SUPER RESOLUTION MAPPING OF SATELLITE IMAGES TO ESTIMATE THE CAPACITY OF RESERVOIRS AROUND CHENNAI CITY

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ABSTRACT: Reservoir capacity estimation is often carried out by field surveys, which is a time consuming and tedious process that cannot be performed periodically. To overcome this issue, satellite images are used, where the area estimation is made by the conventional per-pixel classification algorithms. These techniques, however, result in inaccurate estimation of reservoir capacity because the per-pixel classification techniques assume one class per pixel and classify the remotely sensed images. This paper presents a super resolution mapping technique, which predicts and maps the location of several land cover classes within the pixels of the images of Poondi and Chembarambakkam reservoirs of Chennai city.

The Hopfield Neural Network algorithm was developed and applied Landsat OLI image of the reservoirs. The fraction images of the reservoir sites, obtained by sub-pixel classification, were subjected to super resolution mapping to accurately estimate the water-spread area and the capacity of the reservoirs. Thus, the pixels with mixed land cover classes along the periphery of the reservoirs were accurately classified in terms of the abundance of water. The water-spread area estimated using super resolution mapping approach can be used as an input in the volume estimation equation to estimate the volume at different water levels of the reservoirs. Super-resolution Mapping approach gives minimum error when compared to sub-pixel approach which inturn gives less erroneous result when comparing per-pixel approach.

1. INTRODUCTION

There are no perennial rivers in Chennai city and it largely depends only on the rainwater stored in lakes and reservoirs located in its periphery. Landuse change, climate cycles and variability; demography and occupation of marginal lands, interception and diversion of surface water, ground water mining and pollution have resulted in several issues in these lakes and reservoirs. Erosion in the catchment area, movement of sediment and its deposition in various parts of the reservoir require careful consideration in the reservoir management.

The silt that is deposited at different levels reduces the storage capacity of the reservoirs (Smith and Pavelsky 2009) Chembarambakkam and Poondi. Reduction in the storage capacity beyond a limit prevents the reservoir from fulfilling the purpose for which it is designed. Periodic capacity surveys of the reservoir help to assess the rate of sedimentation and reduction in storage capacity. Conventional techniques for the estimation of the capacity of a reservoir, such as hydrographic survey and inflow-outflow approaches, are cumbersome, time consuming and expensive, and they involve significant manpower. As an alternative to conventional methods, the remote sensing technique provides cost and time effective estimation of the capacity of a reservoir (Sabastian 1995, Jain 2002).

Many researchers have carried out works pertaining to capacity estimation of reservoirs using remote sensing techniques, which is cost and time effective. Such work has been reported by Garde and Kothyari (1987) for Upper Lake, Bhopal, Manavalan (1993) for Bhadra and Malaprabha reservoirs in the Krishna river basin, Sakthivadivel (1999) for Malaprabha reservoir in Karnataka, Jain et al., (2002) for Bhakra reservoir in Himalayas, Jeyakanthan (2002) for Peechi reservoir located in Tamilnadu, India, Rathore et al., (2006) for Hirakud reservoir in Mahanadhi basin, Bryant et al., (1999) for the Painted Rock Reservoir, southwest of Phoenix, Arizona, Peng et al., (2005) for Dongting Lake and Fengman reservoir in China.

Thus, these works proves that the remote sensing based capacity survey is economical and time effective. However, the remotely sensed images are composed of mixed pixels. Hence, the conventional hard classification techniques assign the mixed pixels to the dominant classes and it ignores the impact of the mixed pixels. Sub-pixel mapping attempts to overcome this problem by predicting the fraction of class components within a pixel.

