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Regional assessment of lake ecological states using Landsat: A classification scheme for alkaline–saline, flamingo lakes in the East African Rift Valley

E.J. Tebbs[a,d,*], J.J. Remedios[a], S.T. Avery[c], C.S. Rowland[d], D.M. Harper[b,c]

[a] University of Leicester, Department of Physics and Astronomy, University Road, Leicester LE1 7RH, United Kingdom
[b] University of Leicester, Department of Biology, University Road, Leicester LE1 7RH, United Kingdom
[c] University of Leicester, Centre for Landscape & Climate Research, University Road, Leicester LE1 7RH, United Kingdom
[d] Centre for Ecology and Hydrology, Lancaster Environment Centre Library Avenue, Bailrigg, Lancaster LA1 4AP, United Kingdom

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ABSTRACT

In situ reflectance measurements and Landsat satellite imagery were combined to develop an optical classification scheme for alkaline–saline lakes in the Eastern Rift Valley. The classification allows the ecological state and consequent value, in this case to Lesser Flamingos, to be determined using Landsat satellite imagery. Lesser Flamingos depend on a network of 15 alkaline–saline lakes in East African Rift Valley, where they feed by filtering cyanobacteria and benthic diatoms from the lakes' waters. The classification developed here was based on a decision tree which used the reflectance in Landsat ETM+ bands 2–4 to assign one of six classes: low phytoplankton biomass; suspended sediment-dominated; microphytobenthos; high cyanobacterial biomass; cyanobacterial scum and bleached cyanobacterial scum. The classification accuracy was 77% when verified against *in situ* measurements. Classified imagery and timeseries were produced for selected lakes, which show the different ecological behaviours of these complex systems. The results have highlighted the importance to flamingos of the food resources offered by the extremely remote Lake Logipi. This study has demonstrated the potential of high spatial resolution, low spectral resolution sensors for providing ecologically valuable information at a regional scale, for alkaline–saline lakes and similar hypereutrophic inland waters.

1. Introduction

High spatial resolution satellite sensors, such as Landsat, can be used for quantitative monitoring of water quality parameters in small inland waters (Brezonik et al., 2005; Vincent et al., 2004). Due to the broad spectral bands of these sensors, the algorithms employed are typically empirical and require tuning for each water body. This study explored an alternative approach which used the shape of the water-leaving reflectance to classify the ecological states of lakes at a regional scale. This approach was applied to alkaline–saline (soda) lakes in the East African Rift Valley. These lakes support dense blooms of cyanobacteria and extensive areas of microphytobenthos which are important food sources for Lesser Flamingos (Tuite, 2000). In East Africa, the flamingos' survival depends on the food availability throughout a network of 15 alkaline–saline lakes within the Eastern Rift (Childress et al., 2008). Limited *in situ* data are available for these lakes due to their remoteness; hence, remote sensing has potential as an alternative method for monitoring.

Alkaline–saline lakes undergo large fluctuations in water levels that impact strongly on primary producers (Smol and Stoermer, 2010) and the capacity of these lakes to support Lesser Flamingos. At high levels, the shallower lakes can be relatively fresh and support single celled cyanobacterial phytoplankton, which are too small to be filtered by flamingos (Vareschi, 1978), while at intermediate levels they support dense blooms of filamentous cyanobacteria (primarily *Arthrospia fusiformis*; several hundred $\mu g\ l^{-1}$; Oduor and Schagerl, 2007b) which provide a rich supply of food for the flamingos (Vareschi, 1978). Finally, when shallow, the lakes support microphytobenthos, providing a secondary food source for the flamingos (Tuite, 2000). Hence, in terms of value to Lesser Flamingos, the lakes can exist in different states. Often multiple states can occur within a single lake in different areas.

* Corresponding author at: Centre for Ecology and Hydrology, Lancaster Environment Centre Library Avenue, Bailrigg, Lancaster LA1 4AP, United Kingdom. Tel.: +44 01524 595858; fax: +44 01524 61536.
E-mail addresses: emmbbs@ceh.ac.uk, emma.tebbs@gmail.com (E.J. Tebbs), jjr8@le.ac.uk (J.J. Remedios), sean@watres.com (S.T. Avery), clro@ceh.ac.uk (C.S. Rowland), dmh@le.ac.uk (D.M. Harper).

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Water-leaving reflectance spectra contain information about the optically-active water constituents (Kirk, 1994), and hence, these signals can be exploited in order to infer lake ecological states. Previous studies have classified natural waters in terms of their optical properties (Jerlov, 1976; Case I/Case II, Morel and Prieur, 1977), including the shape of the water-leaving reflectance spectra (Lobo et al., 2012; Kutser et al., 2006; Kurekin et al., 2014). Reflectance-based classifications have been used to inform algorithm selection prior to water quality parameter retrieval (Li et al., 2012; Sun et al., 2012; Shi et al., 2013; Liu et al., 2013). For hypereutrophic lakes, the red and NIR bands of multispectral sensors have been used to classify trophic status, by utilising the strong NIR peak which is characteristic of these waters (Matthews et al., 2012; Tebbs et al., 2013b).

