Unsupervised classification of hydrological conditions in non-perennial rivers

Classification non supervisée des conditions hydrologiques des rivières non pérennes

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RÉSUMÉ

Les pressions anthropiques, comme changements climatique, d'utilisation des sols et prélèvements d'eau, entraînent des modifications significatives des cycles hydrologiques, augmentant l'extension spatiale des rivières non pérennes (NPRs). Cependant, la connaissance de la fréquence et de la durée des intermittences fluviales est fortement limitée par le faible nombre de stations de mesure des débits et la fiabilité réduite des modèles hydrologiques pour prédire la présence d'eau de surface. Dans ce contexte, les images Sentinel-2 peuvent fournir des informations précieuses pour l'étude des processus hydrologiques dans les NPRs, offrant une résolution spatiale et temporelle adéquate. La combinaison des images satellites multispectrales et des réseaux neuronaux convolutionnels (CNNs) peut être exploitée pour distinguer automatiquement les trois conditions hydrologiques des NPRs : "en écoulement" (F), "stagnant" (P) et "asséché" (D). Dans cette étude, à partir des images Sentinel-2 en fausses couleurs (B11-B8-B4), différents modèles de CNNs (à 2, 3 et 4 classes) ont été entraînés pour classifier cinq tronçons de rivière, en considérant classes de prédiction distinctes. Dans certains cas, les CNNs ont été entraînés pour identifier aussi la classe "nuageux" (C). L'exactitude des CNNs variaient en 0.87-0.98 pour les modèles à 2 et 3 classes, et diminuait en 0.71-0.92 avec la distinction des P et D (modèle à 4 classes). Malgré la petite taille du jeu de données (1555 images), les résultats sont prometteurs et méritent améliorations pour être un puissant instrument de classification automatique des conditions hydrologiques en NPRs.

ABSTRACT

Anthropogenic pressures, such as climate change, land use change and water withdrawals, are leading to significant shifts in hydrological cycles, increasing the spatial extension of the non-perennial rivers (NPRs) network. However, knowledge about the frequency and duration of flow intermittency is severely constrained by the small number of streamflow gauges and the limited reliability of hydrological models in predicting surface water presence when discharge is close or equal to zero. In this context, Sentinel-2 images can provide useful information for studying hydrological processes in NPRs, offering effective ways to observe water surface dynamics at an adequate spatial and temporal resolution. The combination of multispectral satellite imagery and Convolutional Neural Networks (CNNs) can be exploited to distinguish the three hydrological conditions which characterize NPRs automatically: "flowing" (F), "ponding" (P) and "dry" (D). In this study, learning on Sentinel-2 false-color images (B11-B8-B4), different CNNs (2-, 3-, 4-class models) were trained to classify hydrological conditions in five river reaches, considering distinct output classes. In some cases, CNNs were also trained to identify the "cloudy" (C) class. Accuracy of CNNs ranged from 0.87-0.98 for 2- and 3-class models, decreasing to 0.71-0.92 range when the distinction between P and D classes was considered (4-class model). Despite the small size of the dataset (1555 images), the obtained results were promising and deserves further refinement, with the purpose of having a more powerful tool for the automatic classification of hydrological conditions in NPRs.

KEYWORDS

Convolutional Neural Networks, Hydrotypes, Multispectral images, Non-perennial rivers, Sentinel-2 satellites.

Réseau de neurones convolutif, Hydrotypes, Imagerie multispectrale, Rivières non pérennes, Satellites Sentinel-2.

1 INTRODUCTION

Non-perennial rivers (NPRs) are water courses characterized by the occurrence of non-flowing events, represented by dry stream beds or isolated ponds of water, for some periods of time within the year (Arthington et al., 2014). More than half of the river network worldwide is estimated to have a non-perennial flow regime and this percentage is expected to increase in the near future due to water abstractions, climate change and transition in land use (Datry et al., 2014; Messager et al., 2021). The temporal evolution of the NPRs hydrological conditions ("flowing", "ponding", "dry") is a primary determinant for ecosystem processes and biological communities and its definition is crucial for identifying the river hydrotype for a proper river management (Datry et al., 2014; Gallart et al., 2012; Munné et al., 2021). However, there is still a general lack of information about the frequency and duration of non-flowing periods. Indeed, streamflow gauges are rarely present in NPRs network (Krabbenhoft et al., 2022) and hydrological models have high uncertainty in predicting zero-flows (Ivkovic et al., 2014). In this context, satellite remote sensing offers huge potential for observing NPRs dynamics. In particular, Sentinel-2 imagery has proven to be effective in monitoring the spatial and temporal evolution of the hydrological conditions in NPRs (Seaton et al., 2020; Cavallo et al., 2022).

