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OPTICAL SYNERGY (SENTINEL-2 / SPOT6-7) FOR ANNUAL DETECTION AND MAPPING OF COASTAL WETLANDS IN THE CROZON PENINSULA USING MACHINE AND DEEP LEARNING METHODS

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ABSTRACT

Coastal wetlands are critical from an ecological, hydrological, and biodiversity point of view [1]. Today, these areas are under threat and have been declining every year since they were first studied [2]. Satellite images are an invaluable tool for understanding wetlands. Thanks to the revisit capability of satellites, coastal wetlands can be mapped in real time, allowing us to understand how they are changing. This work aims to map these ecosystems as accurately as possible. In order to achieve this, two types of sensors were used: a Sentinel-2 time series, a SPOT6/7 image, and altimetric data (RGE Alti©). Two automated learning algorithms were used: random forest (RF) and convolutional neural networks (CNN). Two methods were also used: a pixel approach and an object approach. The results show that the synergy of Sentinel-2 and SPOT with the contribution of indices and an object method works best, with an overall accuracy of 0.90 compared to 0.78 for a SPOT-6 pixel-by-pixel approach.

Index Terms: Coastal wetland, remote sensing, machine learning, hydrology, fully convolutional neural network (FCNN).

1. INTRODUCTION

Coastal wetlands are of great ecological importance [3] and are responsible for a large number of ecosystem services [4]. However, the number of coastal wetlands has decreased drastically in recent years due to natural and anthropogenic influences and agricultural practices [5]. According to Lee et al. (2006) [6], a coastal wetland is a biologically diverse and productive transition zone (“ecotone”) between land and water, characterized by shallow water overlying waterlogged soil and interspersed submerged or emergent vegetation. As transition zones between terrestrial and marine ecosystems, coastal wetlands, which include salt marshes, mangroves, intertidal mudflats, seagrass beds, and shallow subtidal habitats, form the interface of the coastal landscape. In the case of our study, we also consider inland wetlands near the coast, as they also play an important role in the interaction between upstream and downstream wetlands. Artificial intelligence and remote sensing have become powerful tools [7] for monitoring wetlands. A large amount of data is available to study the evolution and

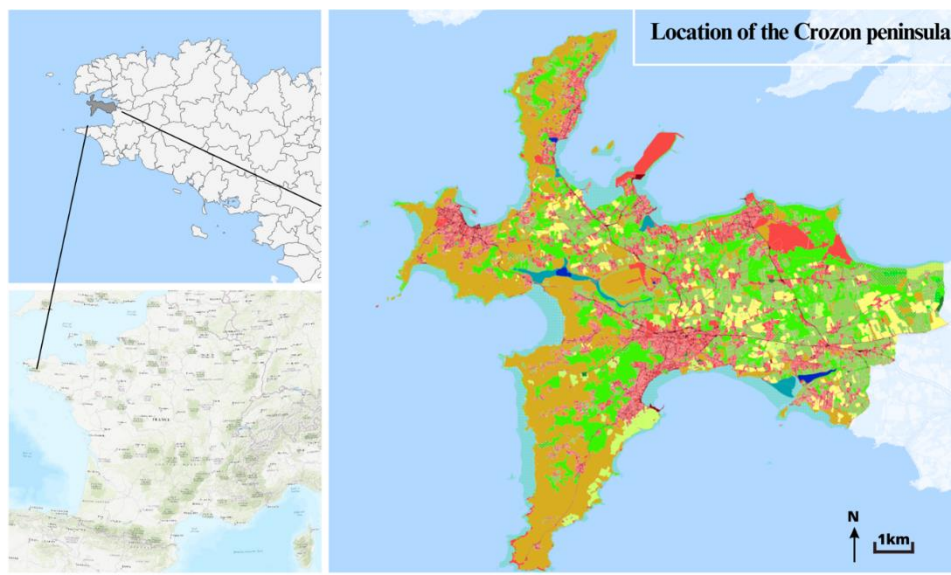
health of these areas using various sensors (radar and optical). Thanks to the revisit capability of satellites, it is possible to obtain a very regular image of the same area with adequate spatial, spectral, and radiometric resolution [8]. Satellite sensors can characterize wetland vegetation and habitats in detail [9] [10].