Sub-pixel mapping techniques such as Spectral Mixture Analysis (SMA), Fuzzy C Means (FCM), Artificial Neural Network (ANN) etc., are used for vegetation mapping (Peddle and Smith, 2005), land cover mapping (Foody et al., 1994, Rodrigo sagardia, 2005, Zhang et al., 1998), water-spread area estimation (Carola et al., 2010). However, these sub-pixel mapping techniques do not predict the location of class components with in a pixel. Thus, super resolution mapping techniques are introduced where the fraction images from the sub-pixel classification are given as input to super resolution mapping algorithms. It is expected that the super resolution mapping algorithm will accurately locate the class components with in a pixel.

Super resolution mapping techniques (pixel swapping, Hopfield Neural Network, Gentic algorithm etc) are used for accurately mapping the location of the classes within a pixel. Shanmugapriya et al., (2004) compared per-pixel approach, sub-pixel approach and super resolution mapping approach for estimating the water-spread area of Peechi reservoir, southern India. This paper proposes a super resolution mapping technique, which predicts and maps the location of water-spread areas of the Poondi and Chembarambakkam reservoirs of Chennai city at sub pixel level and then, the capacity of the reservoirs are estimated.

2. STUDY AREA OF THE TWO RESERVOIRS

2.1 Poondi Reservoir

Poondi Reservoir was constructed in 1944 across the Kosathalaiyar River in Thiruvallur district Tamilnadu State, south India, with a capacity of 3,231 Mcft. Surplus water flows down the river which is again intercepted by Tamaraipakkam Anicut and diverted to Cholavaram Lake and Puzhal lake. The bed level of the reservoir is32m and the full reservoir level is 42.67m. The water-spread area at full reservoir level is 34.58 Sq.Km.

2.1 Chembarambakkam Reservoir

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The Chembarambakkam reservoir has a capacity of 3,645 Mcft. The reservoirs lose 5 Mcft daily due to evaporation. Chembarambakkam reservoir is located near Chennai in Kanchipuram district of Tamil Nadu, India. A part of water supply of the metropolis of Chennai is drawn from this reservoir. The Full Tank Level is 26.03m. The water-spread area at full reservoir level is 15.38 Sq.Km. Fig 1 shows the location map of Poondi and Chembarambakkam reservoirs.

