Int J Appl Earth Obs Geoinformation 66 (2018) 135–145

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Monitoring the dynamics of surface water fraction from MODIS time series in a Mediterranean environment

Linlin Li[a,*], Anton Vrieling[a], Andrew Skidmore[a,b], Tiejun Wang[a], Eren Turak[c,d]

[a] University of Twente, Faculty of Geo-information Science and Earth Observation, P.O. Box 217, 7500 AE Enschede, The Netherlands
[b] School of Environmental Sciences, Macquarie University, NSW 2019, Australia
[c] NSW Office of Environment and Heritage, 10 Valentine Avenue, Parramatta 2150, NSW, Australia
[d] Australian Museum, 6 College St, Sydney, NSW 2000, Australia

ARTICLE INFO

Keywords:
Wetlands
Hydrology
Spain
Machine learning
Multi-temporal images
Time series

ABSTRACT

Detailed spatial information of changes in surface water extent is needed for water management and biodiversity conservation, particularly in drier parts of the globe where small, temporally-variant wetlands prevail. Although global surface water histories are now generated from 30 m Landsat data, for many locations they contain large temporal gaps particularly for longer periods (> 10 years) due to revisit intervals and cloud cover. Daily Moderate Resolution Imaging Spectrometer (MODIS) imagery has potential to fill such gaps, but its relatively coarse spatial resolution may not detect small water bodies, which can be of great ecological importance. To address this problem, this study proposes and tests options for estimating the surface water fraction from MODIS 16-day 500 m Bidirectional Reflectance Distribution Function (BRDF) corrected surface reflectance image composites. The spatial extent of two Landsat tiles over Spain were selected as test areas. We obtained a 500 m reference dataset on surface water fraction by spatially aggregating 30 m binary water masks obtained from the Landsat-derived C-version of Function of Mask (CFmask), which themselves were evaluated against high-resolution Google Earth imagery. Twelve regression tree models were developed with two approaches, Random Forest and Cubist, using spectral metrics derived from MODIS data and topographic parameters generated from a 30 m spatial resolution digital elevation model. Results showed that accuracies were higher when we included annual summary statistics of the spectral metrics as predictor variables. Models trained on a single Landsat tile were ineffective in mapping surface water in the other tile, but global models trained with environmental conditions from both tiles can provide accurate results for both study areas. We achieved the highest accuracy with Cubist global model (R^2 = 0.91, RMSE = 11.05%, MAE = 7.67%). Our method was not only effective for mapping permanent water fraction, but also in accurately capturing temporal fluctuations of surface water. Based on this good performance, we produced surface water fraction maps at 16-day interval for the 2000–2015 MODIS archive. Our approach is promising for monitoring surface water fraction at high frequency time intervals over much larger regions provided that training data are collected across the spatial domain for which the model will be applied.

1. Introduction

Terrestrial surface water bodies play an important role in the global carbon cycle and climatic processes (Chahine,1992; Tranvik et al., 2009). They support a high level of biodiversity and provide a range of ecosystem services (Dudgeon et al., 2006; Zedler and Kercher, 2005). Globally-consistent maps of surface water extent at high spatial and temporal resolution are a major information need for assessing progress towards the Aichi targets for 2020 of the Convention of Biological Diversity (Turak et al., 2017). One of the challenges for producing these maps is that surface water can exhibit a strong seasonal and inter-annual variability. For example, in arid and semi-arid regions, surface water bodies are often small and their size varies in time in response to changes in precipitation and evapotranspiration (Ruiz, 2008). Hydrological changes may strongly affect ecosystem functioning and result in shifting species distributions and composition (Koning, 2005; Robledano et al., 2010). Therefore, monitoring the dynamics of surface water is of critical importance for understanding the health and functioning of wetlands, and the ecosystem services they provide.

One option for monitoring dynamic surface water is using multi-temporal optical imagery of 10–30 m spatial resolution (e.g., the Landsat-series and Sentinel-2). A suite of recent studies has exploited

* Corresponding author.
E-mail address: l.li-1@utwente.nl (L. Li).

https://doi.org/10.1016/j.jag.2017.11.007
Received 24 July 2017; Received in revised form 16 November 2017; Accepted 16 November 2017

the Landsat archive to assess long-term variability of surface water and flooding extent at the regional (Halabisky et al., 2016; Heimhuber et al., 2016; Tulbure et al., 2016), continental (Mueller et al., 2016) and global scale (Donchyts et al., 2016; Pekel et al., 2016). Although Landsat sensors can provide accurate spatial information on surface water extent and those with small sizes, until recently their revisit interval was too long (16 days and more) to capture rapid changes in water extent due to seasonal hydrological fluctuations or extreme weather events. Furthermore, Landsat archive features some temporal gaps depending on geographical location (Pekel et al., 2016). For areas that suffer from persistent cloud cover, there might be large temporal gaps between two clear observations. In a Landsat-based study of surface water monitoring, Halabisky et al. (2016) could effectively reconstruct surface-water hydrographs (i.e. temporal details on seasonal, intra-annual and long-term changes in surface water extent) for 750 wetlands in Douglas County, Washington, USA from 28 years of Landsat data, they indicated that their approach would not give meaningful results for wetlands with frequent cloud cover or with short hydroperiods. While revisit times are reducing for high resolution sensors (e.g., Sentinel-2 offers a 5-day repeat since March 2017: Du et al., 2016), it will be some years before it becomes possible to construct long-term (> 10 years) and dense time series of surface water over large regions.

