A Semi-automatic Algorithm for Wetland Detection using Multi-temporal Optical Satellite Data

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Abstract: Wetlands are valuable ecosystems providing a variety of important ecosystem services such as water purification, flood control and food supply. Due to climate change and increasing human water demand, wetlands are increasingly threatened and degraded. An effective monitoring for wetlands is therefore necessary to preserve and restore these endangered ecosystems. In this study, a semi-automatic algorithm for water and wetness detection based on multi-temporal optical imagery and topographic data is presented. Suitable spectral indices sensitive to water and wetness were identified using stability selection. Water and wetness were mapped based on monthly image composites using split-based Otsu thresholding. The monthly water and wetness masks were aggregated to water and wetness frequencies, which were fused in the end to derive a wetland classification and the Water Wetness Probability Index. The algorithm was applied to two study sites in Kenya/Uganda and Niger using Sentinel-2 MSI imagery. For both study sites overall accuracy was above 88%. User's and producer's accuracy were generally higher for water than for wetness, but mostly reaching more than 80% in both classes. Due to the high degree of automation and low processing time, the proposed method is applicable on a large scale and is a first step towards the implementation of global wetland mapping and monitoring service.

1 Introduction

Wetlands are very important ecosystems providing habitat for a variety of flora and fauna as well as many valuable ecosystem services such as flood control and food supply. However, with advancing climate change and increasing human water demand for agriculture, livestock and, cities, wetlands are becoming increasingly threatened and degraded especially in water scarce regions (RAMSAR CONVENTION 2016). In order to preserve and restore wetlands, a cost-effective and efficient monitoring of these ecosystems is necessary. Satellite data offers great potential for wetland monitoring and has been the subject of many studies. Yet, a large scale monitoring system that captures the seasonal dynamics and long-time trends of wetlands has not been implemented so far.

The most common classification methods for wetland mapping are unsupervised (DOGAN et al. 2009; CHEN et al. 2014), supervised (BWANGOY et al. 2010; CORCORAN et al. 2011; FLUET-CHOUINARD et al. 2015) and hybrid classification combining supervised and unsupervised classification approaches (MWITA et al. 2012; LANE et al. 2014). For open water body mapping, DONCHYTS et al. (2016) used Otsu thresholding and a Random Forest classifier based on the

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mNDWI and HAND index to map water bodies. MARTINIS et al. (2009) applied split-based Otsu for water body mapping using SAR imagery.
In this study, a semi-automatic algorithm for wetland detection using multi-temporal optical imagery and topographic data is proposed. Water and wetness detection is hereby performed using a modified form of split-based Otsu Thresholding. To evaluate the performance of the method in different bio-geographical regions it was applied to two study sites in northern Africa: the Sio-Siteko Wetland (Kenya / Uganda) and the Namga-Kokorou Wetland Complex (Niger). In section 2, the components of the processing chain are outlined. The results of the study sites are briefly summarized in section 3 and section 4 gives a conclusion and outlook.

2 Data and Methods

2.1 Data

The algorithm is mainly based on a time series of high-resolution optical imagery. In this study, the algorithm is demonstrated using Sentinel-2 MSI imagery, but it is also applicable to the Landsat imagery for historical analyses. In addition, a digital elevation model generated from the NASA Shuttle Radar Topography Mission (SRTM) in 2000 is used to calculate the Topographic Wetness Index (TWI).

