Natural Resources, 2016, 7, 495-504
http://www.scirp.org/journal/nr
ISSN Online: 2158-7086
ISSN Print: 2158-706X

Utilization of Landsat Data for Quantifying and Predicting Land Cover Change in the Bumbuna Watershed in Sierra Leone

Abubakarr Mansaray, Abdulai Barrie

Bumbuna Watershed Management Authority, Bumbuna, Sierra Leone
Email: absmansaray@gmail.com

How to cite this paper: Mansaray, A. and Barrie, A. (2016) Utilization of Landsat Data for Quantifying and Predicting Land Cover Change in the Bumbuna Watershed in Sierra Leone. *Natural Resources*, **7**, 495-504.
http://dx.doi.org/10.4236/nr.2016.79042

Received: August 10, 2016
Accepted: September 6, 2016
Published: September 9, 2016

Abstract

Rural communities in third world countries are concerned over land use changes resulting from resource exploitation. This is the case for the Bumbuna watershed in Sierra Leone following impoundment of the Bumbuna reservoir in 2009. Farmers have increased activities along the riparian zones in protest against inundation of their farmlands. The dam operators warn this practice would threaten sustainable power supply; the farmers contend the reservoir is increasing and taking over their farms. However, it is difficult to resolve this issue without a means of quantifying the change and developing early warning systems for land cover in the watershed. This research presents a case for the use of remotely sensed Landsat data for quantification of land cover change and the development of predictive models to inform preparedness for imminent problems that may arise from land use practices. *In situ* water loggers, in combination with manual readings, recorded water levels in 30-minute intervals since 2009. These datasets combined with spectral values of Landsat 7 and Landsat 8 for the development of regression algorithms for predictive purposes. Digital photographs and satellite imagery illustrated the changes in land cover over time (a 33% water rise and 44% NDVI change from 2009 to 2015). These visual and spectral pictures confirm the usefulness of remotely sensed data for early warning systems in the watershed. Results of the regression analysis show Band 1 (Blue) and Band 4 (NIR) as statistically significant predictors for water level in the reservoir. The tests accounted for 84% (R^2) of the data with p-values less than α at the 0.05 confidence level. However, future trials of the model will consider reducing the 4.6 error margin to minimize deviations from the observed data.

Keywords

Watershed, Hydroelectric Power, Farming, Water Loggers, Landsat, Remote Sensing, Spectral Data

1. Introduction

Rural communities in third world countries are becoming increasingly concerned over land use practices that may lead to major changes in land cover and pose threats to their chances of survival [1]. This is the case in the Bumbuna watershed in Sierra Leone. There are two main concerns over land cover change in the watershed [2]. Firstly, the Bumbuna Hydroelectric Project (BHP), the largest source of electricity supply to the nation's capital, is under accusation from local farmers and settlers for land degradation. The dam operators, on the other hand, worry about the frequency and magnitude of slash and burn farming as a threat to river flow in the area.

During the farming season, local farmers cultivate plots of forestland mainly for rice production. Traditionally, farmers would allow the farmland to fallow for a minimum of 7 years before coming back to that same plot. However, this fallow period has dramatically reduced to about every other year due to increase in other livelihood activities that also depend on the same piece of land. This farming concern became more obvious when the Government of Sierra Leone (GoSL) commissioned the Bumbuna power plant in 2009. The dam filled up and expanded into a reservoir taking over farmlands, communities, and some vegetation.

The stakeholders have been in a heated debate over the impact of these two activities. The dam operators warn that farming along the shoreline would change the fluvial geomorphology of the area and affect electricity generation. The farmers, on the other hand, contend that the water level keeps rising and shifting the riparian buffer inwards towards their farmland. Farming is an integral part of their tradition, in addition to being their major means of livelihood.

In anticipation of this controversy, the GoSL, in 2008, developed a policy to promote best management practices (BMPs) and alleviate environmental and social problems in the watershed [2]. This law ushered in the Bumbuna Watershed Management Authority (BWMA) to facilitate implementation of the BMPs. The BWAMA and development partners have worked with farmers to establish a 100-m width riparian buffer to protect the stream banks and minimize sedimentation into the Bumbuna reservoir. However, keeping the riparian buffer intact has challenged the stakeholders over the years.