The aim of this study is to propose a comprehensive and reproducible methodology for the detection and mapping of coastal wetlands. The interest also lies in proposing a methodology capable of producing mapping at a good spatial scale from data that do not necessarily have a good input resolution. This study suggests a more comprehensive methodology than the one proposed in a previous study on a similar topic [11]. In addition, it makes it possible to carry out this mapping with lower-resolution images. Furthermore, this study extends our knowledge of the area by making a scientific contribution to our understanding of the Crozon peninsula, complementing the remote sensing studies already published on Crozon by Guanyao Xie and Niculescu [12].

2. STUDY AREA AND WETLAND TYPOLOGY

The study focuses on the Crozon peninsula, located in the extreme east of France in Brittany (cf. Fig. 1). Crozon is an integral part of the Armorique Regional Nature Park. It is an area with a long coastline, estimated at 120 km. The area is relatively well preserved, thanks in part to its military installations, which have limited the spread of urbanized areas over time [15].

There are numerous wetland typologies, but in this case, a typology of six wetland types was chosen: wet forest, wet meadow, peat bog, salt meadow (or salt marsh), mudflat, and lake (or continental water). This methodology was inspired by several wetlands’ typologies (RAMSAR, EUNIS). There are multiple data points used for this study: two optical satellite data points, altimetric data points, and a wetland inventory. In this case, a Sentinel-2 time series from 2018 over Crozon was used together with a high-resolution SPOT6/7 image over Crozon from May 5, 2018. The elevation data come from RGE Alti, a 5 m resolution Digital terrain model (DTM) available free of charge throughout France. Finally, the wetland inventory is a regularly updated inventory carried out by the different local administrations in Brittany. This database is used to generate the training and validation data.



Legend : Urban/Artificial Road network Marsh Moor
Arable land Meadow Forest Pond

Fig. 1. Location map of the Crozon peninsula

3. METHODOLOGY

The methodology is divided into three sections. The first part focuses on the method of processing satellite images in order to classify them. The second part explains the method used to detect wetlands, and the last part describes the method used to map wetlands.

3.1. Image processing

Data processing is primarily focused on the Sentinel-2 time series. The SPOT6/7 image (cf. Table 1) has only been pansharpned to extract the four spectral bands at 1.5 m resolution. Sentinel-2 images have already undergone extensive processing prior to download, as they are in L3A format, a monthly synthesis of all images taken during the month. This format provides images with better radiometric quality and less cloud cover. In order to achieve synergy between Sentinel-2 and SPOT6/7 data, resampling was performed using an intercubic-spline method and then a sharpening filter (cf. Fig. 2).

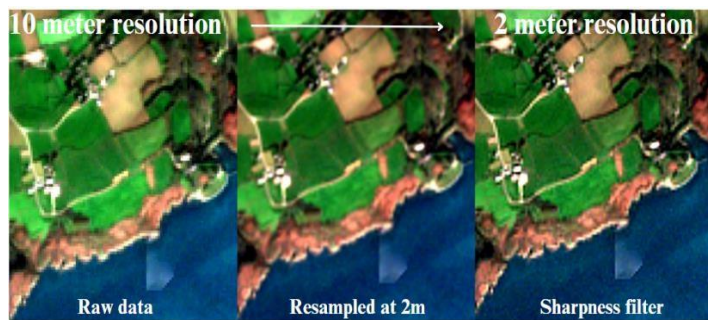


Fig. 2. Resampling method

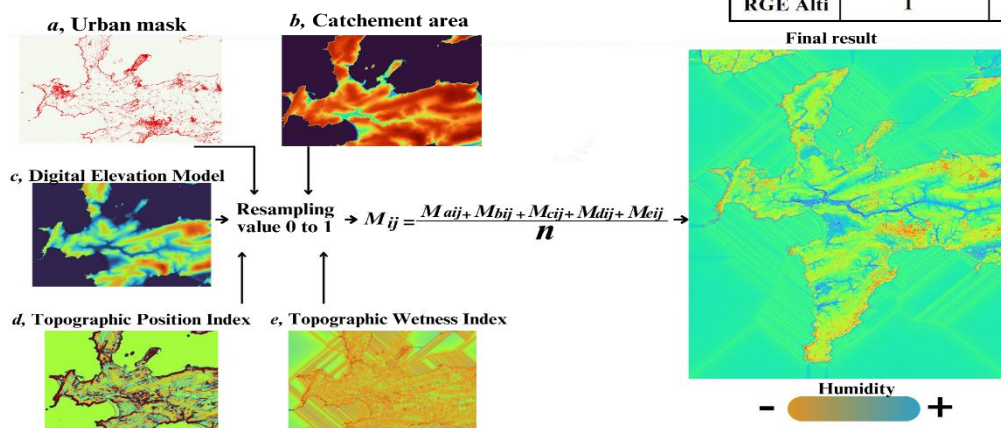


Table 1. Table of satellite imagery data

Satellite	Number of images	Spectral bands	Spatial resolution	Date
Sentinel-2	12 (L3A Format)	1,2 (Blue), 3 (Green), 4 (Red), 5,6,7,8 (NIR), 8A,9,10,11,12	10 to 20m	1 per month
SPOT-6	1	1 (Blue), 2 (Green), 3 (Red), 4 (NIR)	1,5m	07.05.2018
RGE Alti	1		5m	

