Reservoir Capacity Estimation Using Remote Sensing Data—Perpixel Classification and Super Resolution Mapping Approaches

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Abstract

Sediments carried by the rivers are deposited in the reservoirs and cause several detrimental effects, which include loss of storage capacity, upstream aggradations, effect on water quality and damage or impairment of hydro-equipments. The deposition of sedimentation not only reduces the capacity but also the water-spread of the reservoir. Satellite data has long been in use to estimate the water-spread area at different elevations of a reservoir, which in turn can be used to quantify the capacity of the reservoir. The methodology to estimate the capacity of a reservoir using remote sensing data involves hard or per-pixel based classification to delineate the water-spread area at a particular elevation. One of the limitations of this approach is that the border pixels, representing soil class with moisture, are classified entirely as water pixels, thereby giving inaccurate estimate of the water-spread area. To estimate the water-spread area of Somasila reservoir, Andhra Pradesh accurately, super resolution mapping approach which converts the pixels in to higher resolution one has been adopted in this study. IRS-1C and 1D satellite image data (24 m) of seven optimal dates ranging from minimum draw down level (MDDL) to full reservoir level (FRL) were used to estimate the water-spread area of the reservoir. The extracted water-spread areas using per-pixel and supper resolution approaches were in turn used to quantify the capacity of the Somasila reservoir. The estimated capacity of the Somasila reservoir, Andhra Pradesh using per-pixel and supper resolution approaches was 1128.13 Mm^3 and 1133.70 Mm^3 respectively.

Introduction

India is a vast country with high spatial and temporal variability of rainfall. In order to tap the available water resources and to utilize the water in accordance with the requirements, a number of river valley projects have been constructed for serving various conservation purposes, such as water supply for domestic and industrial purposes, irrigation, hydropower generation, navigation and recreation. One of the principal factors that threaten the life of such projects is the accumulation of sediments in the reservoirs. Sedimentation reduces the storage capacity of reservoirs and hence their ability to conserve water for various intended purposes. Sedimentation also reduces the survival of aquatic life and restricts the use of water for multiple purposes. For assessing the sedimentation deposition pattern in a reservoir, systematic capacity surveys of the reservoir are conducted periodically. Present conventional techniques of sediment quantification in a reservoir, like the hydrographic surveys and inflow-outflow methods are cumbersome, expensive and time consuming. Remote sensing through its spatial, spectral and temporal attributes can provide synoptic, repetitive and timely information regarding the water spread area of the reservoir. Estimated water spread areas were used in a simple volume estimation formula to compute the storage capacity of the reservoir. In this study maximum likelihood classification and super resolution approaches have been used to compute the water spread area of Somasila reservoir and in turn to estimate the cumulative capacity of the reservoir.

Study Reservoir

Somasila reservoir is located on the river Pennar which flows through the Nellore district in Andhra Pradesh, India. The reservoir is at a distance of about 80 k.m from Nellore town which is also the district capital. The river basin receives rainfall during both the monsoon seasons (NE and SW) with major contribution from the Northeast monsoon. The normal annual rainfall at Nellore is 988 mm. The mean maximum and mean minimum temperatures are 40.9°C and 16.9°C respectively. The principal soil types in the basin are red loam, red sand, black loam and black clay. Red soils cover major portion of the basin. The general crops grown in the basin are paddy, groundnut, Bajra, Jowar, Ragi, Vegetables and Sugarcane. With the aforementioned topography, rainfall and landuse, it is evident that an appreciable amount of sediment is carried by the streams in the basin into the Somasila reservoir, thereby reducing its capacity.

Satellite Data Used

The image data used in this study were obtained by the Indian Remote Sensing (IRS) satellites IRS-1C and 1D (LISS-III sensor) which provides a spatial resolution of 24 m and spectral resolution in four different bands (0.52–0.59, 0.62–0.68, 0.77–0.86, 1.55–1.70 µm). Reservoir water level data on the day of satellite pass and the available hydrographic survey details have been collected from the Somasila Reservoir Authority responsible for collection of required data and operation of the reservoir. The different dates of the satellite data used and the respective water level during the pass of the satellite over the reservoir are given in Table 1.

Methodology

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). Per-pixel classification and super-resolution mapping approaches have been used in this study to extract the water spread area of the reservoir. Estimated water spread areas were used in a simple volume estimation formula to compute the storage capacity of the reservoir. Estimation of the water spread area and the computation of the capacity of the reservoir are discussed in the following sections.

