Estimation of Reservoir Capacity using Geo-Spatial Techniques

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Abstract— Satellite faraway sensing of near real-time reservoir storage versions has critical implications for flood tracking and water resources control. However, satellite altimetry data, which can be crucial for estimating storage versions, are only available for a restricted wide variety of reservoirs. This loss of excessive-density spatial coverage directly hinders the capacity use of remotely sensed reservoir facts for improving the competencies of hydrological modeling over noticeably regulated river basins. To remedy this problem, a reservoir storage dataset with high density spatial insurance become advanced by using combining the water surface area estimated from SENTINEL imageries with the Digital Elevation Model (DEM) records collected via the CARTOSAT-1. This reservoir dataset represents the overall storage potential of NAGARJUNA SAGAR. With the general availability of Sentinel and DEM data, this set of algorithm may be potentially carried out for observing worldwide reservoirs at a high density.

Keywords: Reservoir Storage; SENTINEL; DEM

I. Introduction

Human-made reservoirs, which can be controlled by way of storing and freeing water underneath predetermined operation regulations, play an essential role in mitigating floods and improving the performance of the water deliver for municipal, business, and agricultural demands. Although maximum (if no longer all) human operated reservoirs are monitored in real-time, reservoir storage statistics is not usually to be had to the general public. Indeed, this directly limits the effectiveness of reservoir flow regulation with regard to flood control, water supply, and other purposes especially for those reservoirs located within trans boundary river basins. For instance, the lack of reservoir statistics will create demanding situations in regards to flood forecasting inside the region. In addition, while assessing and predicting the impacts of droughts, the lack of reservoir storage information reduces the reliability of drought analysis structures.

II. Objectives

To estimate storage capacity using Geographical Information Systems (GIS) and remote sensing techniques for purpose of planning and management of water resources in the Nagarjuna Sagar Reservoir.

– Specific objectives

1) To identify reservoir in the study area in terms of its spatial distribution.
2) Develop a methodology to estimate the reservoir storage capacity as a function of its surface area and elevation obtained from satellite imageries.
3) Compare reservoir storage capacity for three years obtained from the algorithm using surface areas and elevations.

III. Study Area

Nagarjuna Sagar is one of the international’s biggest masonry dam built throughout the Nagarjuna Sagar is one of the world’s largest masonry dam built across the river Krishna at Nagarjuna Sagar which straddles the border among Nalgonda District of Telangana & Guntur district of Andhra Pradesh India, between 1955 and 1967. The potential of Nagarjuna Sagar reservoir at FRL (Full Reservoir Level) at some stage in impoundment became 11,472 million cubic meters. The dam is 490 fts. (150 m) tall and 1.6 km long with 26 gates which can be 42fts. (13 m) wide and 45fts. (14 m) tall. Nagarjuna Sagar become the earliest inside the series of massive infrastructure initiatives initiated for the Green Revolution in India; it is also one of the earliest multi-motive tasks in India.

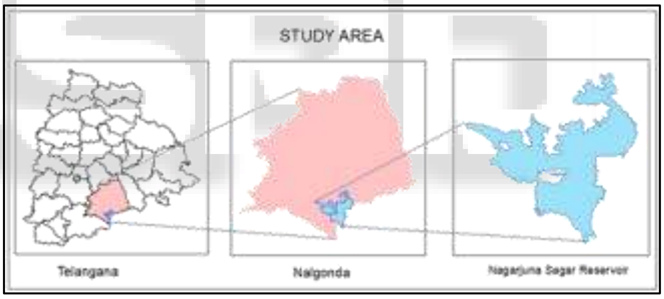

Fig. 1: Study area

IV. Methodology

The algorithm for estimating the reservoir storage contains the following steps:

1) Estimation of water spread area of the reservoir based on SENTINEL'S NDVI images from 2016 to 2018.
2) Extraction of the reservoir surface elevations from CARTOSAT-1 DEM data.
3) Establishment of the area-elevation relationship for the reservoir and then retrieving the water surface elevation value from the water surface area value using the established relationship.
4) Calculation of the reservoir storage over time from water surface elevation and area time series.

Figure below shows the flowchart of the algorithm. More details of the algorithm are described in the following paragraphs.