Meanwhile, no data exists to show the mechanisms of catchment change in the area, the impact on these activities, and to what magnitude they matter. Advances in the availability of remote sensing datasets and the understanding of their benefits and limitations provide the potential to assist in overcoming this challenge [3]. Combining these datasets with ground truth data and an understanding of the underlying mechanisms is an active area of scientific research that could address such unexplored area.

The underlying principles behind satellite remote sensing for natural resource research include but are not limited to electromagnetic radiation, image acquisition and processing, and field data gathering [4]. Data from electromagnetic radiation combines with environmental data to simulate trends and processes. The simulation happens through computer software packages that synthesize information into useful formats for algorithm development. The computer algorithms deploy information from these variables and build models that can be useful for predictive purposes as well as accounting for past events [5].

Birth and McVey [6] were among the first scientists to utilize remote sensing techniques to explore new areas of natural resource research. They evaluated the color of grass turf using a ratio of Near Infra-Red (750-nanometer [nm]) to red (650-nm) reflectance, and called it the turf color index. Their work utilized a two-filter instrument called Ratiospect to measure this index on eight samples of turf of three species. The high correlation coefficient (98.4%) confirmed a strong relationship between the Ratiospect readings and the visual score of turf color. This mathematical relationship gave birth to the development of computer simulations in ecosystems studies.

Several studies have followed Birth and McVey [6] in utilizing satellite remote sensing to overcome natural resource monitoring challenges in terms of space and time. One such study is the need for a better knowledge of the spatial and temporal distribution of surface water resources [7]. Spatially, many sampling programs are limited to few locations, owing to factors such as lack of sufficient financial, institutional, and/or human resources. Hence, the need for a wider coverage of sampling points has been an area of active natural resource remote sensing application [8]-[11]. Similar factors may also impede frequent monitoring programs. Such gaps in sampling periods may pose the risk of missing important incidents, such as flooding, and diminish the robustness of management strategies [8]-[11]. Because of these limitations, researchers have explored new remote sensing tools to understand the mechanism of catchment changes over time.

This work follows from those methodologies in the literature, postulating that Landsat spectral data can enable development of predictive models as early warning systems for impacts of land use changes in the Bumbuna watershed. The objective is to show case the usefulness of Landsat data in providing scientifically proven evidence to pinpoint cause-effect relationships between land-use practices and land cover changes in the study area. To achieve this objective, this work will exemplify a regression algorithm relating water level fluctuations in the reservoir and spectral reflectance values of Landsat 7 Enhanced Thematic Mapper (ETM) and Landsat 8 Optical Land Imager (OLI).

This work will lay the foundation for utilization of Landsat data to solve complex environmental problems in this data scarce region. The results will show case and provide the basis for project management using these approaches. Hence, future actions will not suffer from lack of information in clarifying land cover boundary limits and common interest. In addition, future predictive models from satellite studies will inform management strategies for biodiversity conservation. This is more obvious giving study findings of high species diversity of primates and other large mammals, birds, herptiles, butterflies, bats, and flora [2].

2. Materials and Methods

2.1. Description of Study Area

2.1.1. The Bumbuna Watershed

The Bumbuna watershed drains into Rokel River, one of the major river basins in Sierra

Leone. The Rokel basin starts in Koinadugu District, in the northeast, and empties into the Atlantic Ocean in the Western Area. Figure 1 shows a Google Earth map of the Rokel basin with the Bumbuna watershed in the upper catchment (circled).

Several communities, companies, and the GoSL depend on Rokel River for various purposes. Communities depend on it for fishing, transport, farming, and domestic use; ADDAX Bio-energy abstracts water from the river for irrigation; London Mining Ltd. utilizes the river to preprocess iron ore; plenty of mining companies depend on it for sand and gold; the BHP, the nation's biggest hydroelectric power supply source, depends on the Bumbuna watershed.

