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Integrating Satellite Data and *In-situ* Observations for Trophic State Assessment of Renuka Lake, Himachal Pradesh, India

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ABSTRACT

The present study focuses on estimating the Trophic State Index (TSI) of Renuka Lake, the smallest Ramsar site in India, utilizing in-situ observed Secchi disk transparency (SDT) and satellite data. Site-specific algorithms were developed by establishing the relationship between the spectral band ratio of Landsat 8 OLI and LISS-III with that of in-situ measured SDT data. Notably, the exponential regression model outperformed other regression models (linear, logarithmic, polynomial, and power), achieving a better model output (R^2=0.94). Additionally, water quality parameters, namely pH and dissolved oxygen (DO), were measured using the TROLL 9500 multi-parameter instrument. Various interpolation methods were applied to the in-situ data, with the exponential regression model yielding the most accurate results.This method was subsequently selected to generate two-dimensional water-quality images of Renuka Lake. The combined analysis of in-situ and satellite-derived trophic status indicates the eutrophic to hypereutrophic condition of the lake's eastern and western parts. Satellite imagery spanning 2010-2019 consistently reveals a eutrophic state in the lake, with fluctuations in intensity over the period. The sustained eutrophic condition is attributed to escalating human-induced activities surrounding the lake, particularly in the western region.

INTRODUCTION

The Himalayan lakes hold unique significance as self-sustaining entities supporting harmonious freshwater ecosystems, vital for promoting aquatic biodiversity. Lake water, an indispensable natural resource for both human populations and their environments, faces global degradation due to natural processes and escalating human-induced activities (Brönmark & Hansson 2002, Mishra & Garg 2011). This degradation of lake water quality stands as a pressing global water issue, especially given the lakes' pivotal role as lifelines for both humans and ecosystems (Rast 2009, Mohamed M.F 2015, Gholizadeh et al. 2016, Sent et al. 2021). The increasing trophic status of lakes serves as an indicator of this degradation, as highlighted in existing literature, attributing it to factors such as organic and inorganic pollution, siltation, eutrophication, morphological changes, and the impact of climate change, notably manifested through rising water temperatures (Brönmark & Hansson 2002, Dudgeon et al. 2006, Mabwoga et al. 2010, Mishra & Garg 2011, Torbick et al. 2013).

The quality of water not only influences the development of organisms but also determines their survival. Therefore, it is crucial to assess the lake's health through water quality measurements. Various monitoring methods are employed for a comprehensive study to fully understand the lake's water quality and ecosystem (Hestir et al. 2015, van Puijenbroek et al. 2015, Bresciani et al. 2019, Bonansea et al. 2019, Cahalane et al. 2019, Torres-Bejarano et al. 2020). The assessment of trophic states of lakes through in-situ measurements has long been a cornerstone of limnological research. Studies by Carlson (1977) and Vollenweider (1968) laid the foundation for this approach, emphasizing the relevance of key parameters such as chlorophyll-a, total phosphorus, and Secchi disk transparency. The Secchi disk transparency test, introduced by Carlson (1977), emerged as a fundamental tool in categorizing lakes into trophic states. This method involves lowering a white disk into the water until it disappears, providing a measure of water clarity.

While in-situ methods are crucial for understanding the ecological dynamics of lakes, they come with inherent limitations. One major constraint lies in the spatial coverage, as in-situ measurements are often point-specific and labor-intensive. The challenge of extrapolating localized data to represent entire lake ecosystems is acknowledged by Hestir et al. (2015). Additionally, the temporal resolution of in-situ observations may not capture short-term fluctuations in trophic conditions, as noted by Bresciani et al. (2019) and Bonansea et al. (2019). Despite these limitations, the wealth of information obtained through in-situ measurements remains invaluable for validating satellite-derived algorithms and enhancing the overall accuracy of trophic state assessments. In recent years, the use of satellite-based observations alongside traditional in-situ methods has emerged as a powerful approach for studying the trophic states of lakes. This integrated methodology offers a comprehensive understanding of water quality dynamics.