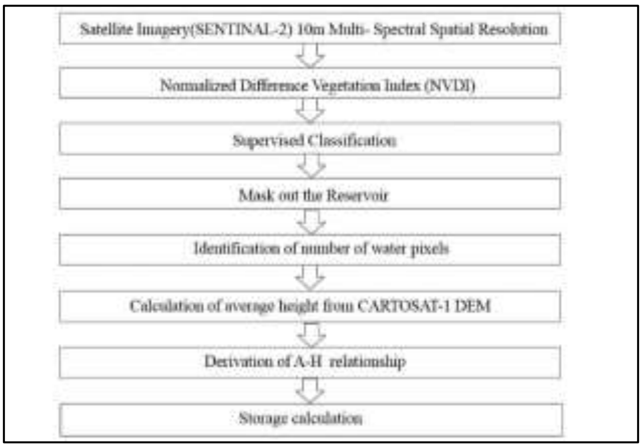

Fig. 2: Flow chart of the methodology adopted

V. SURFACE AREA ESTIMATION

The surface area estimation technique is a modification of the set of rules created by way of Gao et al. [2012]. Given the aim of this take a look at is to use SENTINEL surface area (thinking about the constrained availability of CARTOSAT DEM elevation observations) as the number one input for estimating storage, it's far essential to improve upon the sooner SENTINEL's region algorithm. Therefore, a class enhancement technique changed into developed for this observe. The principal concept is to decorate individual scenes based on the percentile records from the 3 year water opportunity reference statistics to correct misclassified pixels, and to assign the suitable magnificence to the unclassified pixels. The basic precept is to apply the spatial and temporal records from the NDVI pics in conjunction with the fact that internal parts of the reservoir are more likely to be categorized as water (in comparison to outer components). This technique enables enhance the location retrieval accuracy and facilitate successful retrieval—even within the case when a large portion of a picture is of low information fine (e.g., cloud contaminations).

Here we explain the updated algorithm entirely using the following steps:

A. *Mask creation:*

For every 10-day NDVI picture from 2016 to 2018 (three images in total), an index threshold-based method became used—such that pixels with NDVI values much less than 0.1 had been taken into consideration as water. As a result, 3 water coverage photographs were created. A water insurance percentile image (herein after known as a masks) become then calculated with every pixel value representing the proportion of that pixel have been counted as water. Then, an extension turned into generated by means of expanding the mask to a buffer place which covered any ''non-water'' regions that fell within a (10 10 10 pixels) moving window centered on every water pixel. This way the mask and its buffer region could be able to cover all possible water pixels for the studied reservoir.

B. *Image classification:*

The picture category algorithm turned into applied to categorize all pixels of the SENTINEL'S NDVI photo in the extended mask location. The pixels were divided into three instructions: ''water,'' ''non-water dry surface,'' and ''non-water moist surface.'' The classification inside the prolonged masks location alone can successfully lessen the amount of computation and boom the accuracy of SENTINEL's water vicinity estimation (relative to now not the usage of a masks as a constraint).However, the accuracy of this class approach also depends on the great of the SENTINEL's NDVI data and the purity of pixels. In order to remedy the problems due to pixels with horrific best, the following screening technique turned into used: if the reliability of a pixel was not denoted as ''right statistics'' (i.e., the pixel became identified as ''cloudy,'' or ''snow/ ice,'' or ''marginal''), then it became particular as ''unclassified'' (i.e., neither ''water'' nor ''non-water''). Used a majority filter as a post type processing mechanism to take away the ''salt and pepper''.

Nonetheless, this filtering does now not improve the accuracy a lot while the low-first class SENTINEL'S NDVI pixels cowl a large portion of the photograph. The pixel purity trouble, that is due to a combination of surface components inside a pixel, is a great deal less a concern. This is because the purity trouble best occurs inside the boundary pixels, and the errors (overestimation/underestimation) typically cancel out (until the NDVI values for the non-water component have a totally huge annual variant).

1) *Mask zones division:*

The masks image (without the buffer area) are grouped into various zones primarily based on the percentile data, using a hard and fast increment percentile cost of 2%. This threshold (of 2%) allowed us to slim down the differences among pixels within a given sector. In different words, all of the pixels in the equal sector imply that they have got a similar possibility of being categorized as water. Here we use a easy synthetic instance (with simplest 3 zones) to provide an explanation for the concept and technique. In the example, the masks photo carries 8 3 8 pixels with the percentile values as shown in Figure 3. Using a threshold of 1/3 (which is one divided by using the range of zones), the masks place may be divided into 3 unique zones. Each pixel in the masks photo is then assigned to a sector (sector 1, 2, or three) in step with its percentile value. For instance, for the reason that pixels inside the top row of Figure have the percentiles of 0.1 and 0.2 (which can be each among 0 and 1/3), they're every assigned to zone 1.

