Characterization of Urban Waterbodies using Deep Learning

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Abstract

The temporal availability of satellite data over the years can be used to churn in valuable information. Satellite data can be used not only to detect the water bodies but also to extract the areal extent of water retained in them i.e., the water spread area (WSA). In this study, Deep Learning based approach has been developed for water surface area (WSA) extraction and characterization using multi-temporal and multispectral satellite data. This information can be used to characterize the water bodies as persistent / rejuvenated / extinct or new. In this study, a DL-based U-Net model has been implemented for processing and analysis of WSA dynamics information across seasons and years. This information is used to extract waterbody boundaries which in turn helps in their characterization. Open-source technologies (Python and corresponding libraries), Google Earth Engine, and Google Colab using AI & ML framework (Tensor Flow, Keras, etc.) have been used to develop a methodology which is used to automatically identify suitable data scenes, extract surface extent of waterbodies for a given scene using 6 bands (including SWIR 1 and SWIR 2) (which provide better results even in sparse and thin-cloud areas), deriving waterbody boundaries, statistics, trends and water quality. This approach has been successfully used to process 150 satellite data scenes online for Mehsana town, Gujarat to generate the WSA statistics for 33yrs (1988-2021). The TAT is around 2 hours. Further, the temporal results are utilized to understand the WSA dynamics which helps in characterizing the waterbody such as persistent / rejuvenated / extinct / new. In this study for Mehsana town waterbodies more than 2.5 ha area were considered. It is found that 3 waterbodies got extinct while one new waterbody is obtained around 1980.

Keywords Water Spread Area, Urban water bodies, Remote Sensing, Deep Learning

Introduction

Due to Outpaced population growth, experiencing severe water scarcity, Govt. of India Initiatives in achieving water security Rejuvenation of water bodies and green spaces and parks through various Govt. Initiatives such as Catch the rain, where it falls, when it falls etc., Rejuvenation of waterbodies is one of the objectives under AMRUT 2.0 project of Government of India to meet the Sustainable Development Goals (SDG-6, PIB, 2021). For this, understanding the spatiotemporal behavior of urban waterbodies such as water availability and their quality is essential for prioritization. For prioritization of waterbodies historical remote sensing data can be very processed and analyzed to characterize the urban water bodies within the city, which can aid decision makers in short-listing urban waterbodies for their rejuvenation, conservation etc., Remotely sensed data can reinforce the abilities of water resources researchers and decision makers to monitor waterbodies more effectively. Availability of open-source multi-temporal Remote sensing satellite data from various space agencies over the Indian region gives plenty of opportunities to understand the Spatio-temporal dynamics of Natural resources (Huang c, et al, 2018, Paul Shane Frazier and Kenneth John Page, 2000). With the online availability of such resources, it enables the user to process the data quickly and effectively. Also, satellites with a greater number of bands in visible and infrared region gives opportunities to understand the water quality indices and with these opportunities urban waterbodies can be studied for their status and scope for rejuvenation.

Materials and Methods

Study Area: Mehsana is a city and municipality in Mehsana district in the state of Gujarat. For this study, the Mehsana town and its surroundings are considered for the understanding the spatio-temporal dynamics of water bodies to arrive their status. The location map of the study area is given in Figure 1.