The Bumbuna watershed has a 21 Km^2 flooded area that drains into a 2,500,000-m^3 reservoir, which supports hydroelectric power supply to major cities in the nation [12]. The three affected chiefdoms are Diang and Kansunko chiefdoms in Koinadugu District and Kalasongia chiefdom in Tonkolili District. Figure 2 shows a map of the Bumbuna watershed bounding the Rokel River and the three affected chiefdoms.

2.1.2. Water Level Determination in the Reservoir

This study utilized both manual level readings and *in situ* "Rugged TROLL" absolute pressure data loggers. These loggers respond to changes in water and air pressure and require compensation to remove the effects of air pressure using a separate barometric logger (Rugged BARROW). The rugged troll and rugged barrow, both are easy-to-use software aquatic data logging instruments. The rugged troll measures water temperature and water level while the rugged barrow measures atmospheric pressure. Both instruments have completely sealed bodies that contain non-vented pressure sensor, temperature sensor, real-time clock, microprocessor, lithium battery, and internal memory. The Rugged TROLL 100 hangs by a back-shell hanger from a suspension wire.

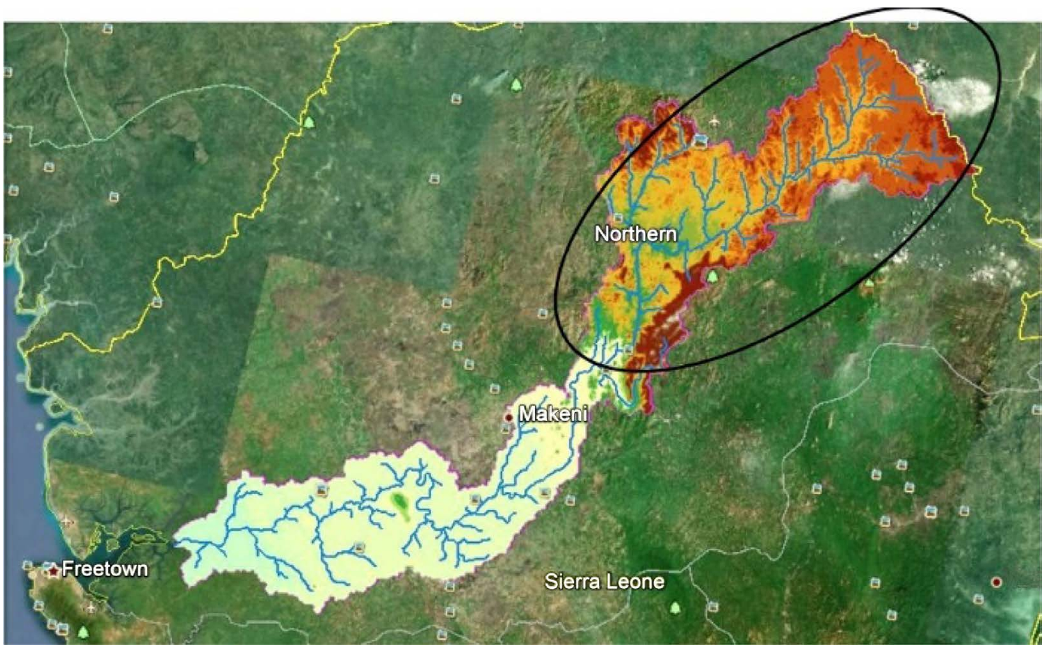


Figure 1. Google earth map showing the Rokel River Basin and the Bumbuna watershed (circled).