Moderate resolution imagery derived from satellite sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) provides observations at a much higher frequency over long time-spans, with obvious advantages for monitoring surface water dynamics. A number of studies have used MODIS for surface water mapping (e.g. Kaptue et al., 2013; Khandelwal et al., 2017; Ovakoglou et al., 2016; Pekel et al., 2014; Sharma et al., 2015). These studies have in common that they provide a binary classification for each grid cell and time period, i.e. water or no water. However, binary classifications cannot represent water-bodies that are smaller than the grid cell itself. For example, Khandelwal et al. (2017) successfully analyzed temporal variations in surface extent of global reservoirs using MODIS time series, but their method was only applicable for large water bodies comprising more than ten MODIS pixels. In areas with many (temporal) small water bodies that are equal or less the size of a grid cell, binary classification could result in large omission errors. Such omission errors may be trivial when tracking global changes in surface area, but can be essential for assessing biodiversity, which is greatly influenced by the density of small wetlands (Deane et al., 2017; Semlitsch and Bodie, 1998).

To overcome the problem outlined above, it is possible to estimate surface water fraction; i.e., the percentage of surface water within a single grid cell. Existing studies on surface water fraction mapping have used techniques like linear spectral mixture modeling (LSMM) and machine learning. For instance, Weiss and Crabtree (2011) developed a multi-linear regression model to estimate surface water fraction from MODIS using spectral indices, i.e. normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and tasseled cap indices for the Yukon Flats National Wildlife Refuge (Alaska, USA), but achieved a moderate model accuracy ($R^2 \approx 0.625$) between reference and modelled surface water fraction. LSMM has been widely used for the estimation of fractional cover of land surface components such as vegetation (Gan et al., 2014; Guerschman et al., 2015; Lu et al., 2003; Song, 2005; Xiao and Moody, 2005), snow cover (Painter et al., 2009; Vikhamar and Solberg, 2003), urban area (Yang et al., 2014), and water (Hope et al., 1999; Li et al., 2013; Olthof et al., 2015; Schroeder et al., 2015; Sheng et al., 2001; Sun et al., 2011). This approach is based on the premise that a pixel's observed reflectance can be modelled as a linear combination of all end-member spectra of the features within the pixel, weighted by their respective fractional abundance (Adams et al., 1995). A substantial challenge in linear unmixing is to determine the spectra and number of endmembers, which can be at a maximum of one endmember less than the number of spectral bands. For example, studies that used LSMM to estimate surface water fraction used between two and four endmembers. Nonetheless, this number may be inadequate to spectrally characterize a complex and heterogeneous landscape. Moreover, endmembers in LSMM are considered pure surface components, but they often show important spectral diversity themselves. For example in the case of water, the spectral signature varies according to water composition (e.g. algae, sediment and dissolved organic matter), submerged aquatic vegetation and bottom reflection, which also depends on water depth (Hommersom et al., 2011; Jensen, 2007).

An alternative approach for surface water fraction estimation is the use of machine learning techniques such as support vector regression, multivariate adaptive regression splines, artificial neural networks and regression-tree (RT) algorithms. Research comparing algorithms have shown that RT algorithms are often among the top performers across a range of applications on fractional surface cover mapping (e.g. Drzewiecki, 2016; Xia et al., 2017). Unlike LSMM that needs to consider and estimate fractional cover for all endmembers within each pixel, RT is a nonlinear algorithm that can be used to derive fractional cover for a single specific land surface component. RT has been used extensively in remote sensing, for example to derive the percentage of tree cover (Hansen et al., 2002; Kobayashi et al., 2014), and to estimate fractional impervious surface area in the National Land Cover Data (NLCD) product by USGS (Xian et al., 2011). To our knowledge, only few researchers have attempted to estimate surface water fraction through time using RT algorithms. Rover et al. (2010) compared various methods to map surface water fraction in the Yukon Flats and showed that the RT method produced the highest accuracy ($R^2 = 0.93$, RMSE = 11%), outperforming the LSMM. In a case study of the 2005 Louisiana floods, Sun et al. (2012) applied a RT algorithm to derive water fraction from MODIS using as predictors MODIS band reflectance and spectral water indices and achieved high accuracy. Hence, RT algorithms seem to be promising for accurate mapping of surface water fraction over large regions. However, several important issues regarding the application of the RT algorithm have not yet been addressed in current literature. First, existing studies merely incorporated reflectance or reflectance-derived predictor variables, whereas the inclusion of ancillary environmental variables (e.g., digital elevation model) may potentially improve the accuracy of the regression tree models. Second, the transferability of trained regression tree models to larger areas is unknown, as existing studies focused on small areas with homogeneous climate characteristics. Third, no studies have examined how different surface water fraction and water-permanence types may affect model performance. In this study we aim to:

(1) Evaluate two rule-based regression-tree methods that incorporate MODIS spectral information and a topographic metric derived from digital elevation model (DEM) for accurately mapping and monitoring surface water fraction;
(2) Assess the transferability of the resulting models to different geographic and climatic zones;
(3) Assess the accuracy of the method outcomes as a function of surface water fraction and of the variability in surface water presence.

2. Study area

We selected two study areas in Spain for building and training the models (see Fig. 1(a)). The two areas have different characteristics in terms of climate, and each is defined by the spatial extent of a Landsat tile (i.e. P199R031 and P202R034, hereinafter referred to as T_1 and T_2).

The first area is located in the middle and lower Ebro river basin, north-eastern Spain. The area has a wide variety of climatic environments due to the complex topography (Fig. 1(b)), with annual precipitation ranging from 348 mm to 1020 mm, based on the WorldClim database (Hijmans et al., 2005). The Ebro is the largest river on the Iberian Peninsula and one of the largest in the Mediterranean region. Multiple dams are built along the Ebro river and its major tributaries,