Numerous studies have recognized the limitations of relying solely on in-situ data and have explored the potential of satellite observations to bridge gaps in lake monitoring. Remote sensing applications have proven effective in both terrestrial and aquatic ecosystem monitoring (Andrew et al. 2014, Walshe et al. 2014, de Araujo Barbosa et al. 2015). Optical satellite data is used to monitor water quality indicators, including trophic status, suspended sediment concentration, turbidity, and chlorophyll content. Various studies have utilized different band ratios of satellite data (Landsat TM, Landsat ETM, Landsat-8 OLI, LISS-III, SeaWiFS, MERIS, MODIS, Sentinel-2A, NOAA AVHRR) to assess water quality, with the Landsat series data being particularly successful globally due to its spatial, temporal, spectral resolution, and cost-effectiveness in water quality assessment (Khorram & Cheshire 1985, Harrington et al. 1989, Koponen et al. 2002, Wang et al. 2004, Usali & Ismail 2010, Bilgehan et al. 2010, Mishra & Garg 2011, Palmer et al. 2015). Satellite data offers a synoptic perspective and spatiotemporal coverage over wider areas, providing features unattainable during ground truth observations.

The significance of this study lies in its approach to assessing the trophic state of Renuka Lake, the smallest Ramsar site in India, by integrating satellite-based observations with traditional in-situ methods. Several studies have contributed to understanding Renuka Lake's limnology. Previous works by Das & Kaur (2001) and Das et al. (2008) explored major ion chemistry and geochemistry, providing insights into weathering processes affecting the lake's trophic state. Subsequent studies by Singh & Sharma (2012) and Kumar et al. (2019) focused on trophic status assessment, contributing valuable information on local ecological dynamics. However, these studies relied solely on traditional in-situ methods to explore the trophic condition of Renuka Lake. Unlike these predecessors, our study is novel and unique as it employs advanced satellite-based observations, a methodology successfully used in various lake studies but not yet applied to Renuka Lake, the smallest Ramsar lake site. By combining satellite technology with in-situ observations, our research aims to provide a more comprehensive understanding of Renuka Lake's trophic state. This innovative approach not only adds a new dimension to the current understanding of the lake's dynamics but also addresses a significant research gap in the monitoring and assessment methodologies applied to the unique ecological setting of Renuka Lake. The integration of satellite-based observations is expected to enhance the precision and scope of trophic state assessments, ultimately contributing to more effective conservation and management strategies for this ecologically vital Ramsar site.

MATERIALS AND METHODS

Study Area

Renuka Lake is an oval-shaped lake situated in the foothills of the Lesser Himalaya, with geographical coordinates between 30°36′30″ N latitude and 77°27′6″ E longitude in the Sirmaur district of Himachal Pradesh (Fig. 1). The lake is 204 m wide, 1.05 m long, and 13 m deep, with a catchment area of 254.3 hectares. The subtropical climate of the lake area receives an annual rainfall of 150 to 199.9 cm (Das & Kaur 2001). The lake is surrounded by Lesser Himalayan rocks (Das et al. 2008) and flows along a riparian path between two forested, steep hill slopes. Renuka Lake is connected to Parashram Tal through a narrow channel, both located along the course of the Giri River. The majority of the lake's water is sourced from small watersheds, collected as surface runoff or groundwater seepage. The lake continuously discharges water to low-lying areas through Parshuram Taal. Declared a Ramsar site and protected as a National Wetland on 8th November 2005, the lake hosts rare, endangered plant and animal species, attracting large populations of avifauna during winter from Siberia and Eastern Europe. A popular tourist attraction in Himachal Pradesh, the lake's natural beauty, boating facility, and abundant wildlife draw thousands of visitors annually. The lake is a socio-economic lifeline for the mountain people directly or indirectly dependent on its resources. The Wildlife Wing of the Himachal Pradesh Forest Department implements various development programs to safeguard the lake ecosystem and monitor its condition through water quality evaluation.

