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Assessment of Water Spread Area by Sub pixel Classification in Umiam Reservoir, Meghalaya, India

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***Abstract*—A reservoir is a natural or artificial lake, or an impoundment from a dam where water is collected and stored for use. The extraction of the water spread area of the reservoir by conventional methods is time consuming, expensive and requires significant manpower. As an alternative to the conventional methods, remote sensing techniques are preferred as they are cost and time effective in estimating the water spread area of the reservoir. In this study, Landsat 8-OLI satellite data of nine dates pertaining to the years 2013, 2014 and 2015 were used and sub pixel classification approach was adopted to extract the water-spread area of the reservoir. The procedures of sub-pixel classification try to improve the limitations of the imagery with coarse resolution. This classifier try to reveal possible mixtures and define the area fractions for each pixel which are covered by different cover types. The water levels and water spread areas of the respective dates were collected from the Umiam Reservoir authority and were compared with the water spread area of the respective dates derived through sub pixel classification.**

Keywords— Reservoir; water level; water spread area; sub-pixel classification.

I. INTRODUCTION

Water is the essence and foundation of life and it is essential for socio-economic development. Management of water resources often requires construction of dams or reservoirs across rivers for creating storages and regulating flows. Reservoirs are large, artificial lakes created by constructing a dam across a river and subject to sedimentation. Reservoir sedimentation process is a universal phenomenon which has been considered as the most critical environmental hazard of modern time (Jain and Kothyari, 2000) [7]. Due to sediment deposit, the water spread of reservoir is generally reduced. The capacity of the dam reduces, when the eroded material brought by the water is settled in the water spread and near the periphery of the dam. So, with the help of remote sensing and Geographic Information System (GIS) approach, the reduced water spread areas of reservoir at different elevations can be determined using digital image analysis techniques.

The ability to map and estimate water spread from satellite data is well understood, and different techniques such as visual interpretation of satellite imagery, density slicing, and digital classification of water bodies have been employed for the delineation of water bodies (Work and Gilmer, 1976; Thiruvengadachari et. al., 1980) [5]. Hanumantha Rao et. al. (1985) adopted visual interpretation of enlarged MSS images to estimate the water spread at eight different levels of the Sriramsagar reservoir [5]. Suvit et. al. (1988) used digital techniques in which density slicing of Landsat MSS near-IR (0.8- 1.1 µm) data was used to extract the water spreads of the Ubolratana Reservoir of five different dates. White (1978) examined a variety of measuring techniques for determining reservoir surface areas extracted from Landsat MSS near-IR imageries of different scales and compared their accuracy with field data [5]. He concluded that none of the measuring techniques used was able to measure the reservoir water spread with consistent accuracy and no reason was attributed [5]. Mangond et.al. (1985) employed digital classification techniques to estimate the water spread of the Malaprabha reservoir on March 02, 1973 using Landsat MSS data and reported a discrepancy of 8.29% from the actual water spread [5]. This discrepancy was attributed to the probable misclassification of boundary pixels [5].

The extraction of the water spread area of the reservoir by conventional methods is time consuming, expensive and requires significant manpower. As an alternative to the conventional methods, remote sensing techniques are preferred as they are cost and time effective in estimating the water spread area of the reservoir.

The need for this study is to accurately compute the water spread area of the Umiam Reservoir to the maximum possible extent using sub-pixel classification. The main objective of this study is to extraction the water spread areas using sub-pixel classification and to make a comparative analysis between the water spread areas of the field data and those extracted through sub-pixel classification. The scope of this study is to assess the difference in the water spread areas.

II. STUDY AREA

The Umiam Reservoir is located at 25.6532° N latitude and 91.8843° E longitude 15 km to the North of Shillong in Ri Bhoi district of the state of Meghalaya, India. It is also known as Barapani and was created by constructing a dam across Umiam River in the early 1960s. This reservoir has a length of 175m with a maximum height of 73m above foundation and catchment area of 221.5 square km. It is the first Hydro Electric Power Project in the North-east region of India. It also provides numerous ecosystem services at micro, meso and macro levels, apart from being a source of power generation, domestic consumption, aquaculture and irrigation. It also serves as a major tourist attraction for the state of Meghalaya and a popular destination for water sport as well as adventure facilities. The reservoir in the present day has become highly polluted due to the rapid urbanisation and rising population of Shillong which is situated upstream of the reservoir. Also, there is the problem of heavy silting and it has been estimated that 40,000 cubic metres of silt enter Umiam Reservoir every year. The excessive silt load in the reservoir has lowered the storage. The location map of Umiam Reservoir is shown in Fig. 1.

