Application of Multi-spectral Satellite Imagery in Monitoring of Aquatic Vegetation and Water Quality Parameters in Large Inland Waters

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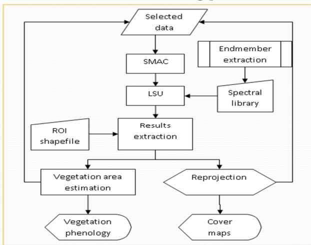
Abstract

Following the great potential of optical remote sensing and its increased application in quality assessment of inland waters, we have developed time dependent vegetation abundance prediction models based on its statistical relationship with the concentrations of total suspended matter (TSM) and phytoplankton chlorophyll (Chl-a) water quality (WQ) parameters in the lake as well as the amount of rainfall in its drainage basin.

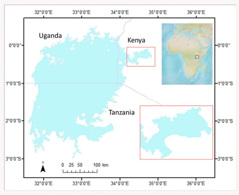
We start by retrieving the selected WQ parameters from MERIS (Medium Resolution Imaging Spectrometer) multispectral satellite imagery of Lake Victoria based on their optical properties, and obtain their seasonal variations over the period 2003 to 2010. We then carry out regression analysis to establish the time dependent statistical correlation between estimated vegetation abundance and the retrieved WQ constituents as well as rainfall after various response periods, and identify an optimal response period for each precursor.

Methodology



- Atmospheric corrections with SMAC
- Sub-pixel classification with spectral unmixing
- Vegetation is detected based on its spectral responsiveness
- WQ values were retrieved from the satellite imagery using the radiative transfer models
- Time dependent statistical correlations established and prediction models developed

Introduction



Availability of clean fresh water is one of the greatest environmental challenges worldwide. Lakes require regular monitoring in order to assess the quality of their water. Monitoring of water quality parameters through traditional methods of laboratory analysis is both time consuming and expensive. Application of remote sensing techniques for the assessment of WQ has proved to be effective as it enables continuous monitoring of WQ parameters over large water bodies (Zimba and Gitelson 2006). Optical remote sensing has a great potential in quality assessment of inland waters (Doerffer and Schiller 2008), and is an essential tool to understand the spatial distribution of the factors involved in the ecology of aquatic systems.

Results & Discussion

Vegetation detection

Spectral unmixing

$$R_k = \sum_i^n a_i \cdot E_{i,k} + \varepsilon_k$$

$E_{i,k}$ is reflectance of endmember i at wavelength k, a_i is the abundance of endmember i, n is the number of endmembers, and ε_k is the error at wavelength k.

Constraints:

$$0 < a_i < 1 \qquad \sum_i^n a_i = 1$$

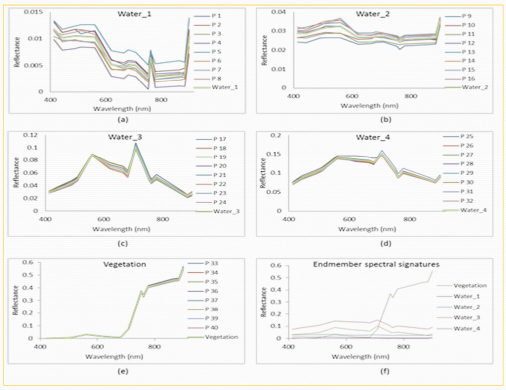


Fig 1. The image derived endmember spectral library consisting of five spectral signatures, four for various water classes 1(*a*)–1(*d*) and one for vegetation class feature 1(*e*). 1(*f*) is the endmember spectral library compiled from the mean spectra of all the five class features

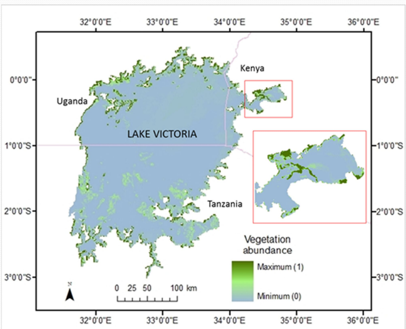


Fig 2. Spatial distribution of aquatic vegetation in Lake Victoria on 15-12-2010. The map displays the fractional abundance of vegetation per pixel, where minimum means the pixel displays open water and maximum means pixel is fully covered by vegetation.