Fig. 3. Method for detection of coastal wetland

3.2 Detection of coastal wetland

The goal of wetland detection is to map wetlands as a single entity. The objective is to create a mask that maps wetlands as a whole before characterizing them. To achieve this, a large amount of data is integrated to produce a wetland probability map. A number of data points were calculated or collected for scoring purposes to create this map. These included the following: a mask (binary) for year N (in this case, 2018) based on SPOT6/7 imagery to exclude impervious surfaces; a topographic soil moisture index (TWI) from the RGE Alti (5 m resolution); a buffer zone around the TWI to characterize wetlands near the watercourse; a topographic position index (TPI) from the RGE Alti; and finally, the catchment area. All these data were resampled to the same spatial resolution and normalized from 0 to 1. We then sum the values of each pixel divided by the sum of the number of rasters (cf. Fig. 3).

3.3 Mapping of coastal wetland

To create a complete wetland map with a typology of six habitats, we perform a two-stage classification. For this purpose, based on the wetland detection approach carried out previously, an extraction into two zones is performed: a “wetland” mask and a “non-wetland” mask (cf. Fig. 4). The training data are based on the photo interpretation and the wetland inventory created for these two zones. We then performed two different classifications on these two zones and merged the two classifications to obtain a complete map of wetlands and land use on the Crozon peninsula.

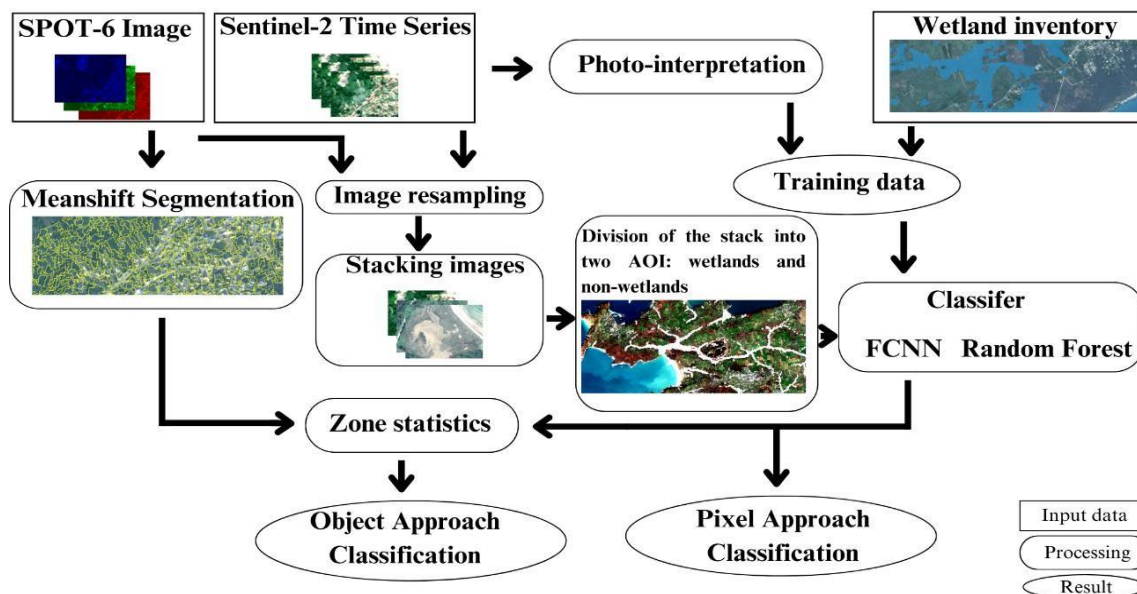


Fig. 4. Method for mapping wetlands

4. MACHINE LEARNING

5. RESULTS

4.1 Random Forest

In this study, random forest (RF) was used with a specific configuration to optimize model performance. The algorithm was parameterized with a maximum of 200 decision trees, a maximum depth of 15 for each tree, and a minimum threshold of 25 samples per class. These parameters were rigorously adjusted to balance the complexity of the model while ensuring efficient generalization. This methodological approach aims to exploit the diversity of individual trees while controlling the variability inherent in RF.