2.2 Methodology

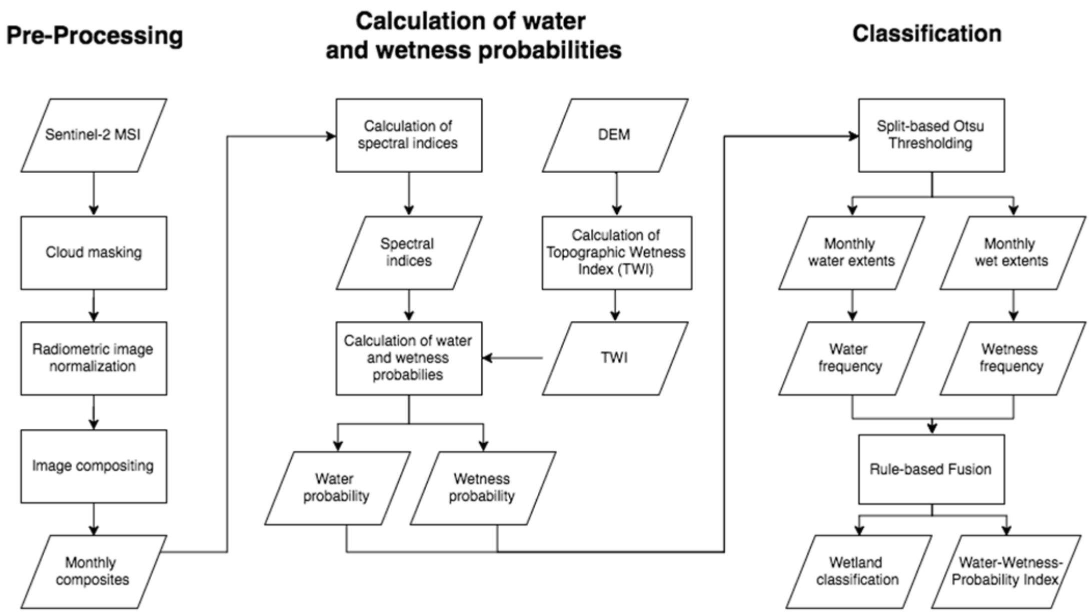

Fig. 1: Graphical workflow diagram of the algorithm for wetland detection

The proposed algorithm consists of three main components: data pre-processing, the calculation of water and wetness probabilities and the wetland classification (Fig.1). During pre-processing cloud and cloud shadow removal is performed for all Sentinel-2 scenes. Subsequently, monthly image composites are produced with all Sentinel-2 scenes belonging to the same composite being radiometrically normalized to each other prior to compositing. For all composites, a selection of spectral indices sensitive to water and wetness are calculated. Suitable index combinations for water and wetness mapping were identified using a feature selection technique called stability selection. The selected indices and the TWI are subsequently aggregated using different image enhancement techniques to increase the contrast between open water, wetlands and other land cover types. This yields water and wetness probability images for each month. By applying split-based Otsu thresholding to these probability maps monthly water and wetness extents are derived. Aggregating all monthly extents yields the water and wetness frequencies which indicate how often a region is flooded or wet during the observation period. Based on these frequencies the final wetland classification and the Water Wetness Probability Index (WWPI) are derived. To get an estimation of the overall classification accuracy, single water and wetness masks derived from two monthly composites were validated.

3 Results and Discussion

Overall accuracy values for both study sites are very satisfying reaching values above 88%. User's and producer's accuracy were mostly higher for water than for wetness, but mostly reaching more than 80% for both classes. Water was mapped very accurately with omission errors only occurring over floating vegetation (Fig.2) and narrow streams. Considering wetness, most commission errors occurred within forests and agricultural fields, which might however be irrigated at times. Comparisons to precipitation data suggest that the final wetland classification product gives a plausible representation of the presence of water and wetness throughout the year.

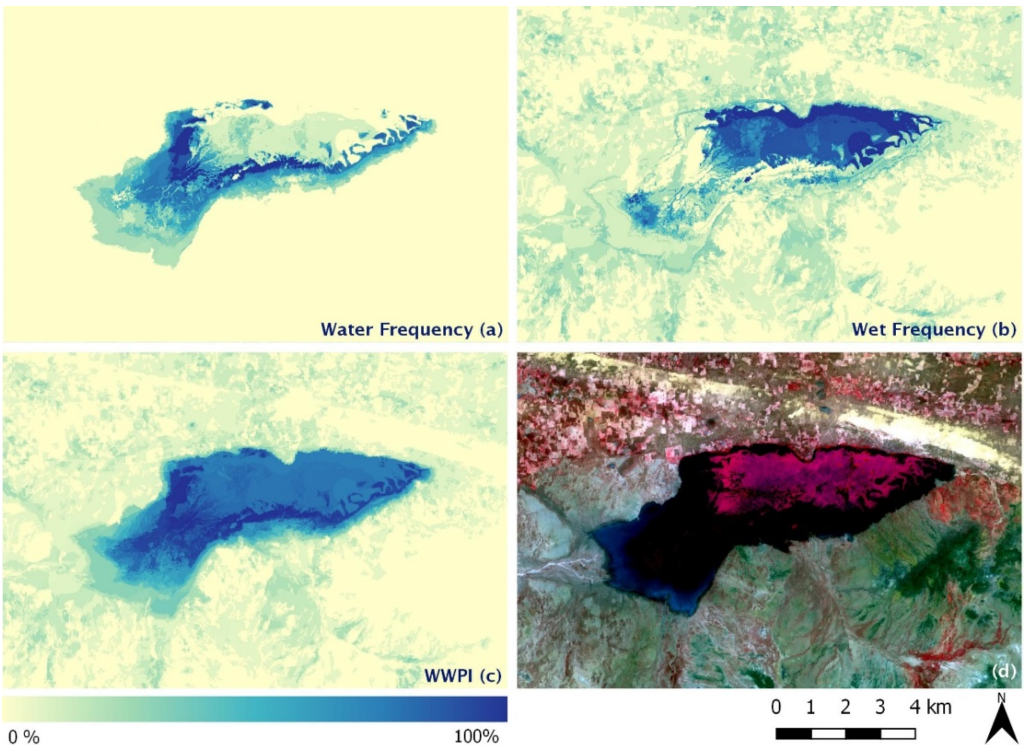

Fig. 2: Water frequency (a), wetness frequency (b) and WWPI (c) of the Kokorou Wetland in the period of December 2015 to October 2016. (d) FCC of the Kokorou wetland in October 2016. Floating vegetation within the lake appearing in red in the FCC image is classified as wet.

4 Conclusion and Outlook

The good validation results and plausible representations of water and wetness occurrence in both study sites prove that the method is applicable in different bio-geographic regions in Africa. Further investigations have to be conducted to increase classification accuracy and to evaluate the method's applicability in other climatic regions. Considering the relation between classification quality and computational effort, the method has the potential to be applicable for large-scale water and wetness mapping and monitoring. In this way, the method has already been successfully applied using additional SAR data within the production of the Copernicus Pan-European High Resolution Layer 2015 and the European Space Agency's GlobWetland Africa project.

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