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A new synergistic approach for monitoring wetlands using Sentinels -1 and 2 data with object-based machine learning algorithms

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ABSTRACT

In this work the synergistic use of Sentinel-1 and 2 combined with the System for Automated Geoscientific Analyses (SAGA) Wetness Index in the content of land use/cover (LULC) mapping with emphasis in wetlands is evaluated. A further objective has been to develop a new Object-based Image Analysis (OBIA) approach for mapping wetland areas using Sentinel-1 and 2 data, where the latter is also tested against two popular machine learning algorithms (Support Vector Machines - SVMs and Random Forests - RFs). The highly vulnerable iSimangaliso Wetland Park was used as the study site. Results showed that two-part image segmentation could efficiently create object features across the study area. For both classification algorithms, an increase in overall accuracy was observed when the full synergistic combination of available datasets. A statistically significant difference in classification accuracy at all levels between SVMs and RFs was also reported, with the latter being up to 2.4% higher. SAGA wetness index showed promising ability to distinguish wetland environments, and in combination with Sentinel-1 and 2 synergies can successfully produce a land use and land cover classification in a location where both wetland and non-wetland classes exist.

1. Introduction

Wetland systems are precious natural environments of a thriving flora and fauna biota, multifaceted hydrological network and critical biogeochemical cycles. They are highly effective at preventing flooding (Loveline, 2015), protect coastlines from breaching tidal waters (Gedan et al., 2010), act as carbon sinks whilst being large suppliers of oxygen (Kayranli et al., 2009), provide fertile farming lands (Rippon, 2009) and have intrinsic qualities which can help the human mind (Gesler, 2005). Despite their importance, many wetlands around the globe are under threat due to natural and anthropogenic climate change, as well as, changes in land use brought about by increasing populations and urban expansion. Over the last century, it has been estimated that 50% of the world's wetlands have disappeared, with an increased rate of 3.7 times that during the 20th and 21st centuries (Davidson, 2014). Therefore, it is becoming increasingly important to study and monitor wetlands due to their sensitivity to external and internal changes, as these can initiate the detrimental process of wetland degradation, thus, depleting the biodiversity and affecting the livelihood of many people around the globe that rely on them.

Remote sensing and Geographical Information Systems (GIS) technologies provide a valuable tool when monitoring the Earth's surface. Satellite imagery can capture specific moments in time that can be analyzed and processed to offer an extensive range of products to be used in a vast array of applications. Remote sensing also provides the ability to monitor large regions of land which may be inaccessible for *in situ* strategies (Gauci et al., 2018; Aune-Lundberg and Geir-Herald, 2014). Land use and land cover (LULC) mapping is one such application, allowing for short or long-term change detection and monitoring in vulnerable habitats (Xu et al., 2017). Is also allows for effective evaluation of any management practices that are introduced, which is in great need in protected

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conservation areas (Bassa et al., 2016). This ability to study changes in the environment with Earth Observation data, presents decision makers with critical visual and statistical information that can be used to mitigate or adapt before a threshold is crossed, after which the chances of landscape regeneration may become too high.

Vast quantities of data are being produced by satellites with numerous sensors launched just in the last decade. The introduction of the Sentinel satellite systems by the European Space Agency (ESA) is contributing to this whilst carrying on the long-term continuity missions of past and present satellites, offering relatively high spatial, temporal and spectral resolution imagery and doing so with a variety of sensor types (optical, radar and thermal) (Berger et al., 2012). The key purpose of the Sentinel Mission is to support policy making for the Global Monitoring for Environmental Security (GMES) program, while providing new opportunities for the scientific community (Aschbacher and Milagro-Pérez, 2012). Sentinel satellites can play a pivotal role in future land surface monitoring programs, especially if the synergistic collaboration between them is explored, therefore this has to be a key area to develop (Malenovský et al., 2012).

The application of classification algorithms in remote sensing is often based on per-pixel classifiers (Xu et al., 2017; Murray-Rust et al., 2014). Those techniques are based on assigning individual image pixels with a user-defined class based on the spectral characteristics of the individual pixels, either identified computationally, with minimum user input (unsupervised), or through user-defined training pixels (supervised). Although pixel-based classifications have been successfully used in wetland classifications, many researchers believe that object-based image analysis (OBIA) can provide more accurate classification results. Dronova (2015), in a review of 73 studies reported that OBIA improves wetland classifications by 31% compared to pixel-based methods. Mui et al. (2015) underlined that although OBIA is a promising concept, further research is needed to test it in a range of environments, with a variety of sensors. There have been many remote sensing studies that have implemented OBIA for mapping land cover. These include glacier delineation and debris cover (Ardelean et al., 2011; Rastner et al., 2014; Robson et al., 2015), urban infrastructure (d'Oleire-Oltmanns et al., 2011), agriculture (Forster et al., 2010; Taşdemir et al., 2012), and forestry mapping (Dorren et al., 2003; Guo et al., 2012; Lindguist and D'Annunzio, 2016), to name but a few. The application of OBIA in wetland mapping has not been to the same extent as the disciplines mentioned above in the literature, but is has seen a growth in the last decade with new advances coming through (Harken and Sugumaran, 2005; Mas et al., 2014).