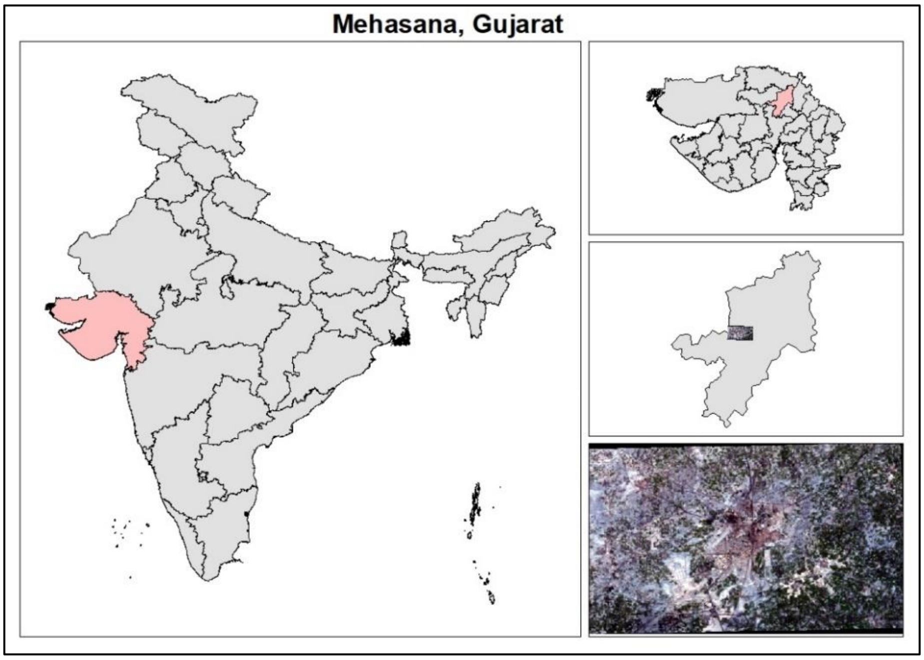

Fig. 1 Location Map.

Tools and Technologies Used: The current study is carried out using majority of online resources for acquiring data and processing. Apart from online resources some of open-source tools are also used. The List of tools/technologies used are given in Table 1.

Table 1 Tools and Technologies Used.

Purpose	Tool/Technology
Online Satellite data Resource	Google Earth Engine
Online Deep Learning Platform	Google Colab
Geo-spatial Data Analysis	QGIS, PyQGIS
Python Libraries	GDAL, Numpy and Skimage
Deep learning Libraries	Tensor Flow and Keras

Methodology: The waterbody boundary information from SOI data is used as the base or initial reference and subsequently based on the availability of medium resolution satellite data from Landsat series is used for temporal analysis availability of water in terms of water spread area (WSA). Google Earth Engine (GEE) is used as the primary source of satellite data using which cloud free satellite scenes are filtered and used to extract the study area portion, which is stacked and used as input/feature layer for Deep Learning (DL) Model. The DL model is a modified version of U-Net model (Leo F. Isikdogan et al, 2019). The model provides the output of water layer in terms of probability value ranging from 0 -1. This image is applied with a threshold value to derive the binary image consisting water and non-water information. Subsequently these layers are used computed the empirical waterbody boundaries, which intern are used to compute the statistics of WSA. Further, the patterns of WSA area analyzed to understand the status for characterization of Urban Water Bodies. The methodology is also depicted as flow chart in Figure 2.

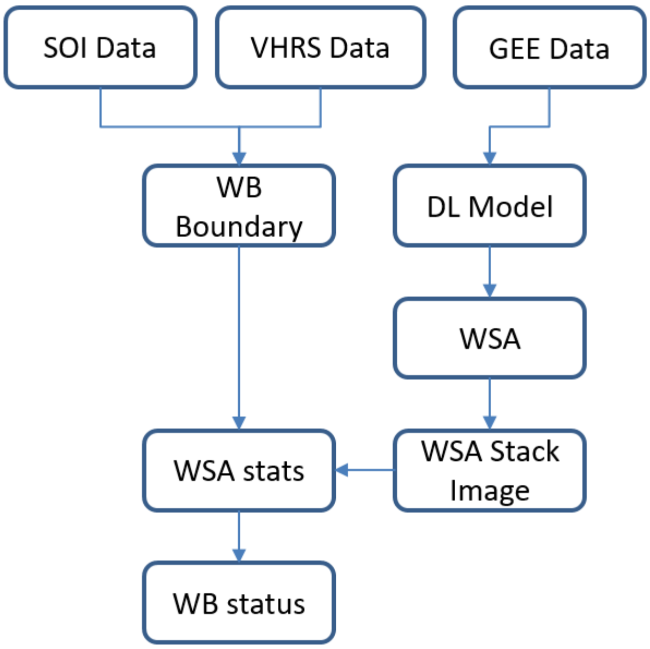

Fig. 2 Methodology Flow Chart.

