Présentation du projet (en langue française ou anglaise, 2 à 3 pages)

Abstract

The coastline is a high-stake area, under pressure from human activities and climate change, making coastal wetlands increasingly vulnerable. Coastal wetlands are among the world's most productive, valuable and yet threatened ecosystems (Millennium Ecosystem Assessment, 2005). On today's time scale, tidal wetlands are biologically productive ecosystems with high biodiversity providing multiple ecosystem services. Yet the benefits of these wetlands are not yet fully recognized, or even precisely known. It is known that these benefits are sometimes crucial in mitigating the impact of floods, delaying the effects of drought, organic production for fisheries and shellfish farming, biodiversity reservoirs, improving water quality and regulating the water cycle, storing carbon in mangrove soils, maintaining green areas at the gates of cities. The research proposed for this project concerns the Machine Learning approach to land-use change in the coastal zone of Brittany. The Atlantic coastal fringe (Brittany, France), constitutes a nerve center of convergence of multiple strong demographic, economic and ecological stakes. The present project aims to characterize the changes that have affected coastal wetlands in the first decades of the 21st century. It analyzes the evolution of land cover/land use within a sample of coastal wetlands, characterizing trends in natural and artificial wetland habitats, adjacent natural terrestrial habitats, and agricultural and urbanized areas considered as pressure factors on wetlands. The overall methodological objectives of the project aim to produce a robust, specific and replicable methodology that focuses on a comparative approach to methods and techniques for the development of new Machine Learning tools and methods for cost-effective land cover/land use monitoring and assessment of changes impacting on the ecosystem services of coastal wetlands. An important phase of the proposed approach is the comparison of different types of data relevant for this type of analysis, namely optical and radar satellite data from the latest European sensors (Sentinel-1, Sentinel-2, Pleiades, SPOT) and images from two complementary types of sensors (hyperspectral and LiDAR). A comparative evaluation of shallow structure learning methods (Random Forest and Rotation Forests with Canonical Correlation Forests) with deep structure learning methods (Artificial Neural Network (ANN) and Convolutional Neural Network (CNN)) is envisaged in this project. An innovative methodological element is proposed: the combination of the CNN with OBIA (Object based-image analysis). A methodology that is currently little used. This methodology (OCNN) relies on segmented objects as functional units rather than convolutional processes at the pixel level, and CNN networks are used to analyze and label objects such as intra-object and inter-object variations.

Detailed presentation of the project :

1 - Hypothesis and questions asked, state of the art, identification of scientific blockage points (4000 characters maxi spaces included).

In order to plan wetland protection and appropriate coastal development, scientists and managers need to monitor changes in coastal wetlands, as sea level continues to rise and the coastal population continues to grow. Advances in remote sensor design and satellite data analysis techniques are providing significant improvements for studying and mapping natural and human-induced changes in coastal wetlands. Despite the latest advances in remote sensing tools, such as the availability of high and very high spatial and temporal resolution satellite data and object-oriented image-by-object analysis tools (Blaschke, 2010), the accuracy of complex land cover classification, as in the case of wetland ecosystems, is insufficient. This could be attributed to the spectral similarity of wetland vegetation types, making the exclusive use of spectral information insufficient for the classification of heterogeneous land-use classes. In addition, several studies have been conducted on the importance of integrating spectral and spatial information for wetland land cover mapping (Tiner et al., 2015; Zhao and Du, 2016). Thus, spatial features can increase the accuracy of spectral information and thus contribute to the success of complex wetland land-use mapping. In addition, classification based solely on spatial features leads to insufficient classification results in most cases and poor generalizability (Zhao and Du, 2016). More recently, Deep Learning (DL), a deep learning tool, has been spotlighted in the field of computer vision and subsequently in remote sensing (LeCun et al., 2015). Indeed, these advanced machine learning algorithms address the main limitations of conventional shallow-structured machine learning tools, such as vector machine (SVM) and random forest (RF) (Ball et al., 2017). Deep Belief Net (DBN) (Hinton et al., 2006), Stacked Auto-Encoder (SAE) (Vincent et al., 2010) and Deep Convolutional Neural Network (CNN) (Krizhevsky et al., 2012; Szegedy et al., 2015) are the current deep learning models, the last of which is the best known. It is important to note that CNN has enabled a series of breakthroughs in several remote sensing applications, such as classification, segmentation and object detection, due to its superior performance in a variety of applications compared to shallow-structure machine learning tools. Among the new Machine Learning methods that will be applied in this project are: shallow structure learning methods - Random Forest (RF) and Rotation Forests with Canonical Correlation Forests (CCF); and deep structure learning methods - Artificial Neural Network (ANN) and Convolutional Neural Network (CNN). These methods are complemented by multi-sensor, multi-resolution and multi-temporal image fusion. These Machine Learning methods will be applied to high (Sentinel) and very high spatial resolution data sets (SPOT and Pleiades), to data from hyperspectral sensors, on LiDAR data. All these methods can contribute to the updating of the inventory of coastal wetlands, to their delimitation, but also to the characterization and monitoring of these environments. Until 2020, there are no remote sensing studies of all coastal wetlands in Brittany. On the other hand, sequential studies have been carried out on the Couesnon watershed, a small coastal watershed of 1,130 km², whose outlet is located at Mont-Saint-Michel by S. Rapinel, L. Hubert-Moy, B. Clément in 2015. The objective of this study is to evaluate the combination of seasonal multispectral and multispectral imagery and LiDAR data to accurately map the distribution of wetland habitats. C. Bilodeau, M. Cohen and J. Andrieu carried out a study in 2008 on the comparison of two methods for mapping the vegetation of the Baie de Saint Michel schorre. The objective of this work was to compare two methods of mapping the schorre vegetation: a method of photo-interpretation of an orthophotograph, validated by floristic data, and a method of automatic classification by species, based on radiometric, topographic (LIDAR), and floristic data.