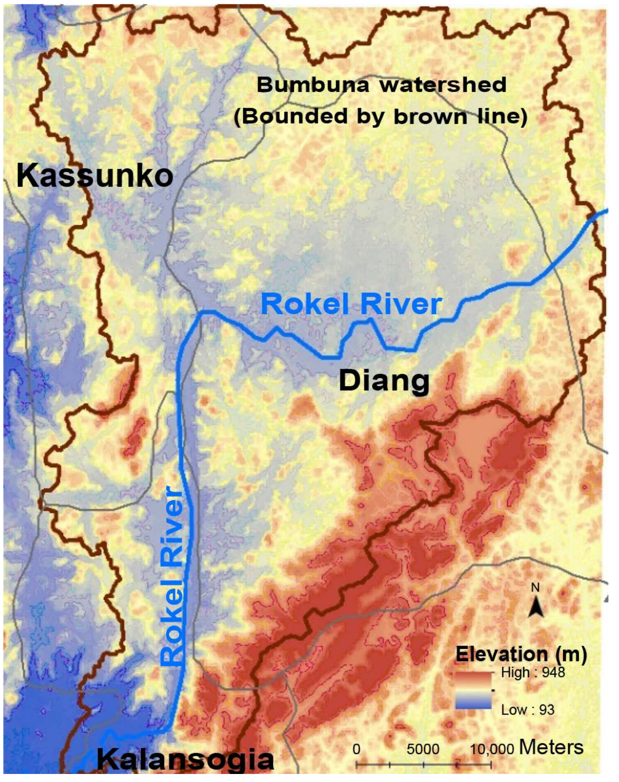


Figure 2. Map of the Bumbuna watershed bounding the Rokel River and the three affected chiefdoms.

Deployment of the instruments followed calibration with manual water levels and customization to take readings at 30-minute intervals. The instrument stored the data in a memory chip installed on the logging device. The Win Situ 5 soft ware utilizes a USB connected docking station to download the data, in CSV file formats, on to a computer.

2.1.3. Acquisition of Satellite Data

The United States Geological Survey (USGS) provides Landsat data in *tagged image file format* (tiff). Using the ESRI Image Classification tool, the mean pixel values (30-m resolution) represented surface reflectance for the overpass dates. The resulting reflectance values informed algorithm development for water level fluctuations over time. The USGS has published, on their web page, band characteristics for Landsat 7 and Landsat 8 [13]. These band characteristics (Table 1) informed inferences from the observed trends.

This research also utilized photographs from digital field cameras. The purpose was to demonstrate visual changes in land cover before and after impoundment of the dam.

2.1.4. Data Analysis

Data analysis utilized multiple regression with ANOVA in the Minitab 17 statistical software. All the bands went through stepwise elimination to account for multicollinearity. There was also stepwise elimination of statistically insignificant bands. The null hypothesis was that no spectral band could predict water level in the reservoir, on a 95% confidence interval.

3. Results and Discussions

3.1. Pre-Impoundment and Post-Impoundment Water Levels

Figure 3 shows two pictures of the Bumbuna dam; the image on the left shows the construction phase of the dam whilst that on the right shows the reservoir in full operations. The water level in the left image shows the original level of the river whilst that on the right shows the current water level in the reservoir.

Figure 4 presents the same information in the form of Landsat images. On the left hand side is a Landsat 7 image acquired on April 9th 2003 and that on the right is a Landsat 8 image acquired on February 24th 2016. The green color represents vegetations cover derived from the normalized differential vegetation index (NDVI) for this area. The blue line running north-south is the Bumbuna reservoir. These two images represent the same location at the two time periods. They show how land cover in this area has changed over the years.

Calculations using spectral values from the Landsat images show that water level in the river (now reservoir) has increased by 45.5% from February 2009 to March 2015 while the NDVI, a related indicator [14], has changed by 44%. Thus, Landsat data for this area can be useful in quantifying changes in land cover over time.

Table 1. Useful characteristics of Landsat spectral bands.