Results

About 150 cloud free satellite images were processed spanning over 33 years from various Landsat satellites (Acharya, T. D et al, 2016) archived in Google Earth Engine. Based on the waterbodies present in the study area and spatial resolution of satellite data, the waterbodies of 2.5 ha and above are considered for this study. All the satellite scene are analysis and presented the statistics in terms of graph to understand the patterns. Some specific waterbodies are given in Figure 3, 4, 5 and 6.

Discussion

In total, there were about 12 water bodies are analyzed out of which 3 waterbodies which were present in SOI topo-sheet were completed disappeared or got extinct through the analysis and also observed with open-source high-resolution satellite data as shown in Figure

6. Other examples for persistent waterbody (Fig 3), new waterbody and revived waterbody are given in Figures 3, 4 and 5 respectively. For better understanding the ground scenario, the high-resolution satellite data of 2021 is considered for representation and visualization purposes.

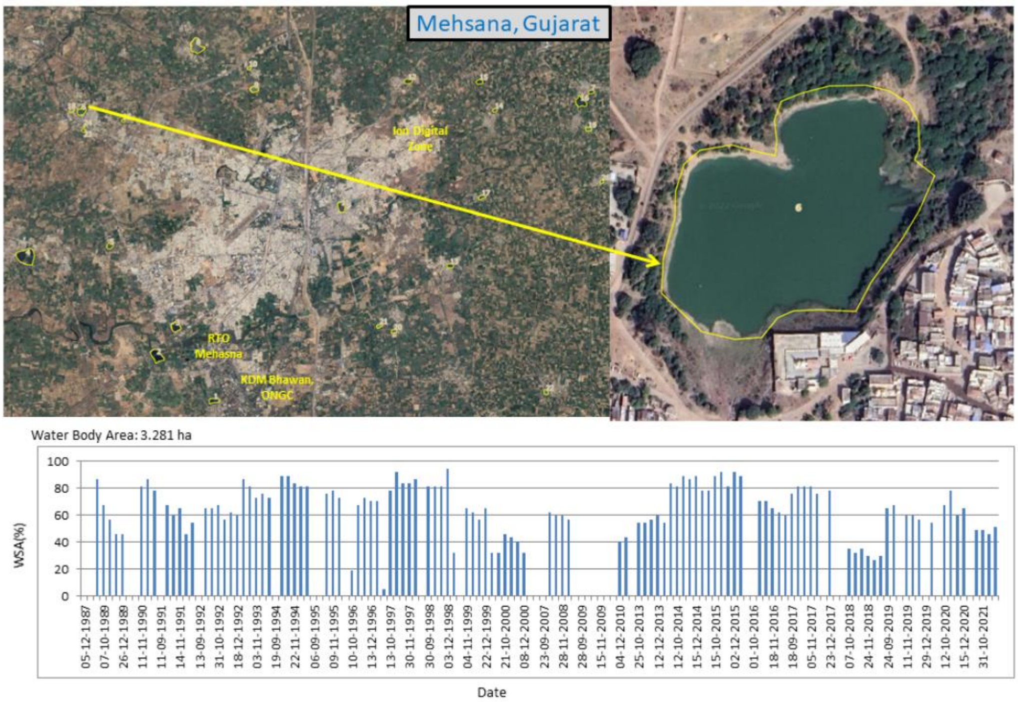

Fig. 3 Persistent Waterbody.