2 - Methodological approach and envisaged techniques : (4000 characters maxi spaces included)

The methodology proposed in this project seeks to meet two methodological objectives. A) To carry out a temporal monitoring of land cover/land use changes in coastal wetlands by Machine Learning Approach: Random Forest and Rotation Forests with Canonical Correlation Forests (CCF) (shallow learning methods) and - Deep learning (Artificial Neural Network (ANN) and Convolutional Neural Network (CNN)) (deep learning methods) of the time series of Sentinel, SPOT and Pleiades images (after the year 2000). Initially, shallow learning methods are proposed for comparison with deep learning methods. B) Monitoring changes in the vegetation cover of coastal wetlands by Machine Learning Approach of hyper spectral and LiDAR measurements at the time scale of the year of observation. Time series of high spatial resolution optical data have demonstrated a great capacity to characterize environmental phenomena, describing evolutionary trends as well as discrete change events. With the increasing number of satellites and the availability of free data, the integration of multisensor images in coherent time series offers new possibilities for land cover analysis. The complementarity of data from optical and radar sensors for the characterization of wetland land cover has been exploited in many recent studies (Pereira et al., 2013; Chatziantoniou et al., 2017; Whyte et al., 2018; Niculescu et al., 2017; Niculescu et al., 2020). Shallow-structure Machine Learning methods will be applied initially. RF is the most intuitive ensemble learning technique for classifying highdimensional data (Breiman, 2001; Gislason et al., 2006). The main advantages of RF are that the complexity of the computation can be reduced and correlations between trees are reduced. The RF algorithm, from 2015 onwards, has been a much studied algorithm for wetland classification (Tian et al., 2016; Mahdianpari et al., 2017; Dubeau et al., 2017; Fu et al., 2017; Muñoz et al., 2019; Felton et al., 2019; Niculescu et al., 2020). Rodriguez et al. 2006 proposed a new overall classifier, namely the Rotational Forest (RoF). This method uses Principal Component Analysis (PCA) to generate the space of rotation characteristics for training samples to promote diversity. In order to preserve information on variability and encourage individual precision, all principal components are retained (Rodriguez et al., 2006). This algorithm has also been successfully applied to the study of vegetation in the coastal zone of the Pays de Brest by Niculescu et al. 2020 using S1 and S2 data. In our previous studies, we have found that the performance of this algorithm is better than AdaBoost, random subspace and random forest. Deep-structured methods have been applied, especially in recent years, for wetland classification (Niculescu et al., 2018; Liu and Abd-Elrahman, 2018; Mahdianpari et al., 2018; Pouliot et al., 2019; O'Neil et al., 2020; Pashaei et al., 2020; Dang et al., 2020). In recent years, deep learning, a concept of machine learning, has become popular, using computational models composed of several processing layers to learn data representations with several levels of abstraction (LeCun, Bengio, and Hinton, 2015). A variety of algorithms are developed, the most common of which are Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), etc. (LeCun, Bengio, and Hinton, 2015). In our study, we will use the ANN and the CNN.