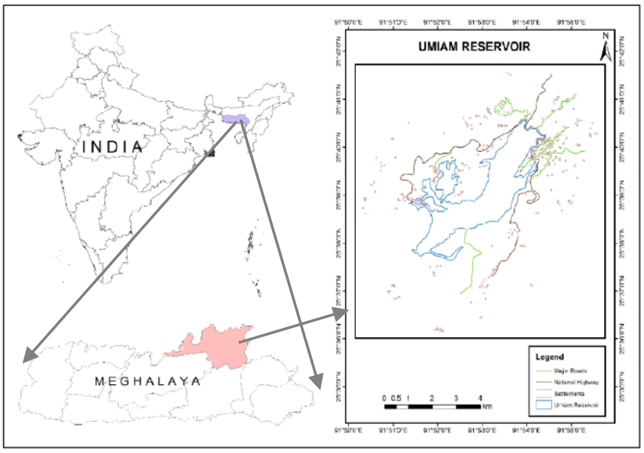

Fig. 1. Location map of Umiam Reservoir

III. DATA USED

Nine different dates of satellite pass acquired by Landsat 8-OLI with a spatial resolution of 30m was used in this study. The different dates of satellite pass along with their respective water spread areas were collected from the Umiam Reservoir authority (field data) are given in Table I.

TABLE I. SATELLITE DATA REQUIRED ALONG WITH THEIR WATER LEVELS AND WATER SPREAD AREAS

Sl. No.	Satellite and Sensor	Date of Satellite Pass	Field data: Water Level (m)	Field data: Water Spread Area (km^2)
1	Landsat 8-OLI	10.03.2015	972.28	6.29
2	Landsat 8-OLI	21.01.2015	975.42	7.61
3	Landsat 8-OLI	20.12.2014	977.41	8.44
4	Landsat 8-OLI	09.11.2014	979.54	9.34
5	Landsat 8-OLI	01.10.2014	981.20	10.03
6	Landsat 8-OLI	07.03.2014	967.92	5.28
7	Landsat 8-OLI	18.01.2014	971.50	6.46
8	Landsat 8-OLI	17.12.2013	975.02	7.62
9	Landsat 8-OLI	06.11.2013	977.37	8.39

IV. METHODOLOGY

A toposheet of Meghalaya with a scale of 1:50,000 was used for preparation of the base map of Umiam Reservoir. The Landsat 8-OLI satellite data used in this study were downloaded from U. S. Geological Survey (USGS) Earth Explorer and pre-processing was done on all the nine dates of satellite pass. The water levels as well as the water spread areas (field data) were collected from the Umiam Reservoir authority - The Meghalaya Energy Corporation Limited. The changes in the water spread could be accurately estimated by analysing the areal spread of the reservoir at different elevations over a period of time using the satellite image data (Morris and Fan 1998, Smith and Pavelsky 2009) [10]. In this study, sub-pixel classification have been used to extract the water spread area of the reservoir. The methodology for this study is given in Fig. 2.