Table 1: Details of the Satellite Data Used and the Water Level during the Pass of the Satellite over the Reservoir

Sl. No.	*Date of Pass*	*Satellite and Sensor*	*Reservoir Water Level above m.s.l (m)*
1.	17.01.2002	IRS 1C - LISSIII	94.39
2.	22.03.2002	IRS 1D - LISSIII	93.47
3.	16.04.2002	IRS 1D - LISSIII	92.10
4.	11.05.2002	IRS 1D - LISSIII	90.14
5.	05.06.2002	IRS 1D - LISSIII	88.30
6.	27.11.2002	IRS 1D - LISSIII	85.69
7.	13.09.2002	IRS 1D - LISSIII	83.17

In the IRS-1C and 1D (LISS-III) satellite data the reservoir water spread area was free from clouds and noise for all of the seven temporal images used. All the images used in the study were geo-referenced using polyconic projection and the nearest neighbour re-sampling technique to create a geo-referenced image with a pixel size of 24 m × 24 m. In every image, 20 to 25 ground control points were used, which resulted in a Root Mean Squared Error (RMSE) of 0.17 to 0.21 of a pixel.

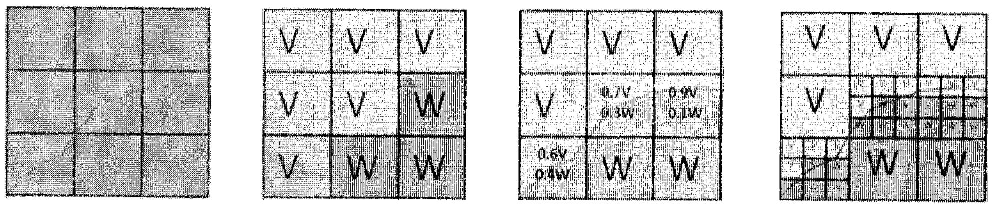
Per-Pixel Based Approach

The most widely used method for extracting information on the surface cover from remotely sensed data is image classification. Digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands and attempts to classify each individual pixel (per-pixel approach) based on this spectral information. A number of commonly used per-pixel based classifiers exist including the maximum likelihood (MLC), the minimum distance to mean, mahalanobis distance and the parallelipiped classifiers. The objective of the per-pixel based classifiers is to assign all pixels in the image to particular classes or themes (e.g. water, forest, urban, agriculture). The resulting classified image is comprised of a mosaic of pixels, each of which belongs to a particular theme and is essentially a thematic map of the original image. MLC is a parametric classifier that assumes normal or near normal spectral distribution for each class of interest. This technique takes in to account the variability of classes by using the covariance matrix; thus, it requires more computation per pixel. MLC requires sufficient representative spectral training sample pixels for each class to accurately estimate the mean vector and covariance matrix. If the training samples are insufficient in number or having multimode distributions this often leads to poor classification results.

Many authors (Manavalan *et al.*, 1993; Bryant *et al.*, 1999; Goel *et al.*, 2002; Peng *et al.*, 2006; Jeyakanthan and Sanjeevi, 2011) have attempted estimation of water spread area of reservoirs using different classification techniques, including the per-pixel classification approach and they reported that the presence of mixed pixels along the periphery of a reservoir may impose serious errors in such estimations, if the per-pixel approach is adopted. Therefore, in this study, water-spread area was extracted using super resolution mapping approach and MLC is also used for comparative purpose.

Super Resolution Based Approach

Super-resolution mapping is a set of techniques for predicting the location of land cover classes within a pixel based on the proportion images produced by soft classification. Hence, the spatial resolution of the resulting maps from super-resolution mapping is higher than those obtained from conventional hard-classification such as maximum-likelihood or minimum-distance-to-means. The super-resolution mapping techniques are based on the assumption that a pixel is composed of a matrix of sub pixels. The location of these sub-pixels can be predicted based on the concept of spatial dependence which refers to the tendency of proximate sub-pixels to be more alike than those located far apart. There have been several techniques proposed for super-resolution mapping: spatial dependence maximisation (Atkinson, 1997), sub-pixel per-field classification (Aplin and Atkinson, 2001), linear optimisation techniques (Verhoeye and De Wulf, 2002), Hopfield neural network optimisation (Tatem *et al.*, 2001, 2002), two-point histogram optimisation (Mertens, 2003), genetic algorithms (Atkinson, 2003) and feed-forward neural networks (Mertens, 2004). These approaches produced the sub-pixel land cover maps which were more detailed and accurate than those obtained from hard classification.