In remote sensing and image analysis, neural networks represent a state-of-the-art method for the transition from supervised to unsupervised classification techniques (Atkinson & Tatnall, 1997). They are a particular type of machine learning algorithms that learn patterns and representations from data, simulating the structure and the functioning of the human brain's interconnected neurons (McCulloch & Pitts, 1943). In particular, Convolutional Neural Networks (CNNs), which are multi-layered neural networks specifically designed for processing and analyzing visual data such as images, have been effectively proven as a reliable method for satellite images classification (Jarallah, 2022; Ouchra & Belangour, 2021). In recent years CNNs have been widely used to recognize water bodies from high-resolution satellite imagery (Gharbia, 2023; Wang et al., 2020; Zhang et al., 2021).

This contribution aims to investigate the use of CNNs on Sentinel-2 satellite images in order to perform the unsupervised classification of the hydrological conditions that characterize NPRs.

2 MATERIALS AND METHODS

The case studies are five NPR reaches located in the Northern Hemisphere, characterized by different non-flowing periods. Four reaches are located in the Mediterranean region, being portions of Palancia (Comunitat Valenciana, Spain), Shushice (Vlöre, Albania) Torre and Natisone (Friuli-Venezia-Giulia, Italy) rivers and one located in the arid Southwest of United States along Hassayampa river (Arizona, USA). Among the multispectral images freely distributed with systematic global coverage, the Sentinel-2 mission of the European Space Agency (ESA) was chosen for its high spatial resolution (down to 10 m) with low revisit time (5 days or less depending on the area).

As first step, the input dataset using Sentinel-2 image series depicting the reaches was created via supervised classification, by labeling the images as "flowing" (F), "ponding" (P), "dry" (D) or "cloudy" (C). Cloudy condition (C) refers to images in which the presence of clouds does not allow a proper classification of hydrological conditions. The false color images (FCIs) composition based on B11-B8-B4, representing respectively SWIR, NIR and red bands, was used to train the CNNs (Figure 1). This combination of bands was identified by Cavallo et al. (2022) as the most suitable for differentiating water from vegetation and sediment inside non-perennial river channels. For every river reach, 3 or 4 years falling in the 2017-2023 timespan were considered. For each case study, the effective revisit time was computed by subdividing the number of cloud-free available images by the total amount of days in the considered timespan.

According to the number of classes to predict, three CNNs were explored: (i) the 2-class model (i.e., binary model) for distinguishing between "flowing" and "not flowing" (NF, grouping the P and D conditions); (ii) the 3-class model for C/F/NF identification; and (iii) the 4-class model for C/D/F/P categorization. These models had the same seven-layers architecture. After the input phase, the sequential layer served for preprocessing steps, the functional layer, that is the core of the convolution, relied on ResNet50 pre-trained model, the pooling layer performed spatial downsampling and the dropout randomly deactivated a fraction of the neurons of the layer during training, helping to prevent overfitting (Krizhevsky et al., 2012). The network's raw predictions were produced by the dense layer and finally transformed into a class attribution by the activation layer. The models were applied to each single river reach (reach-specific models) as well as to the combined dataset, using 70% of the data for training, 20% for validation and 10% for testing. In order to further explore CNN's capabilities, an additional analysis was conducted by training the C/F/NF model on four reaches to predict the complete dataset for the remaining one (Torre river). The predictive performances of considered CNNs were evaluated through cross-validation (k=5) in terms of accuracy (acc) and F1 score.