3 - Positioning and scientific environment in the regional, national and international context :

This project will benefit from an international and national network that operates around the issues presented here and around wetlands in general. The international network is composed of the following laboratories Visualization & Image Processing for Environmental Research (VIPER Lab), University of Santa Barbara, California, USA; Geoinformatics Unit, RIKEN Center for Advanced Intelligence Project (AIP), Tokyo, Japan; Friedrich-Schiller University, Germany; Research and Development Institute of Tulcea, Romania; CEOSpaceTech-Research Centre for Spatial Information/Politehnica University of Bucharest (Romania), University of Haifa - Department of Geography and Environemental Studies (Israel). At the same time, a national network of collaborations works very well with GIS Bretel, Télécom Bretagne (ITM Atlantique), Office National des Forêts, Département Dynamiques de l'Environnement Côtier DYNECO/PELAGOS, IFREMER, LabSTICC, UMR CNRS 3192, UBO, Collecte Localisation Satellite (CLS), Brest, LEGOS (CNRS, UTMIP, CNES, IRD) Toulouse.

4 - Scientific and partnership context: general elements (ERC, CPER, FEDER, Breizhcop ...) (4000 characters maxi spaces included)

The current spatial context is very favourable for this study. The new European satellites in constellation (Sentinel, CosmosSkyMed, Pleïades, etc.) are capable of providing observations of a surface several times a month that are of interest whatever the weather conditions, as in the case of radar sensors. As well as understanding the current evolution of the climatic, economic and societal context due to the profound changes in the occupation/use of coastal wetlands is becoming a fundamental issue. Thus, the inventory, delimitation, but also the characterization and monitoring of change in these environments have become a priority (Rebelo et al., 2018). Millennial, centennial and decadal records of the evolution of coastal wetlands show that they are particularly sensitive to environmental changes (Morris et al., 2002; French, 2006; Mudd et al., 2009). More recent changes in the system also reflect the impacts of human activities interacting with these natural dynamics, such as drainage and conversion to agriculture (Gedan et al., 2009). As coastal wetlands are very complex, human activities and climate change have a dramatic effect on their functioning (Herbert et al., 2015; Parker et al., 2019), affecting vegetation zoning, decreasing biodiversity, altering carbon flows, and exacerbating ecological vulnerability. The pressure induced by human activities on the different spaces contributes to modify, initially, land use. These land-use/land use changes have a considerable impact on coastal wetland ecosystems, mainly due to their fragmentation, area reduction and degradation. Consequently, the transformation of land use categories affects ecosystem processes and services (i.e. microclimates, hydrological regulation, tourism and natural resources). In this context of change, coastal wetlands are subject to significant and accelerating rates of coastal wetland loss globally due to both natural and anthropogenic factors (Adam, 2002; Millennium Ecosystem Assessment, 2005; Barbier et al. 2011; Nicholls et al., 2011; Spencer et al., 2016). Davidson (2014) estimates that natural coastal wetlands have declined by 46-50% since the early 18th century and by 62-63% during the 20th century. Indeed, urban growth has been identified as the main anthropogenic stressor, directly responsible for the loss of more than 67% of coastal wetlands, which has a decisive influence on ecosystems by modifying their structures and habitats (Barbier et al., 2011; Davidson et al., 2014; Li et al., 2018). There is therefore concern about how these future changes will further alter these coastal wetland systems. In this scientific context, partnership relations favourable to this project, in addition to the collaborations (national and international) presented in the previous section, are to be mentioned: first of all in the framework of the European Jean Monnet Chair, a partnership has been established with the CLS de Brest and IFREMER under the aegis of the European partnership of the Chair. As part of another project, Fondation de France has established a lasting partnership with a number of local authorities (Brest-Bretagne Urban Planning Agency (ADEUPA), Brest, Pays de Brest Metropolitan Cluster, Armorique National Park, Finistère Departmental Council). This thesis topic is also part of the UBO / GIS Bretel partnership.

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