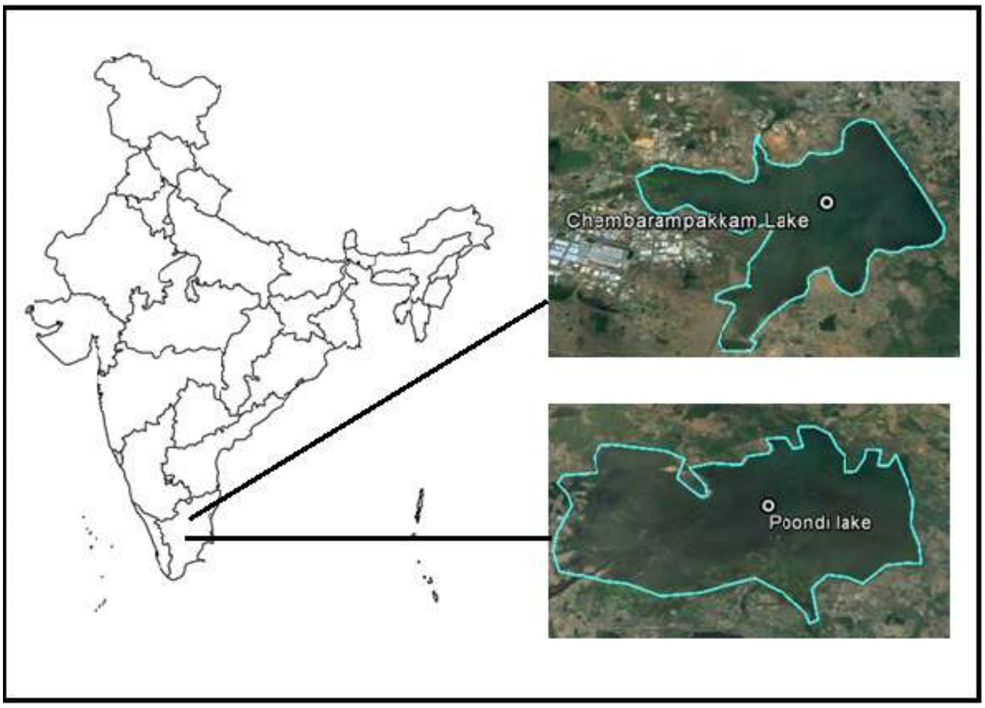


Figure 1. Location map of Poondi and Chembarambakkam Reservoirs

Being the source for drinking water for the metropolitan city, estimation of reservoir capacity conventionally, is time consuming and laborious. Hence the study attempts to suggest the most reliable technique for estimating the capacity of reservoirs using remote sensing by super resolution mapping of satellite images.

3. METHODOLOGY

In this work, per-pixel, sub-pixel and super resolution mapping approaches have been used to extract the water-spread area of the reservoirs. The estimated water-spread areas were used in a simple volume estimation formula to compute the storage capacity of the reservoirs. Estimation of the water-spread area and the computation of the capacity of the reservoir are discussed in the following sections.

3.1 Per-pixel classification using maximum likelihood classification

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood $L_k(X)$ is defined as the posterior probability of a pixel belonging to class k.

$$L_k(X) = P(k/X) = \frac{P(k).P\left(\frac{X}{k}\right)}{\sum P(i).P\left(\frac{X}{i}\right)} \quad (1)$$

where, P(k) is the prior probability of class k, P(X/k) is the conditional probability to observe X from class k, Lk(X) is the likelihood of X belonging to class k

The water-spread area of the reservoir was estimated by multiplying the number of pixels classified as water with the area (15×15 m) of a Landsat 8 image pixel. In the boundary of the reservoir contains mixed pixels of water and sand or water and vegetation. This mixed pixel is sometimes classified as water. This may cause over estimation of water-spread area of the reservoir. To overcome this sub-pixel classification was used.

3.2 Sub-pixel classification using Linear Spectral Unmixing

Linear Spectral Unmixing is used for sub-pixel classification to estimate the class components within a pixel. The Linear Spectral Unmixing classification technique attempts to estimate the proportions of specific classes that occur within each pixel using the linear mixing approach (Aplin and Atkinson 2001). Settle and Drake (1993) and Foody and Cox (1994) proposed a mathematical expression for linear spectral unmixing.

$$R_i = \sum f_k R_{ik} + E_i \quad (2)$$

where $\Sigma f_k = 1$, $0 \le f_k \le 1$, i is the number of spectral bands, k is the number of end-members, R_i is the Spectral reflectance of band i of a pixel which contains one or more end-members, f_k is the proportion of end-member k within the pixel, R_{ik} is the known spectral reflectance of end-member k within the pixel in band i, E_i is the error for band i.

The water-spread area of each pixel is estimated by multiplying the percentage proportion of water with the area (15×15 m) of a Landsat 8 image pixel. By summing up the area occupied by all the pixels in the fraction image, the total water-spread area of the reservoir was computed.

3.3 Super Resolution Mapping using Hopfield Neural Network

The Hopfield Neural Network is used for super resolution mapping. It is an optimization algorithm used to locate the class components within a pixel. It is a feed forward neural network and it can be used for energy minimization problems. The proportion image from the Linear Spectral Unmixing is used as a supplementary data for Hopfield Neural Network. Here, each pixel is resolved in to sub pixels depending on the mapping window size. The network energy function of the sub-pixel mapping task is

$$\mathrm{E} = -\sum_{\mathrm{i}} \sum_{\mathrm{j}} (\mathrm{k1G1} + \mathrm{k2G2} + \mathrm{k3P} + \mathrm{k4M}) \quad (3)$$

where, k1, k2, k3 are constants weighting the various energy parameters with a value = 1, G1 and G2 are output values for neuron of the two goal functions, P is the output value of the neuron for proportion constraint, M is the output value of the neuron for multi-class constraint.