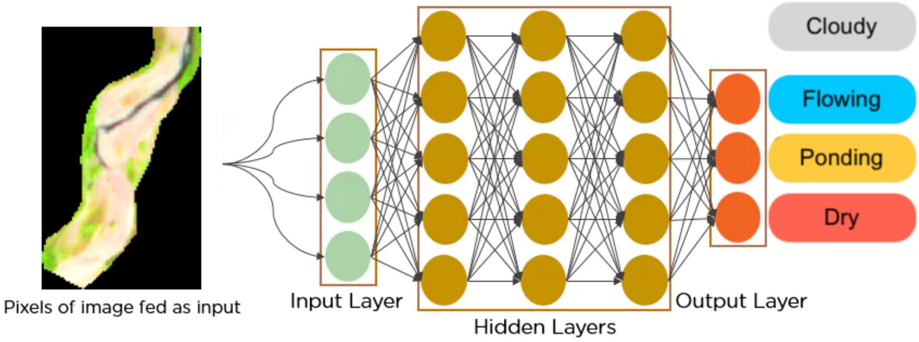

Figure 1: Diagram summarizing the CNN workflow, with Sentinel-2 image input and processing stages for classification task.

3 RESULTS

A dataset of 1555 labeled images was created, with almost 46% of them classified as cloudy, and therefore containing no exploitable information for evaluating the hydrological condition. Considering exclusively the F and NF images, the effective revisit time varied on average from 4.6 days to 7.9 days across the case studies.

The predictive performances for all considered CNNs are reported in Figure 2. Overall, it was possible to observe that the models' accuracy slightly decreased as the number of classes increased (Figure 2a). The F/NF (2-class) model consistently exhibited the best performance, with accuracy ranging in 0.91-0.98 and the F1 score for F and NF in 0.69-0.95 and 0.92-0.99, respectively. Considering the C/F/NF (3-class) model, accuracy was slightly lower across all reaches, despite the cloudy class was on average the best identified (average F1 score=0.94), followed by NF (F1 score=0.90) and F (F1 score=0.81). Accuracies below 0.85 were instead observed by considering the C/D/F/P (4-class) model. The majority of the misclassifications occurred between the P and the D classes, that provided respectively an average F1 score of 0.51 and 0.70. By conducting the binary predictions (F/NF) on the aggregated dataset, excellent results were reached (acc=0.96, Figure 2b). Finally, by training the model on four case studies and using it to entirely predict the fifth reach (30% of the total dataset for testing), the resulting accuracy was 0.88.

a)

ACC	F/NF	C/F/NF	C/D/F/P
Palancia	0.91	0.87	0.79
Shushice	0.94	0.92	0.92
Torre	0.93	0.88	0.71
Natisone	0.95	0.95	0.89
Hassayampa	0.98	0.93	0.88

Legend
Acc>=0.95
Acc=0.90÷0.94
Acc=0.85÷0.89
Acc<0.85

b)

ACC	**F/NF**
Combined 5 case studies	0.96

c)

ACC	**C/F/NF**, TEST on 1, Torre
Combined 4 case studies	0.88

Figure 2: Accuracy results of the CNNs for predictions a) per single reach b) on combined case studies c) on an entire reach, with model trained on the remaining four reaches.

4 DISCUSSIONS AND CONCLUSIONS

This study aimed to investigate the potential of machine learning models for predicting through unsupervised classification the hydrological conditions in NPRs. The supervised classification of Sentinel-2 images revealed that nearly half of the dataset comprised cloudy images. Cloud cover significantly reduced the effective revisit time, posing a key challenge in using passive remote sensing. However, Sentinel-2 satellites provide spatially detailed and frequent data, making them a suitable resource for monitoring surface water dynamics in NPRs.

The CNNs demonstrated strong predictive performances for the classification of the binary model (F/NF), both in reach-specific and combined cases analyses. However, performance decreased as the number of classes increased, with major problems in distinguishing between P and D classes. This decline is likely related to the high spatial variability of disconnected wetted areas characteristic of the P phase, which increases the likelihood of misclassification. A notable outcome was achieved when the CNN was trained on four case studies and tested on the one left out, showcasing the scalability of our approach to new case studies using the entire Sentinel-2 dataset.