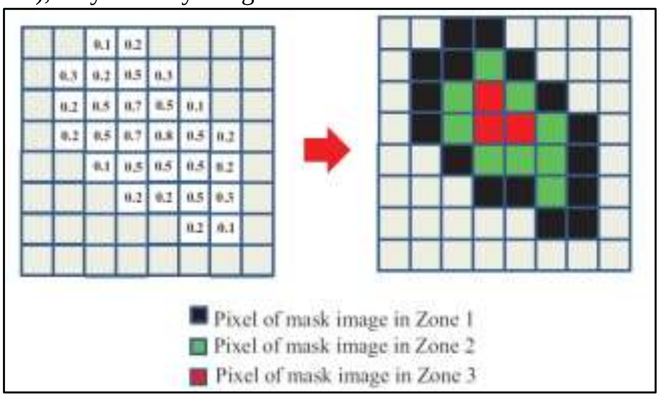

Fig. 3: A simple example of dividing the mask into different zones according to its percentile values (Zone 1: 0–0.33, Zone 2: 0.33–0.66, and Zone 3:0.66–1).

VI. NDVI

The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that makes use of the seen and close to infrared (NIR) bands of the electromagnetic spectrum to research whether the goal being found incorporates green vegetation or no longer. Healthy flora displays extra near infrared (NIR) and inexperienced light compared to different wavelengths. But it absorbs more red and blue mild. Therefore, our eyes see vegetation as colour green. If we may want to see near infrared, then it might be strong for flora too. It is essentially measured via the use of depth.

The density of vegetation (NDVI) at a certain point on the image is equal to the difference in the intensities of reflected light in the red and infrared range divided by the sum of these int

$$NDVI = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

The result of this method generates a value among -1 and +1. If you've got low reflectance (low values) within the red band and high reflectance inside the NIR, this could yield a high NDVI cost and vice versa.

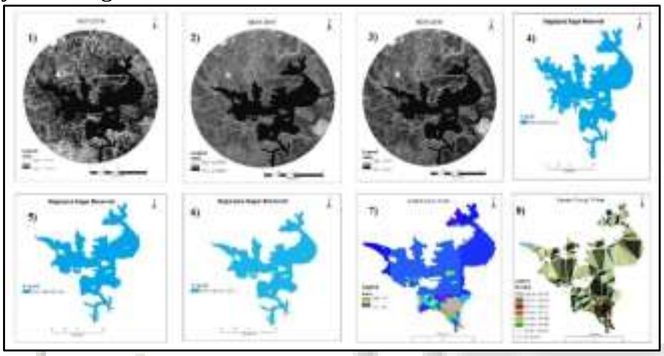

Fig. 4: Satellite imageries 1) NDVI 2016.2) NDVI 2017 3) NDVI 2018 4) Water spread area acquired from SENTINEL-2 (30-10-2016) 5) Water spread area acquired from SENTINEL-2 (05-11-2017) 6) Water spread area acquired from SENTINEL-2 (20-10-2018) 7) DEM of reservoir 8) Elevation through TIN map.

VII. Water Surface Elevation Estimation from CARTOSAT- 1 DEM

The reservoir surface elevation results were retrieved from CARTOSAT-1 orbital measurements in two steps.

First, using the reservoir area boundary identified by the SENTINEL'S water classification (that was closest in time with CARTOSAT-1 overpass) and the CARTOSAT orbital geographical location information, all elevation measurements within the reservoir were extracted. Then, the representative elevation of a reservoir for a given day was estimated as the average of all the measurements within the overpassing orbit.

S. No	Name of the Satellite	Date of Satellite pass	Reservoir Elevation (m)
1	Sentinel-2	30.10.2016	96.7
2	Sentinel-2	05.11.2017	97.5
3	Sentinel-2	20.10.2018	98.2

Table 1: Details of Satellite Data used and the water level during the pass of the satellite over the reservoir

VIII. A-H Relationship Development

The SENTINEL DEM records are used to extract the A-H relationship for each reservoir. As an approximation, the relationship is believed linear. To capture the relationship, we first delineate the reservoir area from the DEM. A constraint is about such that the delineated vicinity of a given reservoir should no longer be large than the maximum reservoir floor region anticipated via SENTINEL. A simplified example of a delineated reservoir from DEM is shown in Figure 4. For any given elevation in the delineated DEM (e. G., H1), the entire location (e.g., A1) at this elevation or lower may be envisioned by counting the number of related pixels. By regressing the cumulative vicinity values towards the elevation values, the A-H relationship for the reservoir of interest may be installed.