The first goal function is aimed to increase the output of the central neuron to 1, if the average output of the surrounding eight neurons is greater than 0.5 and the second goal function is aimed to decrease the output of the central neuron to 0, given that the average output of the surrounding eight neurons is less than 0.5.

G1 (i, j) = (floor (1 + tanh (avg - 0.5))) * (neuronopt (i, j) - 1.0); (4)

G2 (i, j) = (1 – floor (1 + tanh (avg - 0.5))) * neuronopt (i, j); (5)

where, floor is a function which rounds the element to the nearest integer, avg is the average output of the surrounding neurons, neuronopt is the initial random values assigned for proportions, $1 \leq i \leq$ mapping window size, $1 \leq j \leq$ mapping window size.

The value of the multi-class constraint (M) is calculated as follows:

$$M = \left(\sum_{k=1}^{Total\ class} avg_{kij} \right) - 1 \tag{6}$$

where, avg_{kij} is the average output of the k^{th} class for the sub-pixel at position (i, j).

The super-resolved map is obtained for each class. In this work, the image of 15m resolution is classified and enhanced to a 3m super-resolved map. This is because the pixels are resolved in to sub-pixels of mapping window size 5. (Each pixel is resolved in to 25 sub-pixels). The super-resolved map gives information on the spatial distribution of classes within the pixel. The water-spread area of the reservoir was estimated by multiplying the number of sub-pixels classified as water with the area (3×3m) of a Landsat 8 image pixel.

3.4 Reservoir Capacity Estimation

The reservoir volume between two consecutive reservoir water levels was computed using the prismoidal formula, the Simpson formula or the trapezoidal formula (Patra 2001). The trapezoidal formula has been most widely used for the computation of volume (Rao et al. 1985, Goel and Jain 1996, Morris and Fan 1998, Rathore 2006). The water-spread area estimated using the per-pixel, sub-pixel and super resolution mapping approaches were separately used as an input to the volume estimation formula to determine the volume at different water levels of the reservoir. In this study the volume between two consecutive reservoir water levels was computed using the following trapezoidal formula:

$$V = H * (A1 + A2 + \sqrt{A1*A2})/3 \tag{7}$$

where, V is the volume between two consecutive water levels, A1 and A2 are the water-spread areas at the reservoir water levels 1 and 2 respectively and H is the difference between these two water levels. The volumes computed (using equation 7) between different water levels (i.e., from minimum draw down level (MDDL) to full reservoir level (FRL)) were added together to calculate the cumulative or storage capacity of the reservoir.

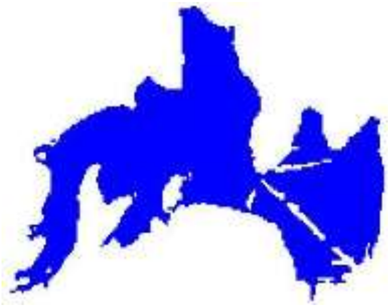
4. RESULTS AND DISCUSSION

Experiments are carried out using multi-date (before monsoon and after monsoon) Landsat 8 (Bands 1-8) image of resolution 15m for Poondi and Chembarambakkam Reservoirs. Per-pixel (maximum Likelihood), sub-pixel (Linear spectral Unmixing) and super resolution mapping (Hopfield Neural Network) approaches are applied to the Landsat 8 FCC image of the Poondi and chembarambakkam reservoirs to estimate the water-spread area of the reservoirs and then the capacity of the reservoirs are calculated.