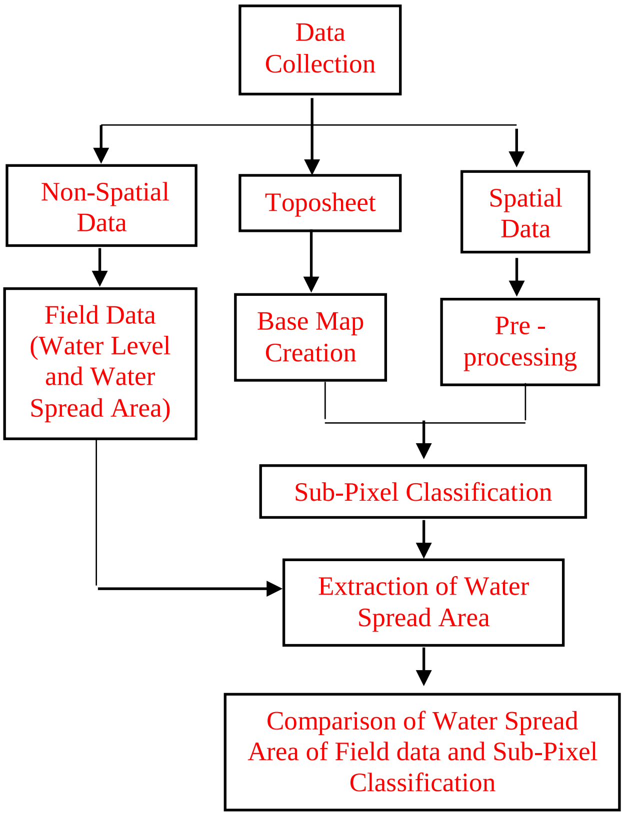

Fig. 2. Flowchart of Methodology adopted

The procedures of sub-pixel classification try to improve the limitations of the imagery with coarse resolution. This classification tries to reveal possible mixtures of the different cover types and defines the area fractions for each pixel. The true class distribution may be well estimated even if the exact location of the class fractions within each coarse resolution pixel remains unknown. Sub-pixel classification approach is usually done using the linear mixture model or neural networks. These algorithms have been applied in the context of both low and high spatial resolution imagery (Van der Meer, 1995; Atkinson et al., 1997; Foody et al., 1997; Klein Gebbinck, 1998; Swinnen et al., 2001; Kavzoglu and Mather, 2003; Lobell and Asner, 2004; Eerens and Dong, 2005) [6].

V. RESULTS AND DISCUSSIONS

Sub-pixel classification approach have been performed on all the nine dates of satellite pass using the following approaches:

- Principal Component Analysis
- End member Collection
- Linear Spectral Unmixing

A. Principal Component Analysis

Principal Component Analysis is used to produce uncorrelated output bands, segregate noise components and reduce the dimensionality of data sets. Multispectral data bands are often highly correlated. This can be attributed to a number of factors such as material spectral correlation, topography and sensor band overlap (Schowengerdt 1997) [9]. Hence, it is difficult to analyze these correlated bands because of redundancy. To remove this redundancy, a feature space transformation known as principal component transformation (PCT) is used. The first PC band contains the largest percentage of data variance and the second PC band contains the second largest data variance, and so on.

PC1 and PC2 are two highly uncorrelated bands. The scatter plots obtained on plotting the different principal components is a spatial distribution of the pixels in a two-dimensional feature space [9]. The shape of the plot gives an idea of the number of end-members (Bryant 1994, Shanmugam 1998 and Schowengerdt 1997) [9]. This means that the number of vertices in the data cloud of the scatter plot of PC1 versus PC2 corresponds to the number of end-members (Bateson and Curtiss 1996) [9]. In the plot, the purest pixels are located at the extreme corners of the data cloud and the other pixels are the mixed pixels which are picture elements representing an area occupied by more than one ground cover type. Classification of mixed pixels leads to errors that make the subsequent area estimation inaccurate [3]. Therefore, the selection of the end-members can be done at the extreme corners of the data cloud in the scatter plot of PC1 against PC2.

B. Endmember Collection

End-members are pure pixels which represents 100% or almost 100% of a ground cover type. The quality of the fraction images derived from linear spectral unmixing depends on sufficient number and the proper selection of endmembers [9]. Spectral un-mixing requires accurate, well-characterised end-members (Milton 1999) [9]. Improper selection of end members may result in computational error of fractions of the ground cover type present in an image. Therefore, it is important to accurately select the end members for the technique of linear spectral un-mixing. The identification and description of the physical and spectral properties of end-members is thus, of great importance in spectral unmixing (Tompkins et al 1997, Milton 1999, Myint and Okin 2009, He et al 2010) [9].