Machine learning algorithms have become an integral part of remote sensing studies in recent years due to their durability and capability in performing LULC classifications (Rogan et al., 2008; Xu et al., 2017; Gauci et al., 2018). Amongst them, the most popular algorithms are Random Forests (RFs) (Breiman, 2001) and Support Vector Machines (SVMs) (Cortes and Vapnik, 1995). Several studies have demonstrated so far that those algorithms consistently outperform many other frequently used classifiers (Shang and Chisholm, 2014), making them suitable for many scenarios over a range of disciplines. These machine learning algorithms are powerful techniques with a great deal of flexibility, thus, allowing them to be implemented on a variety of sensor types and combinations. The use of such classifiers offers promising proficiency in avoiding challenges associated with heterogeneous environments and limited training sample ability, which is often a problem in wetlands, where high resolution imagery and *in situ* measurements may be expensive or difficult to collect. There have been several successful applications of both SVMs (Petropoulos et al., 2012, 2013; Scott et al., 2014; Sonobe et al., 2014; Szantoi et al., 2013; Zhang and Xie, 2013) and RFs (Furtado et al., 2016; Maxwell et al., 2016; Mellor et al., 2013; Sesnie et al., 2010) in remote sensing. Niculescu et al. (2017) conducted a study with RFs, and a synergistic classification using Sentinel-1 and 2 for a coastal wetland in Romania. This study used a pixel based approach and found a synergistic technique provided the highest accuracy. Dronova (2015) called for more studies to be focused on the application of OBIA and machine learning algorithms, with comparisons needed between different algorithms. To our knowledge, the use of these advanced image processing algorithms with OBIA, combined with data from sophisticated satellites launched recently such as Sentinel-1 and 2, has not yet been adequately investigated.

The aim of this study is to develop a synergistic approach between Sentinel-1 and 2 in the context of wetland mapping. In particular, it aims at analyzing a number of secondarily derived products from the sensors mentioned above, along with the topographically derived SAGA Wetness Index (SWI), to evaluate their ability to map a complex area containing wetland and non-wetland LULC classes. A further objective has been to develop a new Object-based Image Analysis (OBIA) approach for mapping wetland areas using Sentinel-1 and 2 data, where the latter is also tested against two popular machine learning algorithms (SVMs and RFs).

2. Materials and methods

2.1. Study site

The study site under consideration is the iSimangaliso Wetland Park, also known as the Greater St. Lucia Wetland Park, located on the east coast of South Africa in the northern stretch of KwaZulu-Natal Province. It lies between the longitudes 32°21′E, 32°34′E, and latitudes 24°34′S, 28°24′S, covering a land surface area of 3280 km^2, making it the largest estuarine system in South Africa and one of the largest in the world (Fig. 1). The east coast consists of a succession of raised sand dunes and indignant woodland; that help protect the wetland from tidal surges and strong winds. The climate is considered to be sub-tropical with mean annual temperatures greater than 21 °C. The park's rainfall varies both temporally and spatially, due to a combination of elevation change (~170 m from the western hills to the coastal wetland), climate zone and sea-land dynamics. Annual precipitation can range from 1200 and 1300 mm (Bassa et al., 2016); however below normal precipitation has been recorded in 2015 (Coppola, 2015) and early 2016, due to drought. The wetland is fed by five contributing catchments and rivers.

The park hosts a variety of wetland vegetation types, making it a highly diverse, heterogeneous environment to study. Much of the vegetation colonized the area in its recent history due to falling lake levels, with depths rarely exceeding 1.5 m (Whitfield and Taylor, 2009). The wetland vegetation consists of salt marsh species that thrive in brackish systems, such as the salt marsh rush (*Juncus kraussii*) and tasselweed (*Ruppia martima*); saline reed swamps, often found at estuarine edges with species such as reed grass (*Phragmites mauritianus*) (Macnae, 1963); sedge swamps, containing *Eleocharis limosa*; floodplain grasses, predominantly Antelope Grass (*Echinochloa pyramidalis*); furthermore, the most dominant wetland vegetation type in the park are from river fed freshwater swamps that host a variety of species (Adam et al., 2009). Since the closure of the St. Lucia mouth to the Indian Ocean in 2002, the once thriving mangrove communities (Macnae, 1963), have fallen dramatically, due to the drop in salinity levels. Adams et al. (2013) explain how this has made way for reed species, whose numbers have risen. The two most notable freshwater swamps in the park are the Mkhuze Swamp located north of the Northern Lake and the Mfolozi Swamp located to the far south of the estuarine system adjacent to the Mfolozi River floodplain. Both swamps are under