Satellite Data Collection and Processing

One critical aspect of the satellite and field data-based integrated approach lies in the selection of suitable satellite platforms and sensors. This study utilized remotely sensed satellite imagery from Landsat-8 OLI for 2013-2020 and

LISS-III for the 2010-2012 period. Cloud-free continuous data was available for the post-monsoon season only, so only data of this season (October to December) has been used and analyzed. The Landsat-8 OLI data is chosen in this study due to its improved sensor features over the previous Landsat series. The Resourcesat-2 LISS-III and Landsat-8 OLI (Operational Land Imager) satellite data are obtained from the National Remote Sensing Centre (NRSC), Hyderabad, India, and the USGS Earth Explorer site (USGS Earth Explorer 2023), respectively. The integration of satellite data with in-situ observations requires careful consideration of atmospheric correction and image pre-processing to ensure reliable results. The spectral image processing and analysis were conducted using ERDAS Imagine software. The Landsat-8 OLI radiance image was obtained using equation 1 (USGS 2023), and similarly, the Resourcesat-2 LISS-III radiance image was obtained using equation 2 (Robinove 1982).

$$L = M \times Q_{CAL} + A \qquad \ldots(1)$$

Where,

L = cell value as radiance

M = multiplicative factor in $(W/m^2sr^*\mu m)/DN$

A = the additive factor in $(W/m^2sr^*\mu m)$

Q_{cal} = quantized and calibrated standard pixel values (DN)

$$L_\lambda = (D_n/D_{max}) * (L_{max}-L_{min}) + L_{min..} \qquad \ldots(2)$$

L_λ = radiance in a single band

D_n = digital value of a pixel

D_{max} = maximum digital number

L_{max} = maximum radiance measured at detector saturation in $(mW\ cm^{-2}\ sr^{-1})$

L_{min} = minimum radiance measured at detector saturation in $(mW\ cm^{-2}\ sr^{-1})$