C. Linear Spectral Unmixing

Spectral unmixing is an excellent approximation for calculating the abundance or fraction of an end-member in an image pixel [9]. The reflectance at each pixel of the image is assumed to be a linear combination of the reflectance of each material (or endmember) present within the pixel. This soft classification technique aims at estimating the proportions of specific classes that occur within each pixel using linear mixing approach (Foody and Arora 1996, Arora and Foody 1997, Bajjouk et al 1998, Aplin 2001, Mertens et al 2006, Weng and Lu 2008, Carola et al 2010) [9]. The number of end members must be less than the number of spectral bands, and all of the endmembers in the image must be used. Spectral unmixing results are highly dependent on the input endmembers; changing the end members changes the results.

The water spread areas for the different dates of satellite pass have been delineated using the sub-pixel classification approach and are shown in Fig. 3.

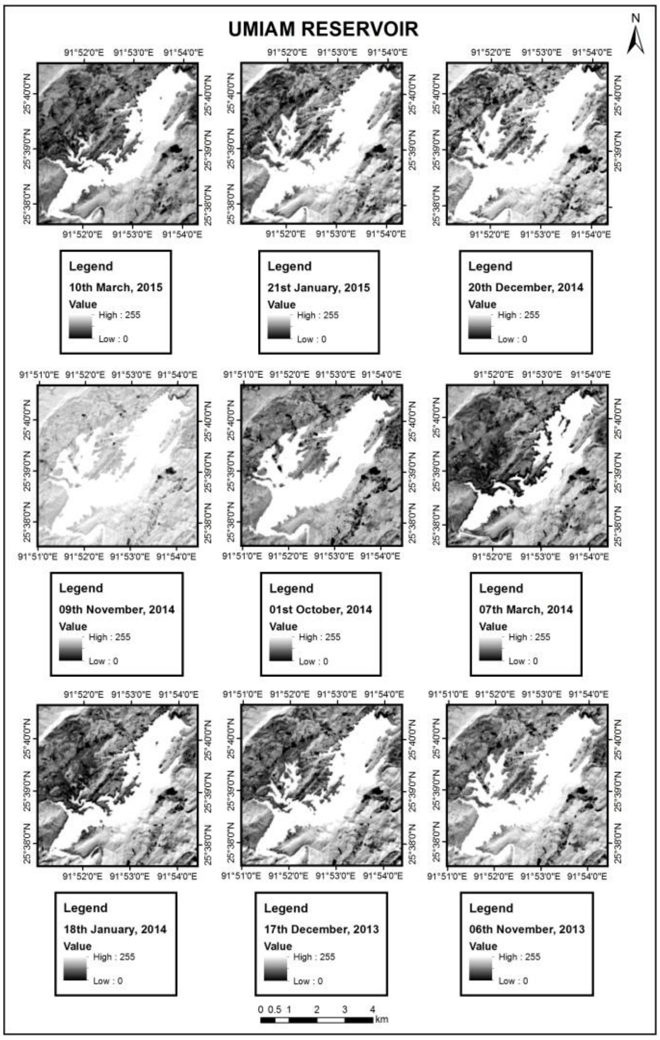

Fig. 3. Sub-pixel classification for different dates of satellite pass

TABLE II. EXTRACTION OF WATER SPREAD AREAS OF DIFFERENT DATES OF SATELLITE PASS AND COMPARISON WITH FIELD DATA

Date of Satellite Pass	Field data: Water Level (m)	Field data: Water Spread Area (km^2)	Extracted Water Spread Area (km^2)	Difference in Water Spread Area (km^2)
10.03.2015	972.28	6.29	5.73	0.56
21.01.2015	975.42	7.61	6.89	0.72
20.12.2014	977.41	8.44	7.70	0.74
09.11.2014	979.54	9.34	8.48	0.86
01.10.2014	981.20	10.03	8.72	1.31
07.03.2014	967.92	5.28	4.60	0.68
18.01.2014	971.50	6.46	5.42	1.04
17.12.2013	975.02	7.62	6.80	0.82
06.11.2013	977.37	8.39	7.86	0.53

Thus, from Table II, it was clearly seen that the water spread areas which were extracted by sub-pixel classification were lesser compared to the water spread areas of the field data.

VI. CONCLUSION

In this study, sub pixel classification approach was performed for the nine dates of satellite pass and the water spread areas were also extracted. Linear Mixture Modelling was adopted for sub pixel classification as it is a widely used technique. Thus, in the next part of the study, the water levels collected from the authority and the extracted water spread areas will be used for estimating the capacity of the reservoir.

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