4.2 Fully convolutional neural network

Artificial neural networks (ANNs) have revolutionized the field of artificial intelligence (AI) over the past few decades. These complex models simulate the behavior of biological neurons to process information and make decisions. ANNs are commonly used in a variety of tasks, including image recognition [14], machine translation, and fraud detection.

The fully convolutional neural network (FCNN) is a type of ANN that specializes in image classification or segmentation. In this task, each pixel in an image is assigned a label corresponding to a particular class, such as the object or texture it represents. FCNNs are able to perform accurate classifications [15] or segmentations, because their network architecture is made up of only convolutional and upsampling layers.

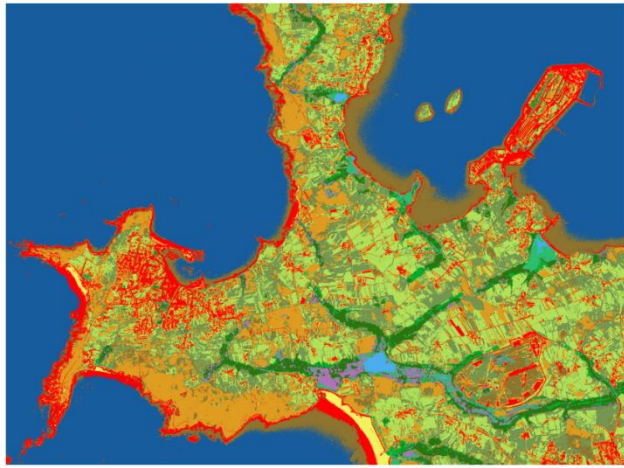
In this study, an FCNN model with a simplified cascade architecture was implemented. In addition, 16x16 training thumbnail patches were integrated. The network consists of four downward convolutional layers, where each layer applies filters to extract features from the input image. Gradient descent is performed using the Adam optimizer, and the categorical crossentropy loss function is applied to the output.

The results are divided into two sections: wetland detection results and classification results. The wetland detection method shows very good results, with an overall accuracy of 0.86. Several combinations were used for wetland mapping: SPOT-6/7 mapping alone, SPOT-6/7 and resampled Sentinel-2, and SPOT-6/7, resampled Sentinel-2, and spectral indices. There was also a pixel-based approach and an object-based approach. The best results were obtained by combining SPOT6/7/S2 and spectral indices with an object approach: overall accuracy: 0.91, kappa: 0.91, F1 score: 0.89. It is important to note that the pixel approach gives similar results to the object approach, with a difference of +/- 0.03 for the same combination. One of the weaknesses of the SPOT6/7 classification alone is the lack of spectral information, so there is considerable confusion between forest and mudflat and between mudflat and heathland, which is a major flaw. On the other hand, if we combine SPOT 6/7 with a Sentinel-2 time series, there is enough spectral information, but the classification sometimes “generalizes” the information too much. As a result, the delineation of the different land cover classes is sometimes slightly less good. However, the predictions are better overall, even if they are less well delineated.

6. DISCUSSION

This study shows that the methodology described here works very well for automated mapping of coastal wetlands. With values ranging from 0.77 (SPOT-6/7, pixel approach) to 0.91 (SPOT-6/7/S2/Index, object approach; Fig. 5), the two-step approach, starting with detection and then mapping in two zones, reduces confusion between wet and non-wet areas. The advantage of this method over the similar method referenced by Le Guillou [11] lies in better detection of coastal wetlands on one more variable (TWI, TPI etc..) and mapping with better geometry despite having similar metrics. This is especially true for reducing confusion between two spectrally similar habitats, such as wet grasslands and mesophilic or dry grasslands. Improvements can be made to this method. Images can be resampled with super-resolution methods, using neural networks rather than mathematical methods. Finally, various deep learning algorithms for classification are likely to improve the results. Semantic segmentation using a U-net algorithm could improve scores but would also be more time consuming.