In-Situ Data Collection

For in-situ data collection, field observation data, including

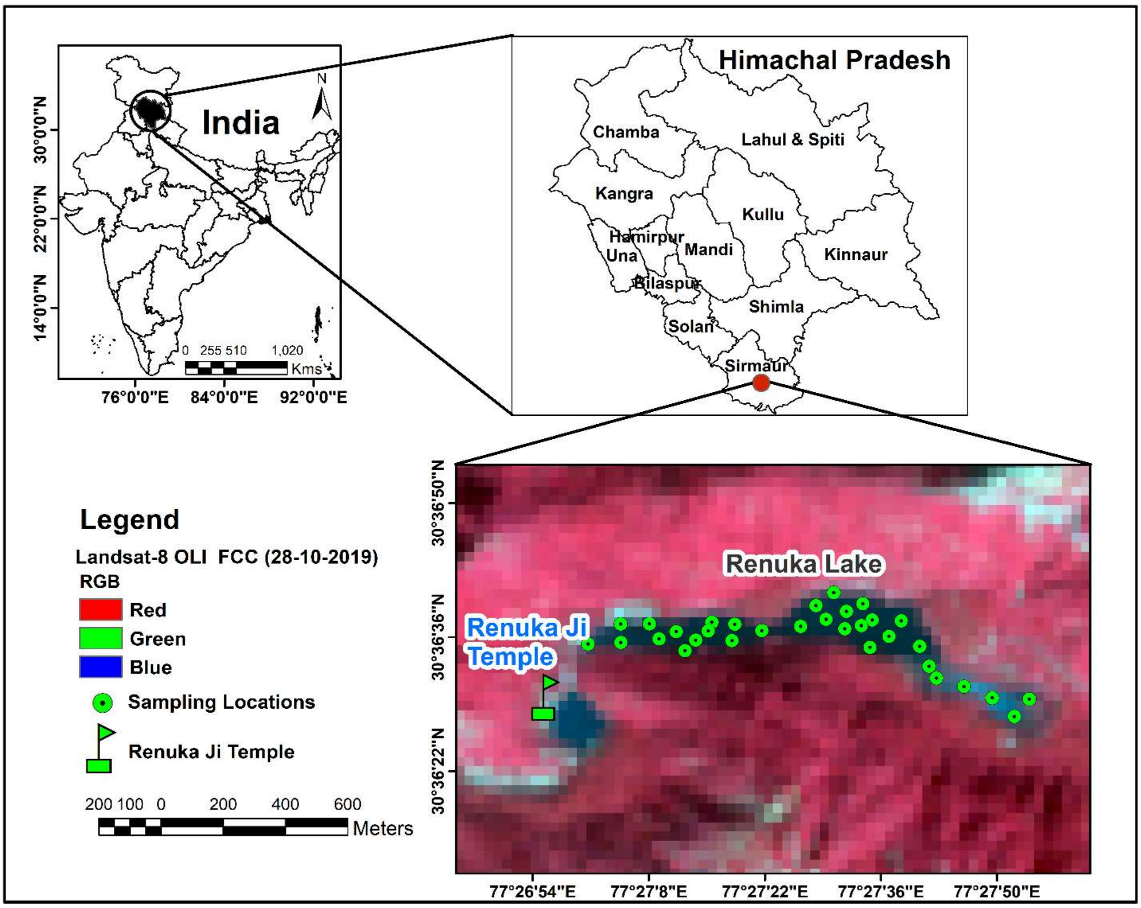

Fig. 1: Landsat-8 OLI satellite map showing water sampling locations in the Renuka Lake.

Fig. 2: Use of Secchi disk in the Renuka Lake.

Table 1: *In-situ* data collected over Renuka Lake on 28 October 2019.

Station	Latitude	Longitude	SDT[m]	pH	DO (Dissolved Oxygen)	Time
1	30.60972	77.45027	0.98	7.12	7.42	7.30 a.m
2	30.60975	77.45138	1.24	7.38	7.49	7.37 a.m
3	30.61028	77.45139	1.50	7.31	7.58	7.43 a.m
4	30.61028	77.45444	1.30	7.21	7.62	7.52 a.m
5	30.61000	77.45611	1.42	8.11	9.87	7.58 a.m
6	30.61000	77.45889	1.32	7.63	8.26	8.05 a.m
7	30.60944	77.45972	1.30	8.82	9.47	8.13 a.m
8	30.60944	77.46139	1.10	8.11	8.01	8.21 a.m
9	30.60982	77.45266	1.40	8.01	9.47	8.32 a.m
10	30.60976	77.45389	1.33	7.32	10.57	8.41 a.m
11	30.60973	77.45511	1.21	7.63	9.89	8.49 a.m
12	30.61010	77.45741	1.40	8.53	8.32	8.57 a.m
13	30.61069	77.45795	1.21	7.48	8.12	9.08 a.m
14	30.61029	77.45827	1.05	7.43	8.35	9.17 a.m
15	30.61050	77.45896	1.23	7.13	6.68	9.26 a.m
16	30.61024	77.45982	1.50	6.98	8.92	9.35 a.m
17	30.61019	77.46079	1.32	7.84	9.89	9.44 a.m
18	30.60975	77.46036	1.43	7.49	10.34	9.55 a.m
19	30.60851	77.46192	1.34	7.30	6.99	10.05 a.m
20	30.60790	77.46379	1.50	7.27	7.56	10.14 a.m
21	30.60784	77.46503	1.31	7.23	7.49	10.23 a.m
22	30.60735	77.46451	1.30	7.09	6.53	10.32 a.m
23	30.61027	77.45235	1.32	7.65	8.32	10.41 a.m
24	30.61002	77.45324	1.30	7.96	7.69	10.50 a.m
25	30.61002	77.45431	1.40	7.34	9.74	11.00 a.m
26	30.61021	77.45521	1.20	7.39	8.14	11.09 a.m
27	30.61071	77.45952	1.31	7.05	6.87	11.20 a.m
28	30.61008	77.45945	1.40	7.41	6.67	11.29 a.m
29	30.60886	77.46169	0.96	7.16	7.56	11.38 a.m
30	30.60947	77.45352	1.30	7.89	10.32	11.47 a.m
31	30.60825	77.46285	1.02	7.21	7.40	11.54 a.m
32	30.61105	77.45855	0.93	7.11	7.31	11.59 a.m

