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Comparing Landsat water index methods for automated water classification in eastern Australia

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ABSTRACT

Automating the accurate classification of water in Landsat imagery will benefit many researchers conducting large-area multi-temporal analyses of the USGS archive. We propose that water index methods based on data normalised to surface reflectance, using thresholds optimised for a large selection of data, provide a simple yet accurate method for automated water classification across large regions. In order to select the best index for this task a comprehensive comparative analyses was required. We assessed the accuracy of seven water index methods for classifying water in 30 m resolution Landsat TM/ETM+/OLI imagery from eastern Australia. These indexes were the Automated Water Extraction Index for images with shadows ($AWEI_{shadow}$) and without shadows ($AWEI_{no\ shadow}$), tasselled cap wetness (TCW_{Crist}), two variations of the normalised difference water index ($NDWI_{McFeeters}$ and $NDWI_{Xu}$), a water index created using canonical variates analysis from top-of-atmosphere data (WI_{2006}), and a new water index created with linear discriminant analysis from data processed to surface reflectance (WI_{2015}). A wide variety of water (50,868), non-water (36,833) and mixed (16,499) validation pixels were selected from Landsat images across the states of New South Wales and Queensland. Water area and the colour of water and non-water features were determined for each validation pixel using coincident high resolution imagery and TM/ETM+ reflectance. A single optimum threshold for classifying each index into water and non-water was determined using pure pixels. In general the WI_{2015}, WI_{2006} and $AWEI_{shadow}$ performed the best, with all indexes achieving overall accuracies of 95–99% for pure pixels, and 73–75% for mixed pixels. Omission errors were more common than commission errors, and water area was usually underestimated, especially where water was green-brown in colour, and/or where water bodies were small or had long perimeters with many mixed pixels. The accuracy of each index was highly dependent on the composition of the validation pixels, with no index performing best across all water and non-water pixel types. All indexes and thresholds were found to perform consistently across images from the TM, ETM+ and OLI sensors, facilitating the automated classification of water to similar levels of accuracy for the growing archive of Landsat data.

1. Introduction

1.1. Background

Automating the classification of surface water in satellite imagery is often required to mask water pixels to allow the effective monitoring of the land surface. For example, when analysing a time-series of satellite derived vegetation cover, water pixels that are not masked will cause spurious temporary reductions in cover that will confound analysis and interpretation. Water masks can also be used for analysing the changing distribution of water across large areas, complementing other research into surface water dynamics. Multi-spectral 30 m resolution imagery from the Landsat satellites has been captured worldwide, approximately every 16 days for the last 30 years. Although surface water movement can be very rapid, changing dramatically between Landsat acquisitions, the data represent an important long-term, large-area, multi-temporal reference for land and water monitoring.

Several studies have classified water in Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) imagery, often using the normalised difference water index ($NDWI_{McFeeters}$) of McFeeters (1996), or the $NDWI_{Xu}$ of Xu (2006) (Duan & Bastiaanssen, 2013; Hui et al., 2008; Murray et al., 2012). These indexes are simple to calculate, each only using two input bands. The water index developed by Danaher and Collett (2006) (referred to here as the WI_{2006})

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combines five bands, was developed for ETM + data from Queensland, Australia, and is routinely used to mask water pixels across Australia by the government organisations that are partners in the Joint Remote Sensing Research Programme (JRSRP). Tasselled cap transformations of Landsat TM/ETM + data (Crist, 1985; Crist & Cicone, 1984; Huang et al., 2002) have also been used to map water. They summarise Landsat data into fewer fundamental views, by rotating pixel vectors in multidimensional space, using all bands. The third fundamental view of the Landsat TM/ETM + tasselled cap transformation relates to wetness, and tasselled cap wetness (*TCW*) has been used as an input into water classification schemes (Bhagat & Sonawane, 2011; Ouma & Tateishi, 2006). Feyisa et al. (2014) recently proposed the Automatic Water Extraction Index, which is actually two indexes: one for images with no shadow ($AWEI_{no\ shadow}$) and another for those with shadows from mountains, buildings and clouds ($AWEI_{sh}$). These indexes use four and five bands respectively.

All the water indexes described above allow water pixels to be classified by applying a simple threshold, which can be adjusted for different images or different classification priorities. We propose that if imagery is processed to surface reflectance a simple global threshold can be selected, allowing automated classification of water pixels across images from different places and times. This was observed by Feyisa et al. (2014), who found little variation in optimum index thresholds across five images processed to surface reflectance. Accurate automated water classification of the multi-temporal global Landsat archive would facilitate analysis of the changing distribution of water, showing where water is permanent or temporary, and allowing research into the long term trends of water extent. This would complement static global water maps that have to date only represented the period circa-2000, such as the global water bodies database (GLOWABO) of Verpoorter et al. (2014) and the global inland water body map (GIW) of Feng et al. (2015). The water classification algorithms developed for these maps used decision trees and various indexes derived from Landsat data, and were specifically designed for a dataset of circa-2000 imagery. Further research would be required before the methods could be applied to Landsat images from different dates. The GLOWABO algorithm as described by Verpoorter et al. (2012) is not reproducible, and the GIW algorithm requires the 250 m resolution water mask derived from Moderate-resolution Imaging Spectroradiometer (MODIS) data and the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM). Feng et al. (2015) also acknowledges that the GIW map does not capture the temporal variability in water extent due to seasonal and extreme events. Simple water index methods however, based on Landsat data normalised to surface reflectance and an optimised threshold, allow dynamic water extent maps to be produced from the Landsat archive, particularly when combined with other automated products such as cloud masks. However, we are unaware of any comprehensive comparative analyses of the water indexes, showing their strengths and weaknesses, so it is difficult to choose the best index for automated, large-area, multi-temporal water classification. The work presented here was designed to allow this decision to be made for eastern Australia, and to demonstrate how similar research could be performed on other large regions, or even the globe.