A site-specific algorithm exists for quantifying cyanobacterial biomass in Lake Bogoria, a key feeding lake for the flamingos (Tebbs et al., 2013b). However, the development of generic or customised algorithms for quantifying primary producers in all soda lakes would be extremely challenging, due to their optical complexity and a lack of sufficient *in situ* data. Hence, an alternative approach was taken, to classify the functional states of the lakes based on their spectral signatures. *In situ* data for selected alkaline–saline lakes was used to determine the spectral characteristics of the different ecological conditions and to develop a Landsat-based optical classification. *In situ* reflectance and water parameter measurements were used to define five reference classes for development and validation of the classification scheme. Examination of Landsat imagery identified additional water types not represented by the *in situ* data and this information was also used to inform the classification scheme development. The classification was applied to produce maps and timeseries for several Eastern Rift Valley lakes, showing the spatial and temporal distribution of the different ecological states and the Lesser Flamingo's food supply.

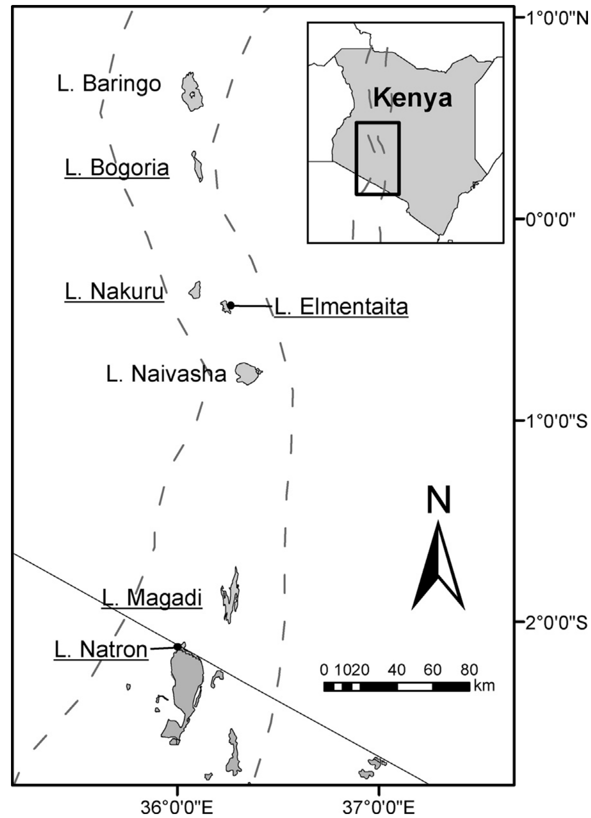

Fig. 1. Map showing locations of the lakes within the East African Rift Valley. Underlined lakes are alkaline–saline, the others are fresh. Lake Oloidien (not shown) is a bay in the SW corner of Lake Naivasha which becomes separated at low water levels. The solid line shows the border between Kenya and Tanzania, the dotted line shows the boundary of the Rift Valley.

2. Study sites

In situ spectral reflectance and water parameter measurements were made at alkaline–saline lakes in Kenya and Tanzania, including Bogoria, Elmenteita, Nakuru, Natron and Oloidien (Fig. 1 and Table 1). These lakes are representative of the range of conditions found in soda lakes: Bogoria and Oloidien are relatively deep and support dense cyanobacterial blooms, while Elmenteita and Natron are shallow, typically supporting benthic diatoms, and Nakuru has an intermediate water level.

3. Method

3.1. In situ reflectance and water parameter measurements

Reflectance and water parameter measurements were collected at the study lakes between 2010 and 2012. At lakes Bogoria, Nakuru and Oliodien, spectral measurements were made from a boat using a GER1500 spectroradiometer. Water samples were collected and analysed for chlorophyll-a (Chl-a), absorption by coloured dissolved organic matter at 440 nm ($a_{CDOM}(440)$), total suspended solids (TSS) and inorganic suspended solids (ISS). Secchi disk depth was also recorded. At Lake Elmenteita and the shallow northern lagoon at Lake Natron the reflectance of algal communities on bottom sediments was measured using a GER1500 mounted on a tripod. Samples of benthic microbial communities were collected using a Gilson corer. Samples of the overlying water were also collected and analysed for Chl-a, a_{CDOM}, TSS and ISS.

When collecting spectoradiometric data, a nadir viewing geometry was used and upwelling radiance was measured between 400 nm and 950 nm. A reference scan of a calibrated Spectralon reference panel was made between each measurement and was used to convert absolute reflectance during post-processing (Robinson and Arthur, 2012). The response of Landsat ETM+ was simulated by convolution of the *in situ* spectra and the spectral response function of each band (Irish, 2000). Chl-a was extracted in 90% acetone after gentle vacuum filtration and followed by manual grinding of the filter paper. Using a spectrophotometer, the absorbance at 663 nm and 750 nm was measured and the Chl-a concentration was calculated (Talling and Driver, 1963). Full details of the procedures used for water parameter and spectral measurements can be found in Tebbs et al. (2013b) and Tebbs (2014).

3.2. Landsat ETM+ satellite imagery

Landsat ETM+ images for the lakes were downloaded from the USGS Global Visualization Viewer, http://glovis.usgs.gov/, for the period 1999–2012. The images were processed using ENVI+IDL software. Radiometric calibration to top-of-atmosphere radiance, L_{TOA}, was performed (Chander et al., 2009). After May 2003 the Scan Line Corrector on Landsat 7 failed and, as a result, affected ETM+ images contain lines of missing data. These gaps were filled using simple spatial linear interpolation.

3.3. Development of the classification

A decision tree (DT) based classification was developed by combining insights gained from *in situ* measurements and satellite image interpretation with knowledge from the literature. *In situ* spectral and water parameter measurements were used to define a set of five classes, 'Low biomass', 'Sediment', 'Scum',