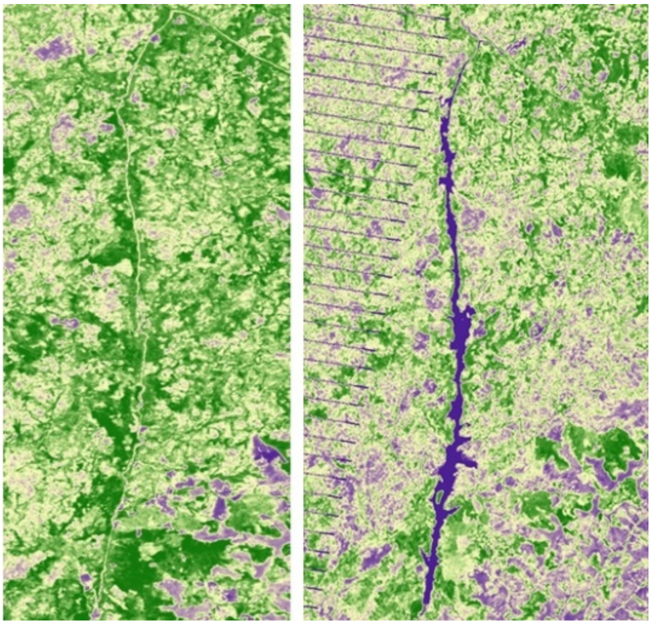
Band number		Wavelength (nm)	Characteristics
Landsat 7	Landsat 8		
1	2	450 - 520	Blue: bathymetry
2	3	520 - 600	Green: peak vegetation
3	4	630 - 690	Red: vegetation slopes
4	5	770 - 900	Near Infrared (NIR): biomass content and shorelines

(a) (b)

Figure 3. Images showing construction (a) and operation phases (b) of the Bumbuna reservoir.

Figure 5 represents water level changes in the reservoir over time. The lowest level in 2009 was 181 m above sea level (a.s.l); the 2014 low level read at 240 m a.s.l, a 33% rise. Figure 5 displays a generally increasing trend of water level over time.

This is a cause for concern giving that the increasing trend become prominent in the rainy season, which is also the farming season. These rural areas, depending primarily on rain-fed agriculture, would need to seek livelihood alternatives if this trend continues [1]. However, early warning systems would help inform BMPs to minimize the likelihood of this problem.



(a) (b)

Figure 4. Landsat images showing pre-impoundment (a) and post-impoundment (b).

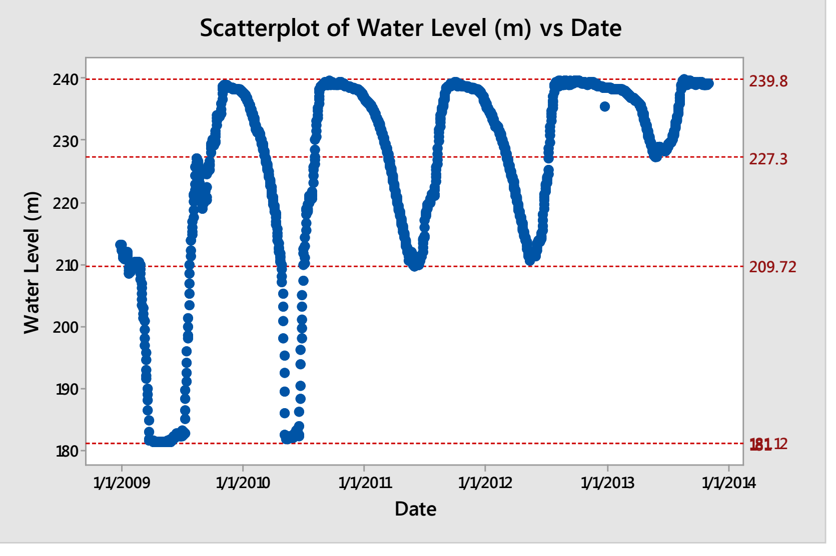


Figure 5. Lowest water level over time since impoundment of the reservoir.

3.2. Visual Relationship between Water Level and Spectral Bands

Figure 6 shows a visual relationship between water level in the reservoir and two Landsat spectral bands. The regression analysis proved Bands 1 and 4 to have statistically significant changes with water level. The gradation in color indicates the range in water level from low to high.

The chart shows a positive linear relationship between water level and band 1, as expected. Depending on the amount of certain substances in a water body, surface reflectance would range in the blue-green-infrared regions of the electromagnetic spectrum. Since water in the reservoir is clear most of the time, the water would reflect high in the blue region [15]. Band 4 has an inverse linear relationship with water level with few exceptions. This trend confirms the fact that NIR differentiates vegetation shoreline from the rest of the water body [13].