Despite the approach was applied to a limited number of case studies, resulting in a relatively small dataset (1555 images), the results were promising. Further refinements are required to enhance CNN's capability to distinguish among all four classes (C/D/F/P). Achieving higher accuracy across all four classes would further enable the automated definition of hydrotypes for specific NPR reaches.

The applicability of this tool is broad, offering a time and cost-effective method for generating multi-year information on NPRs, a crucial requirement for understanding associated ecological processes and, consequently, informing effective management strategies for these ecosystems.

LIST OF REFERENCES

Arthington, A. H., Bernardo, J. M., & Ilhéu, M. (2014). Temporary rivers: linking ecohydrology, ecological quality and reconciliation ecology. *River research and applications*, *30*(10), 1209-1215.

Atkinson, P. M., & Tatnall, A. R. (1997). Introduction neural networks in remote sensing. *International Journal of remote sensing*, *18*(4), 699-709.

Cavallo, C., Papa, M. N., Negro, G., Gargiulo, M., Ruello, G., & Vezza, P. (2022). Exploiting Sentinel-2 dataset to assess flow intermittency in non-perennial rivers. *Scientific Reports*, *12*(1), 21756.

Datry, T., Larned, S. T., & Tockner, K. (2014). Intermittent rivers: a challenge for freshwater ecology. *BioScience*, *64*(3), 229-235.

Gallart, F., Prat, N., García-Roger, E. M., Latron, J., Rieradevall, M., Llorens, P., … & Froebrich, J. (2012). A novel approach to analysing the regimes of temporary streams in relation to their controls on the composition and structure of aquatic biota. *Hydrology and Earth System Sciences*, *16*(9), 3165-3182.

Gharbia, R. (2023). Deep learning for automatic extraction of water bodies using satellite imagery. *Journal of the Indian Society of Remote Sensing*, *51*(7), 1511-1521.

Ivkovic, K. M., Croke, B. F. W., & Kelly, R. A. (2014). Overcoming the challenges of using a rainfall–runoff model to estimate the impacts of groundwater extraction on low flows in an ephemeral stream. *Hydrology Research*, *45*(1), 58-72.

Jarrallah, Z. H. (2022, November). Satellite images classification using cnn: A survey. In *2022 International Conference on Data Science and Intelligent Computing (ICDSIC)* (pp. 111-116). IEEE.

Krabbenhoft, C. A., Allen, G. H., Lin, P., Godsey, S. E., Allen, D. C., Burrows, R. M., ... & Olden, J. D. (2022). Assessing placement bias of the global river gauge network. *Nature Sustainability*, *5*(7), 586-592.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, *25*.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, *5*, 115-133.

Messager, M. L., Lehner, B., Cockburn, C., Lamouroux, N., Pella, H., Snelder, T., ... & Datry, T. (2021). Global prevalence of non-perennial rivers and streams. *Nature*, *594*(7863), 391-397.

Munné, A., Bonada, N., Cid, N., Gallart, F., Solà, C., Bardina, M., ... Prat, N. (2021). A proposal to classify and assess ecological status in Mediterranean temporary Rivers: Research insights to solve management needs. *Water*, *13*(6), 767.

Ouchra, H., & Belangour, A. (2021, August). Satellite image classification methods and techniques: A survey. In *2021 IEEE International Conference on Imaging Systems and Techniques (IST)* (pp. 1-6). IEEE.

Seaton, D., Dube, T., & Mazvimavi, D. (2020). Use of multi-temporal satellite data for monitoring pool surface areas occurring in non-perennial rivers in semi-arid environments of the Western Cape, South Africa. *ISPRS journal of photogrammetry and remote sensing*, *167*, 375-384.

Wang, G., Wu, M., Wei, X., & Song, H. (2020). Water identification from high-resolution remote sensing images based on multidimensional densely connected convolutional neural networks. *Remote sensing*, *12*(5), 795.

Zhang, Z., Lu, M., Ji, S., Yu, H., & Nie, C. (2021). Rich CNN features for water-body segmentation from very high resolution aerial and satellite imagery. *Remote Sensing*, *13*(10), 1912.