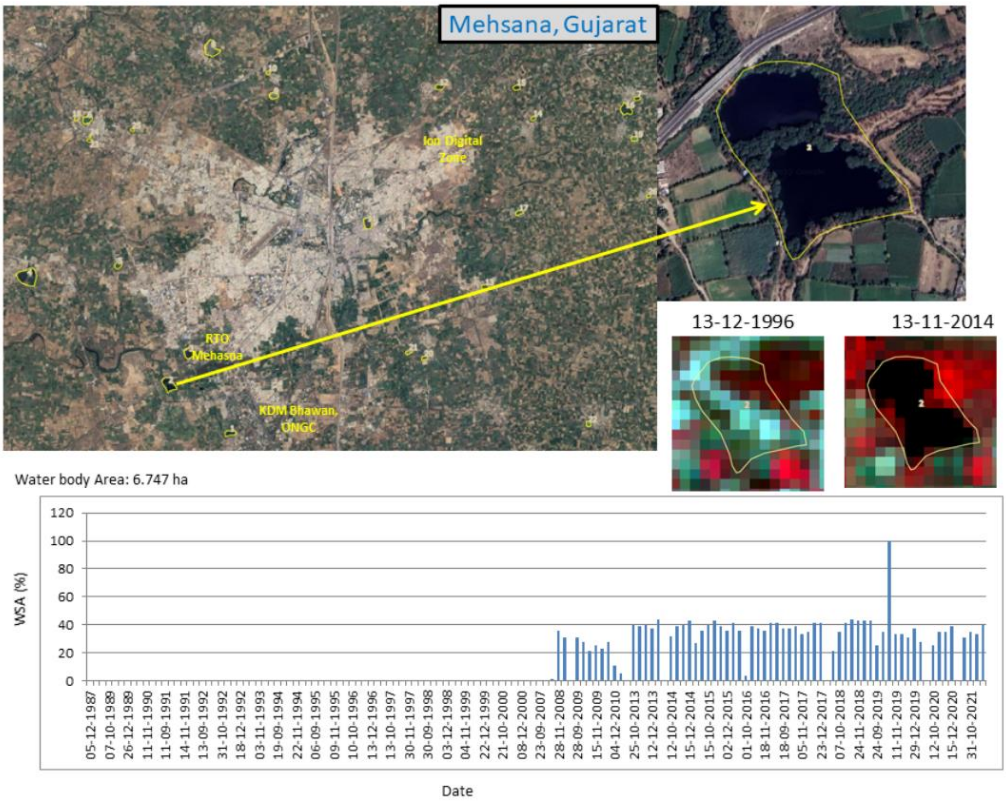

Fig. 4 New Waterbody.