4.1 Experiment 1 – Poondi Reservoir

The first experiment was performed for Poondi reservoir using 15m resolution multi-date Landsat 8 image. The image area consists of three classes namely water, vegetation and sand. Fig 2(b) show the hard classified output of the Poondi reservoir using Maximum Likelihood classification in which each pixel is assigned to a single class. So, for a mixed pixel some information is lost. To overcome this problem, sub-pixel approach (LSU) is performed which results in proportion images of the classes. Fig 2(c) shows the proportion image of the water spread area of the reservoir. The brighter pixels represent the presence of the class and the darker pixel represents the absence of the class. This sub-pixel approach does not locate the proportion of class components with in a pixel. To overcome this problem, proportion image is given as input to super resolution mapping (HNN) approach, in which the super resolved map at sub-pixel level is obtained and is shown in Fig 2(d). From these output images, the water-spread area of the reservoir was estimated and then from the water-spread area, the volume of the reservoir was calculated.

(a)



(b) **(c)** **(d)**

Figure 2. (a) Landsat 8 false color composite image of poondi reservoir, (b) Hard classified output from per-pixel approach (Maximum Likelihood Approach), (c) Proportion image form sub-pixel approach (Linear Spectral Unmixing) and (d) Super resolved map from super resolution mapping approach (Hopfield Neural Network)

Estimation of capacity of Poondi reservoir was carried out for the period 2015-2016. To calculate the prevailing water-spread area of 2015-16, cloud free satellite data of four different elevations have been selected which varies from 37.29m to 42.02 m. River bed and Full Reservoir Level (FRL) of the reservoir is 32.00m and 42.67m respectively. The satellite data pertaining to the selected water levels or elevations were procured and their corresponding water-spread areas were calculated using per-pixel, sub-pixel and super resolution mapping approaches.

From the extracted water-spread areas of the Poondi reservoir at different water levels, the corresponding volumes were worked out using the trapezoidal formula. The storage capacity between the Dead storage (34.14m) of the reservoir and the lowest observed water level (37.29m) could not be estimated using remote sensing methodology due to non-availability of cloud free satellite data. Therefore, the capacity (2.29 Mm^3) between these two levels was adopted from the elevation-capacity table, available with the dam authority. Above the lowest observed level, the cumulative capacities between the consecutive levels were added up so as to reach at the cumulative capacity at the maximum observed level. The estimated cumulative capacity of Poondi reservoir using the various classification approaches is presented in the Table 1.

Table 1. Capacity estimation of the Poondi Reservoir using per-pixel, sub-pixel and super resolution mapping based approaches.

Date of Satellite Pass	Reservoir Level (m)	Water-spread area			Cumulative Volume		
		Per-pixel approach (Mm^2)	Sub-pixel approach (Mm^2)	Super Resolution Mapping approach (Mm^2)	Per-pixel approach (Mm^3)	Sub-pixel approach (Mm^3)	Super Resolution Mapping approach (Mm^3)
03-02-2016	42.02	30.04	31.53	33.28	83.68	88.55	92.08
06-03-2016	41.50	28.54	29.78	32.58	68.46	72.62	75.97
23-04-2016	40.89	19.21	20.1	21.02	53.99	57.51	56.49
14-10-2015	37.29	9.98	11.03	10.05	2.29	2.29	2.29

4.2 Experiment 2 – Chembarambakkam Reservoir

Similarly, the same set of experiment was carried out for the Chembarambakkam reservoir for the period 2015-2016. The water-spread area of Chembarambakkam reservoir using the various classification approaches is shown in Figure 3. The estimated water-spread area and the cumulative capacity of the reservoir using per-pixel, sub-pixel and super resolution mapping approaches are tabulated in Table 2.

(a)

(b) **(c)** **(d)**

Figure 3. (a) Landsat 8 false color composite image of Chembarambakkam reservoir, (b) Classified output from per-pixel approach (Maximum Likelihood Approach), (c) Proportion image form sub-pixel approach (Linear Spectral Unmixing) and (d) Super resolved map from super resolution mapping approach (Hopfield Neural Network)

Table 2 Capacity estimation of the Chembarambakkam Reservoir using per-pixel, sub-pixel and super resolution mapping based approaches