1.2. The interaction of solar radiation and water

Each water index combines the information from TM/ETM + bands, with the goal of separating water and non-water pixels in a single dimension, allowing water pixels to be classified through selecting a threshold. All water indexes exploit the main physical characteristic of water in satellite imagery: a decrease in reflectance from the visible to infrared wavelengths. Solar radiation interacts with water in several ways, such as reflecting and scattering at the surface, while some radiation will penetrate the water column before experiencing subsurface scattering and attenuation. Attenuation of light in clear water is dependent on wavelength, with blue light penetrating the furthest and attenuation increasing with increasing wavelength (Jerlov, 1976; Smith & Baker, 1981). Penetration is dependent on the attenuation coefficient for pure water, the scattering and absorption coefficients for particles, and the absorption coefficient for dissolved organic material (Smith & Baker, 1981). Attenuation shows an exponential increase from visible to near infrared (NIR) wavelengths (Pope & Fry, 1997; Smith & Baker, 1981), while for longer wavelengths water absorption is so great that any reflectance is due to scattering and reflection at the water surface (Martin, 2004). Dissolved organic material (primarily acids from decaying vegetable matter in land runoff and the degradation of phytoplankton), organic particulates (phytoplankton and zoo plankton cell fragments and faecal pellets) and inorganic particulates (products of land erosion) all absorb strongly in blue wavelengths giving water a brownish yellow colour (Martin, 2004). Absorption continues into green wavelengths for some dissolved and particulate matter, while the chlorophyll present in phytoplankton absorbs in red wavelengths (Matthews, 2011). Water with high phytoplankton biomass may also have greater reflectance in NIR wavelengths, due to increased scattering (Blondeau-Patissier et al., 2014; Gitelson et al., 1999). One major difficulty in classifying water in remotely sensed imagery is the variability of reflectance spectra of water with different properties. Although a great deal of research has been conducted into the remote sensing of water properties, these studies were not concerned with the detection of water but focused on sites of known water. Research into water detection meanwhile, has occasionally taken different water colours into account (Sun et al., 2012) but has not quantitatively assessed their detection.

Some examples of reflectance from water pixels in Landsat TM/ETM + images are shown in Fig. 1. For deep-clear ocean water, reflectance in the visible bands decreases exponentially with increasing wavelength, then flattens in the infrared (Fig. 1A). Greater levels of dissolved and particulate material decrease reflectance in blue wavelengths, but if the water is relatively clear and deep, the overall trend of decreasing or flat reflectance is the same (Fig. 1B). Dark-green (Fig. 1C) and green (Fig. 1D) water bodies with high concentrations of phytoplankton have reflectance peaks in the green band, while brown (Fig. 1F) and dark-brown (Fig. 1G) water bodies with high concentrations of sediment have peaks in the red band. Water with a mixture of phytoplankton and sediment appears a green-brown colour, and reflectance in the green and red bands are similar (Fig. 1E). Clear shallow water where the substrate contributes to the reflectance is the most complicated case, and can result in a variety of colours depending on the depth of the water and the substrate type. Despite this variability, water has relatively unique reflectance properties, although some dark features with low reflectance can appear similar. Shadows cast by cloud (Fig. 1K), steep topography (Fig. 1L), deep quarries (Fig. 1M), and tall buildings (Fig. 1N) can appear similar to water. Bare ground appears different to water due to high reflectance in the infrared (Fig. 1H), while vegetation appears different due to a peak in near-infrared reflectance (Fig. 1I-J).

1.3. Objectives

The research had three main objectives. Firstly, to generate a new Landsat water index (WI_{2015}) based on input data processed to surface reflectance. Although the WI_{2006} has been used operationally for land cover and wetland mapping across eastern Australia for more than 10 years, it is based on standardised top-of-atmosphere (TOA) reflectance data. Our hypothesis was that an updated water index developed from surface reflectance data would be more accurate. The second objective was to compare the accuracy of the various index methods in classifying water with a range of properties from validation sites across New South Wales (NSW) and Queensland in eastern Australia. The third objective was to test the applicability of the indexes across data from Landsat 5 TM, Landsat 7 ETM + and Landsat 8 Operational Land Imager (OLI).