water reservoirs can affect human health and infrastructure, the ecosystem, and the economy, among others. Concerning human health, it has been shown that highly turbid water is correlated with increased hospital admissions [1] for gastrointestinal diseases, which cannot always be avoided by the standard filtering procedures from water utilities [2].

Another significant impact which further adds to the negative effects on human health, is the environmental degradation of aquatic fauna, as is evident by different studies (e.g., [3, 4]). High rates of siltation, along with pesticides and industrial waste, that are carried with torrents, result in population decrease and poisoning, which strongly affects the consumers and the local economy. Finally, the siltation in water reservoirs can lead to streams blockage, which in turn can lead to flooding of nearby residential and/or farming areas, causing expensive damages which negatively affect the local economy, as well as potentially increase the soil fertility [5].

2. RELATED WORK

Traditionally turbidity has been measured with *in situ* sensors. The advent of satellite monitoring and especially the free-of-charge Copernicus data offer the opportunity to not only outperform in terms of cost (e.g., material and human resources), but also in spatial and temporal coverage. There is a number of previous studies attempting to monitor highly turbid waters based on satellite remote sensing. Some of them focus on monitoring open sea areas [6] based on proxies rather than muddy waters themselves [7, 8, 9], or focus on local/regional water bodies restricting the generalization power [10, 6, 9, 11, 12, 13, 14] or lacking the necessary spatial or temporal resolution required for the task.

The majority of studies have been focused on parameter retrieval (i.e., regression) with the most recent works focusing on Recurrent Neural Networks [10] rather than classification. Classification has been implemented by traditional methods such as [15], as well as modern deep learning-based ones such as [16] which was based on few data. On top of that, aiming to achieve the aforementioned goals, datasets based on *in situ* and satellite Landsat data have been released recently (e.g., [17, 18]) for regression, although they are not image-based. Only one image-based dataset exists for the classification task, which does not focus specifically on muddy waters and at the same time the annotation procedure has ambiguities [19].

A recent hybrid study by [20] has stressed the importance of muddy water satellite-based monitoring. The authors indicated an alternative way of mapping muddy water using machine learning, as well as presented a number of challenges, limitations, gaps and prospects for future research directions related to annotation, atmospheric correction, availability of benchmark dataset and application of deep learning towards building universal classifiers, being in line with [10].

This paper builds on top of [20] aiming to fill and answer some of the stressed gaps and challenges by 1) providing an image-based Sentinel-2 muddy water dataset which does not exist in the current literature, following an annotation methodology which reduces human biases, i.e., an ensemble of three essentially different techniques, and 2) applying a U-Net as a baseline proof-of-concept for muddy water mapping.

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3. DATASET AND MODEL

MUDDAT is a muddy water dataset based on Sentinel-2 (S-2) Level-2A (i.e., atmospherically corrected) scenes covering a variety of regions and muddy water types and events, that were identified by a remote sensing expert. Each scene along with every band was subjected to a series of preprocessing steps such as band resampling to 10m, spatial subset and pixel-based annotation, preparing each image for a semantic segmentation task. Each scene was split into patches constituting a dataset of size of third to fourth order of magnitude.

The annotation methodology that was followed aims to reduce the human-induced annotation biases as much as possible. This was achieved by implementing an ensemble approach based on majority voting of the results of three techniques of different nature. The first technique is a spectral index-based one which combines the Normalized Turbidity Index (NDTI) [21] and the Modified Normalized Water Index (MNDWI) [22] as described in [20]. In short, an informed subjective threshold is applied on the two indices, and the binary mask of MNDWI is subtracted from the one of NDTI in a pixel-wise sense. The second technique is based on the Spectral Information Divergence (SID) [23] which is a statistical technique using all spectal bands, and is also subject to an informed threshold. Finally, the third and final technique comprises a K-Means clustering [24] utilizing all spectral bands. The subjectivity and noise of each of these techniques is minimized as much as possible by applying a majority voting. The resulting classes are the following: (i) *Non-muddy*, (ii) *Muddy* and (iii) *Ambiguous*. The Non-muddy class comprises various land cover types (e.g., bare land, clean water etc.). The *Ambiguous* class results when two out of three techniques agree on a pixel representing muddy water.

Subsequently, a Convolutional Neural Network model for semantic segmentation was trained and applied on the dataset as a proof of concept for muddy water mapping with deep learning. The model used is a widely used U-Net which has been shown that performs well in semantic segmentation tasks [25]. Several fine-tuning experiments were conducted after proper preparation (e.g., normalization, balancing etc.). Results show an adequate performance of the U-Net for muddy water mapping exceeding 80% performance classification metrics.

4. CONCLUSIONS

In our work we provide MUDDAT, a benchmark image-based per-pixel annotated Sentinel-2 dataset for muddy water mapping with remote sensing. Results are promising indicating that further work on model performance and inclusion of additional water quality classes can be introduced in the future, among others, in order to assist further in water quality enivornmental monitoring. The created dataset, as well as the model will be publicly accessible to the research community.

5. REFERENCES

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