Date of Satellite Pass	Reservoir Level (m)	Water-spread area			Cumulative Volume		
		Per-pixel approach (Mm^2)	Sub-pixel approach (Mm^2)	Super Resolution Mapping approach (Mm^2)	Per-pixel approach (Mm^3)	Sub-pixel approach (Mm^3)	Super Resolution Mapping approach (Mm^3)
03-02-2016	25.35	11.51	12.52	14.63	90.3	95.27	102.61
06-03-2016	25.02	11.12	12.32	14.54	86.57	91.18	97.8
23-04-2016	24.27	11.05	12.15	14.00	78.26	82.01	87.1
14-10-2015	20.31	9.98	10.95	11.70	36.3	36.3	36.3

4.3 Validation of estimated capacity of the reservoirs

The estimated capacity of the reservoirs using the satellite images are compared with the capacity of the reservoirs obtained from the reservoir authority (Table 3). The capacity of the reservoirs is displayed on daily basis in the website of Chennai Metro Water Supply and Sewage Board (CMWSSB).

Table 3 Comparison of capacity of the reservoirs from the reservoir authority and the estimated capacity of the reservoirs using per-pixel, sub-pixel and super resolution mapping approaches

Date of Satellite Pass	Capacity of Poondi (Mm^3)				Capacity of Chembarambakkam (Mm^3)			
	From the reservoir authority	Per-pixel approach	Sub-pixel approach	Super Resolution Mapping approach	From the reservoir authority	Per-pixel approach	Sub-pixel approach	Super Resolution Mapping approach
03-02-16	91.29	83.68	88.55	92.08	103.12	90.3	95.27	102.61
06-03-16	76.83	68.46	72.62	75.97	98.7	86.57	91.18	97.8
23-04-16	55.48	53.99	57.51	56.49	88.5	78.26	82.01	87.1
14-10-15	2.29	2.29	2.29	2.29	36.3	36.3	36.3	36.3

The percentage of error between the per-pixel, sub-pixel and super resolution mapping approaches was calculated. For example the percentage of error for validation was calculated as follow: ((91.29 – 83.68)/91.29) x 100 = 8.33% (Table 4).

Table 4 Percentage (%) of error between the per-pixel, sub-pixel and super resolution mapping approaches

	% Error (Poondi)			% Error (Chembarambakkam)		
Date of Satellite Pass	Per-pixel approach	Sub-pixel approach	Super Resolution Mapping approach	Per-pixel approach	Sub-pixel approach	Super Resolution Mapping approach
03-02-2016	8.34	3.00	0.87	12.43	7.61	0.49
06-03-2016	10.89	5.48	1.12	12.29	7.62	0.91
23-04-2016	2.69	3.66	1.82	11.57	7.33	1.58

It is observed that the average percentage of error using per-pixel, sub-pixel and super resolution mapping approaches are 7.31%, 4.04% and 1.26% respectively for Poondi reservoir. However, for chembarambakkam reservoir the average error for the above mentioned approaches has been found to be 12.10%, 7.52%, and 1.00% respectively.

5. CONCLUSION

This paper has estimated reservoir water-spread area from various approaches, such as per-pixel, sub-pixel, and super-resolution mapping approaches. With this as input, the volume of the reservoirs is estimated; the accurate estimation of the reservoir volume was achieved through the area from super-resolution mapping approach. . Since, the super-resolution mapping approach enhances the spatial resolution of the satellite image, the area is accurately estimated, inturn the capacity of the reservoirs is also accurately estimated. The average error percentage obtained from the super resolution mapping for Poondi and Chembarambakkam reservoirs are 1.26% and 1.00% respectively Super-resolution Mapping approach gives minimum error when compared to sub-pixel approach which inturn gives less erroneous result when comparing per-pixel approach. Hence, Super-resolution approach can be admitted to be a promising technique for estimating the capacity of reservoir in a very less laborious way. The conventional capacity estimation involves the usage of height versus capacity graph, but this super resolution mapping using Hopfield Neural Network give the area versus capacity graph which will be useful for the reservoir authorities for easy and accurate estimation of the reservoir capacity.

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