Water quality assessment

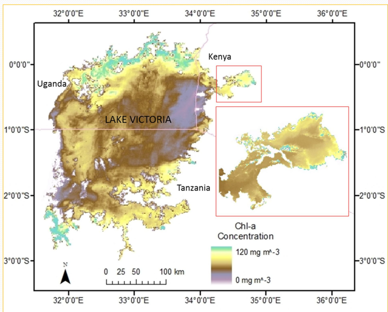


Fig 3. Spatial distribution of Chl-a in Lake Victoria on 15-12-2010

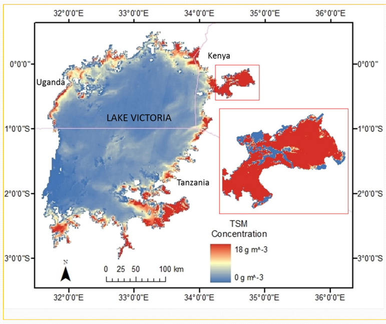


Fig 4. Spatial distribution of TSM in Lake Victoria on 15-12-2010

Statistical correlations

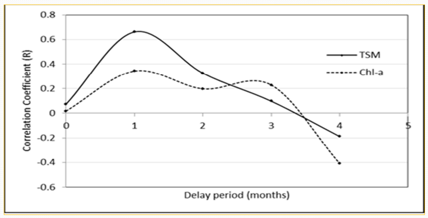


Fig 5. TSM correlates highly with rainfall after two months, while Chl-a has two peaks in first and third month

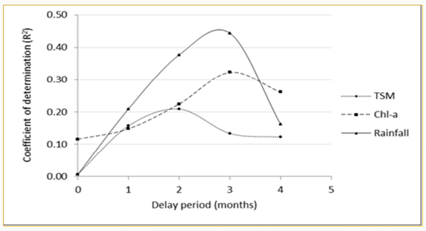


Fig 6. A graph showing the trends of how vegetation abundance responds to the various precursors over a range of delay periods

Vegetation abundance Prediction models

$$A_{n+60} = 9.7 \cdot T_n - 96.6$$

$$A_{n+90} = 20.6 \cdot C_n - 120.3$$

$$A_{n+90} = 7.7 \cdot \left(\frac{R_{n-3} + R_{n-2} + R_{n-1} + R_n + R_{n+1} + R_{n+2} + R_{n+3}}{7} \right) + 36.2$$

Conclusion

It seems the proliferation of aquatic vegetation is enhanced by the presence of TSM and Chl-a in water, which are introduced into the lake by the rainfall in its drainage basin. Regression results revealed that vegetation proliferation responds optimally to the variations in the conditions of TSM, Chl-a and rainfall after a delay period of about two to three months with correlation coefficients R = 0.46, R = 0.57 and R = 0.67 respectively. Early vegetation predictive models are developed based on these statistical relationships.

References

1. Doerffer, R. and Schiller, H., 2008, MERIS Lake Water Algorithm for BEAM, ATBD of bio-optical models, GKSS Research Centre 21502 Geesthacht Version 1.0, 10 June 2008
2. Zimba, P. V. and Gitelson, A., 2006, Remote estimation of chlorophyll concentration in hyper-eutrophic aquatic systems: Model tuning and accuracy optimization, Aquaculture, 256, 272–286.

Acknowledgements

In 2002 ESA under its TIGER initiative (http://www.tiger.esa.int/) launched a capacity building campaign focused on the use of space technology for water resource management in Africa and providing concrete actions to match the resolutions, and this research is part of its second phase. It was facilitated by the University of Nairobi, Kenya, and Delft University of Technology, Netherlands.