Random Forest pixel approach with SPOT-6 image classification



Legend :



Random Forest object approach with SPOT-6 , Sentinel-2 time serie and index synergy image classification

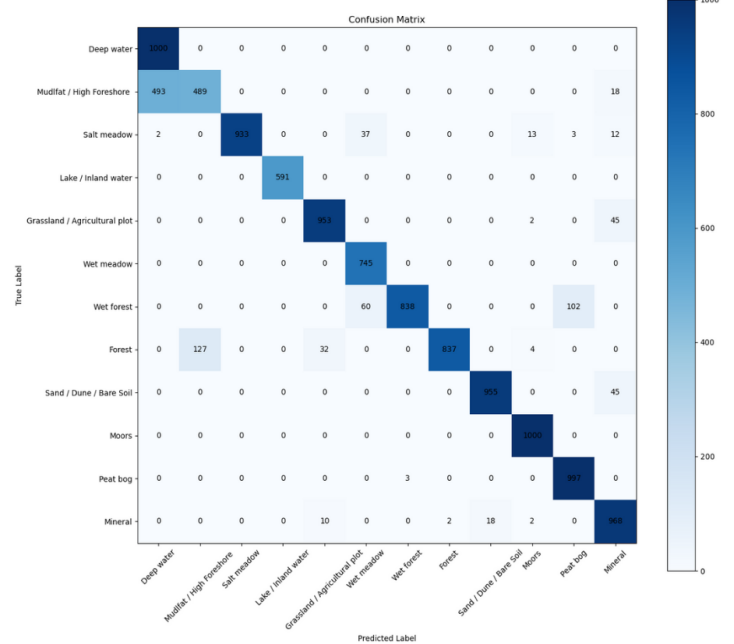
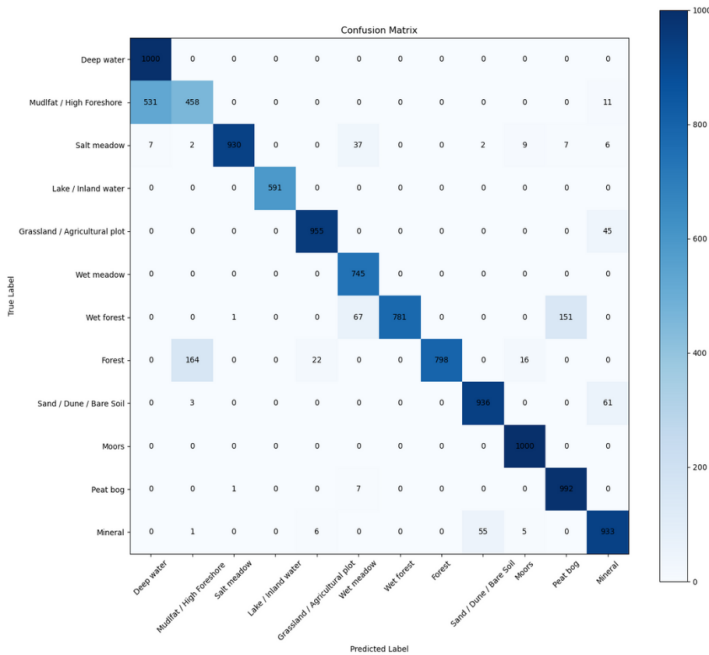
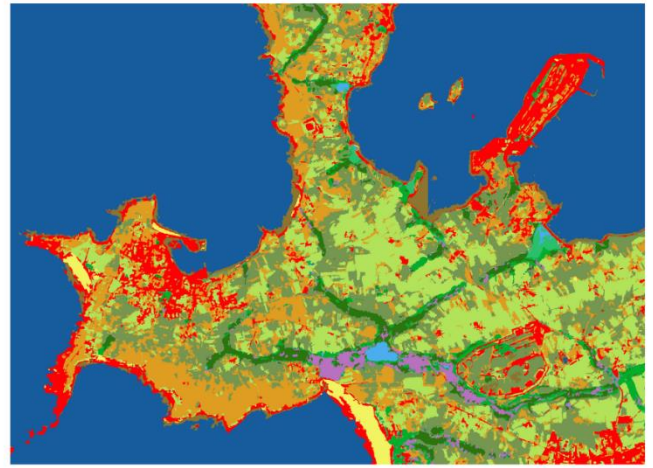


Fig. 5. Coastal wetland map comparison

7. CONCLUSION

The objective of this study is, therefore, quite successful. By proposing a reproducible methodology for mapping wetlands using optical data at different spatial resolutions, it is possible to map these habitats with good results. The strength of this study is also that it proposes a methodology that allows this mapping work to be carried out with optical sensors of any spatial, spectral, temporal, and radiometric resolution without the need for high computing capacity, thanks to the proposed resampling.

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