Actual ground | Per-pixel classification | Sub-pixel classification | Result of Super resolution mapping overlaid with boundary line condition

Fig. 1: Illustration for the Concept of Super-Resolution Mapping

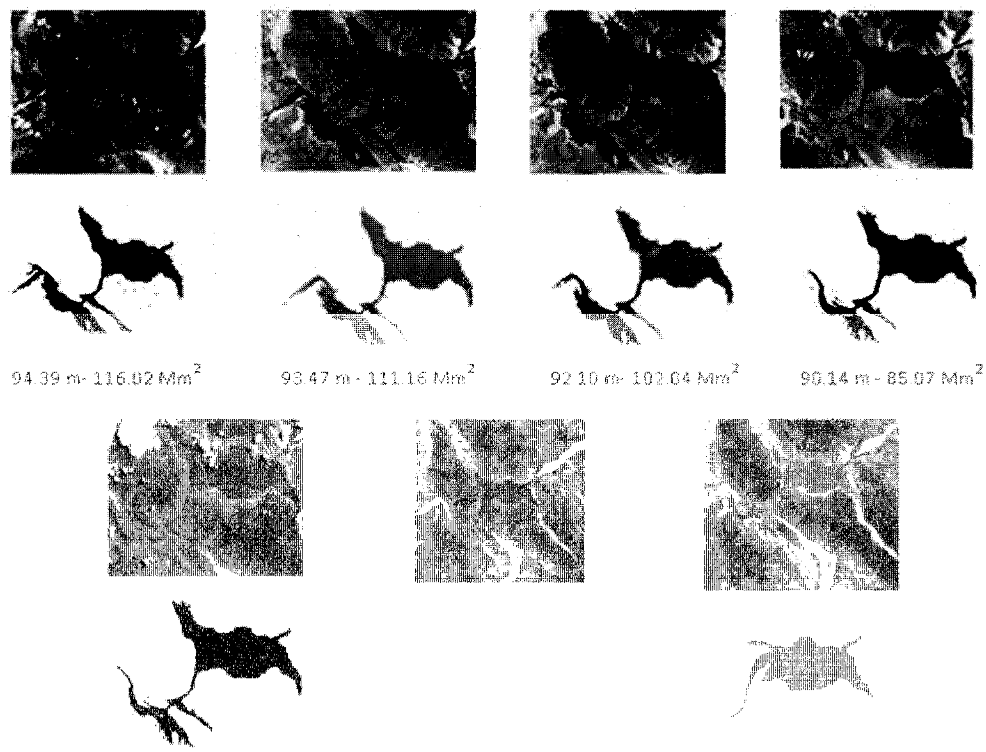


Fig. 2: Extracted Water Spread Area of Somasila Reservoir Using MLC

In this study super resolution technique using Hopfield Neural Network was applied to multi-spectral images. With this technique each pixel was sub-divided and assigned its own class. However, mathematical optimization was carried out to result in better accuracy. In this work, a single pixel of IRS-P6 image which has a resolution of 24 m was sub-divided into 25 pixels. The classes assigned to each sub-divided pixel is based on the fraction image and optimized through Hopfield Neural Netwoln this study super resolution technique using Hopfield Neural Network was applied to multispectral images. With this technique each pixel was sub-divided and assigned its own class. However, mathematical optimization was carried out to result in better accuracy. In this work, a single pixel of IRS-P6 image which has a resolution of 24 m was sub-divided into 25 pixels. The classes assigned to each sub-divided pixel is based on the fraction image and optimized through Hopfield Neural Network. The water spread area estimated from this method of super-resolution mapping is compared with the per-pixel classification approach and presented in the result section. Illustration for the concept of super-resolution mapping and extracted water-spread area of somasila reservoir using MLC shown in the Figures 1&2.

Computation of Volume between Successive Water Levels

Traditionally the reservoir volume between two consecutive reservoir water levels, was computed using the prismoidal formula, the Simpson formula and the trapezoidal formulae (Patra 2001). Of these, the trapezoidal formula has been most widely used for computation of volume (Goel and Jain 1996, Rathore 2006). The water-

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