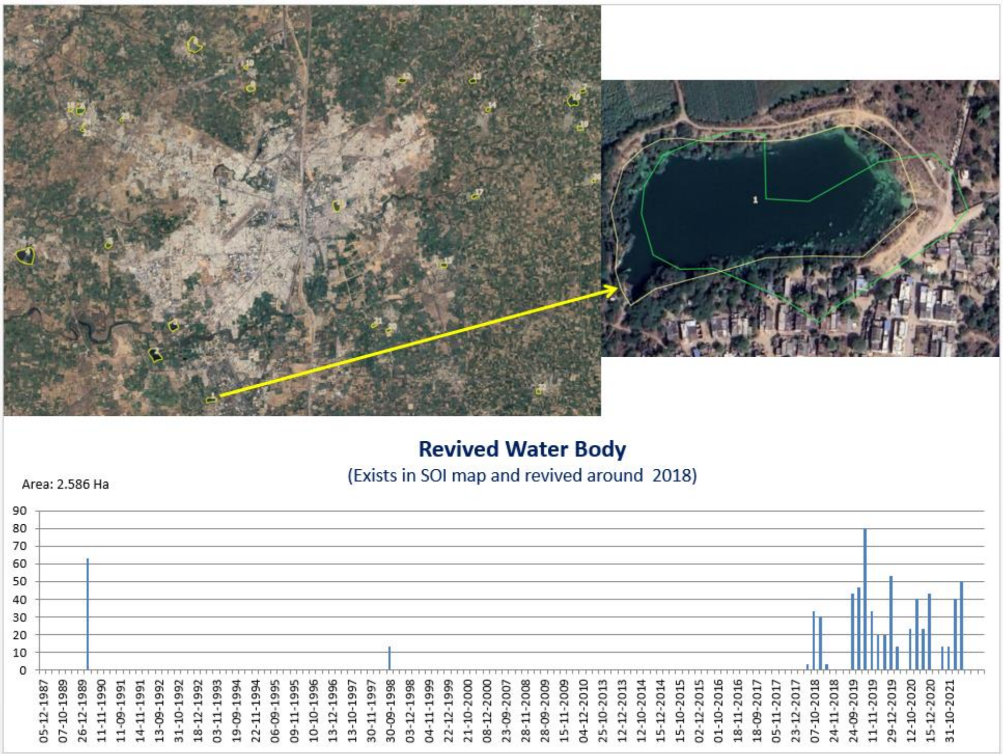

Fig. 5 Revived Waterbody,

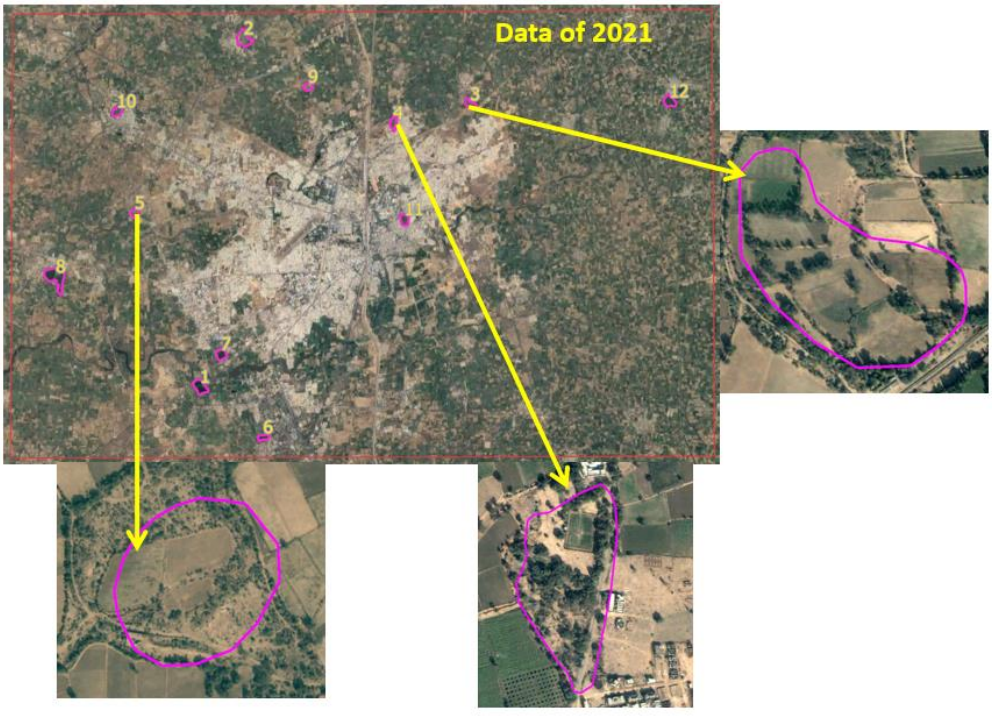

Fig. 6 Extinct Waterbody.

Conclusions

It is observed the multi-temporal optical satellite data is highly potential in deriving the WSA very efficiently. The present DL model which is developed based on modified U-Net approach achieved an accuracy of 95%, which is very helpful in determining the present of water with high confidence. Out of 12 waterbodies, it is observed that 3 got extinct before year 1980, one new waterbody got emerged in year 2008, one waterbody got revived in year 2018 and remaining were persistent. As the majority of study is carried out using online and open-source resources, which reduces the initial time for data accessing and establishing the model is negligible. It enhanced the overall turnaround time (TAT) of study. Also, there is a huge scope of characterizing the urban waterbodies automatically, which can be taken up in further studies. Also incorporating the open-source satellite data from other sources such as sentinel missions, would increase the data availability especially for automation and estimating water resource availability and reasoning the same.

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