3.3. Simulating the Trends

Equation (1) shows the regression model for water level in the reservoir. The output of the multiple regression analysis indicates that Band 1 (Blue) and Band 4 (NIR) significantly predict water level in the reservoir. In this case, we rejected the null hypothesis, which states that Landsat spectral values would not predict water level in the reservoir. The R^2, which indicates the goodness of fit of the model [16], demonstrates that the model can account for at least 84% of water level data on a 95% confidence level (p-value is less than 0.05).

Reservoir Level (m) = 241.74 + 0.0487 Band 1 (nm) − 0.03534 Band 4 (nm).

Equation (1) Predictive equation for water level in the reservoir.

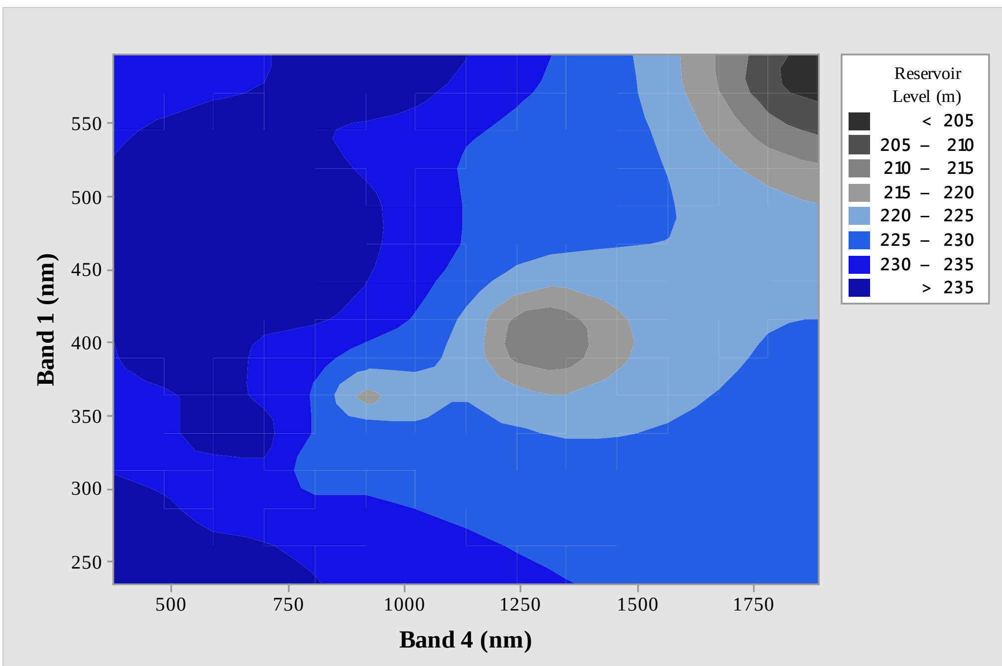


Figure 6. Water level in reservoir and spectral bands.

Hence, the use of Landsat spectral data can be useful in determining water level in the Bumbuna Watershed. Inputting time factor would enable the development of predictive models for the area. However, since the root mean squared error (4.6) indicates a deviation between the predictive and observed trends, a lower value would make the model more powerful [16]. Generally, studies have shown that similar approaches would enhance prediction of other land cover changes [6].

4. Conclusions

The objective of this work was to make a case for the use of Landsat data to predict land cover change in the Bumbuna watershed. Data gathering included both manual and *in situ* recording of surface water fluctuations in 30-minute intervals, temporally coincident surface reflectance values of Landsat over passing the area, and digital photographs.

The results show a minimum of 33% water level rise since impoundment in 2009. Another related land cover change is the NDVI, a 44% change from 2009. The Landsat data indicated that bathymetry changed by 45.5% since 2009. These results strengthened the possibility of quantifying land cover changes using remotely sensed Landsat images.

Results of the regression analysis showed that Band 1 (Blue) and Band 4 (NIR) are better predictors of water level in the reservoir. However, future trials of the regression equation require consideration of the error margin to account for deviations from the observed data. The recommendation is collection of more ground truth data to develop algorithms for predictive models in the watershed. These would serve as early warning systems, informing BMPs for the area.

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