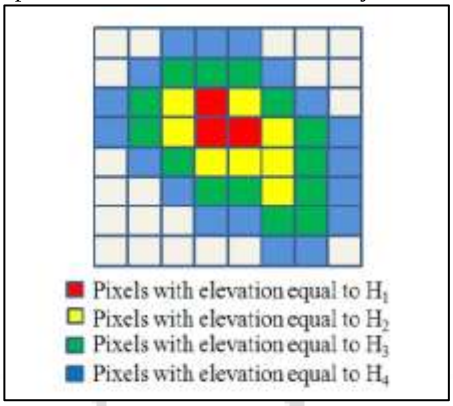

Fig. 4: A simplified example of a delineated reservoir from the SENTINEL DEM, where H1> H2> H3>H4.

IX. Storage Estimation:

Using Equation 1, the storage is estimated based on the SENTINEL water surface area and the elevation inferred from DEM:

VRS=Vc– (Ac + ARS)(Hc – HRS)/2 .... (1)

where Vc, Ac, and Hc represent storage, area, and water elevation at capacity; and VRS, ARS, and HRS are the remotely sensed storage, area, and water elevation.

If HRS is not directly available, it is inferred from the A-H relationship and the area from SENTINEL's (i.e.,ARS).

Therefore, the reservoir storage can be expressed by equation:

VRS=Vc– k(Ac + ARS) (Ac - ARS)/2....... (2)

where k is the slope from the A-H relationship.

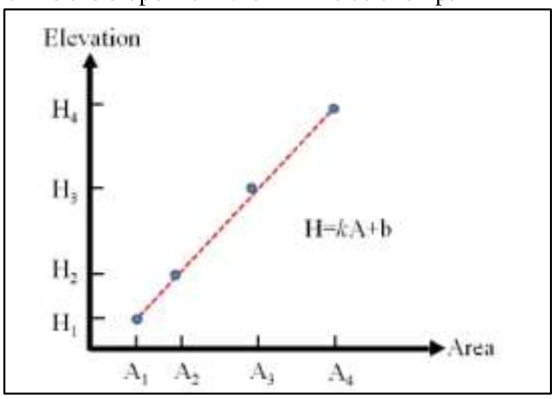

Fig. 5: A-H relationship derived from the SENTINEL DEM

X. RESULTS AND DISCUSSION:

S. No	Date of Satellite pass	Reservoir elevation (m)	Water spread area (Km2)	Volume (Km3)
1	30.10.2016	96.7	172	5.10
2	05.11.2017	97.5	175	5.23
3	20.10.2018	98.2	178	5.36

Table 2: Capacity Estimation of Nagarjuna Sagar Reservoir using the Algorithm

By applying this developed set of rules to the favored reservoir the storage potential reservoir can be monitored. First, considering the fairly high spatial resolution of SENTINEL'S pics, the water surface area at capability for the selected reservoir have to be obtained. Second the SENTINEL DEM imageries obtained need to be of equal time. The uncertainties associated with the garage estimations are from resources. The first one is the A-H relationship. The A-H relationship is largely inferred from the DEM within the ring between the water surface diagnosed by using SENTINEL and the maximum reservoir surface area expected via SENTINEL-2. Since the DEM only captures the bathymetry above the water surface elevation at the SENTINEL flight time for every reservoir, the unmeasured bathymetry beneath the water surface is thought to have the same shape (i.e., a steady A-H dating). Consequently, errors can be delivered if the A-H relationship for a given reservoir varies via elevation appreciably. The 2d supply is the SENTINEL-2 place estimations. According to equation 2, the mistakes related to the SENTINEL-2 water location can immediately influence the reservoir storage estimations.

XI. CONCLUSION & FUTURE WORK:

This study has evolved a brand new algorithm for inferring reservoir garage by combining the SENTINEL-2 based area and the DEM based totally A-H dating. The validation results over the reservoir suggest that the set of rules has done robustly. This technique has a bonus in extending the spatial insurance of remotely sensed reservoirs, which is vital for helping water control decision making. The uncertainties associated with the anticipated storage may be attributed to the discrepancies between the A-H relationships above and below the SENTINEL measured water floor retrieval errors.

A. Future work related to this study will be two-fold:

First, we will apply the algorithm to the reservoir for obtaining the total storage capacity. Second, we will quantify the uncertainties from different sources for each reservoir to be studied.

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