Secchi disk transparency (SDT), pH, and dissolved oxygen (DO), were collected during the post-monsoon season of 2019 at 32 sampling locations across Renuka Lake (Table 1). Secchi disk transparency (SDT) analysis is a simple and cost-effective method for identifying the best indicator for water quality. The Secchi disk, a black and white round metal disk with an approximate diameter of 20 cm, was employed for this purpose. While it was lowered into the lake's water through a calibrated rope, the disk was gradually submerged until it became invisible, marking the Secchi disk transparency (SDT) at that specific depth (Fig. 2). The *in-situ* collected SDT data of Renuka Lake was used to calculate its Trophic State Index (TSI), which classifies lake water into four categories: (1) oligotrophic (clean and nutrient-poor), (2) mesotrophic (good clarity, moderate nutrient content), (3) eutrophic (turbid water, increased nutrient content), and (4) hypereutrophic (extremely nutrient-enriched water) (Carlson 1977). The TSI of sampling locations derived from Secchi disk transparency (SDT) data was further used for estimating the trophic state of the entire lake by developing a regression model with satellite data spectral bands. The pH and DO data collected through TROLL 9500 (a multi-parameter water quality measuring instrument) were used as two additional data to supplement and validate the satellite-derived TSI of the lake.

Methodology

The objective of the study was to assess the trophic status of Renuka Lake using both field observations and satellite data. Therefore, both satellite and ground truth observation data were integrated to assess the trophic state of the lake. The Secchi disk is widely used by lake management experts for monitoring lake water quality. Numerous organizations and institutions are actively researching these issues to improve water quality, identify challenges, and implement sustainable development plans through systematic monitoring efforts (Vörösmarty et al. 2010, Gray & Shimshack 2011, Torbick et al. 2013, Birk et al. 2012, Birk & Ecke 2014, Lim et al. 2015). Monitoring lake transparency is vital for lake ecology, and the trophic state index (TSI) serves as an essential factor in this assessment. The relationship between SDT and TSI has been extensively used by researchers for lake water quality assessment (Carlson 1977, Paukert & Willis 2003, Bio et al. 2008, Mabwoga et al. 2010, Mishra & Garg 2011, Sheela et al. 2011, Torbick et al. 2013, Gholizadeh et al. 2016, Bonansea et al. 2019, Bresciani et al. 2019, Sent et al. 2021). Equation 3 demonstrates this relationship:

$$TSI(SDT) = 10(6 - \ln SDT/\ln 2) \qquad \ldots(3)$$

Both *in-situ* observations and satellite data were utilized for TSI estimation, with in-situ data collected during the post-monsoon season. The lake water is categorized into four classes based on the TSI range, as shown in Table 2 (Fuller & Minnerick 2007). In this study, an algorithm using Landsat-8 OLI radiance data was developed to predict the SDT of Renuka Lake. Field data collection was synchronized with Landsat-8 OLI passes. Fig. 3 illustrates the correlation between SDT and the ratio of Landsat-8 OLI bands (OLI-3:OLI-4). Various regression models (linear, exponential, logarithmic, polynomial, and power) were applied in the statistical analysis. Among these models, the exponential regression model yielded the best result (R^2=0.94), as shown in Equation 4:

Table 2: Lake Trophic State and Carlson TSI.

Lake Trophic State Carlson TSI	Carlson TSI
Oligotrophic	<38
Mesotrophic	38-48
Eutrophic	49-61
Hyper eutrophic	>61

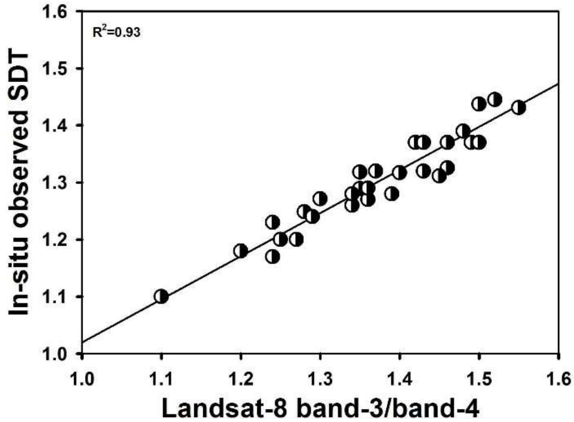

Fig. 3: Scatter plot-showing relationship between the in-situ observed SDT and band ratio of Landsat-8 OLI band-3/band-4.

$$SDT = 0.5869\ exp^{\ 0.5783(OLI3/OLI4)} \qquad \ldots(4)$$

The Landsat-8 OLI bands 3 and 4 spectral wavelength ranges are similar to LISS-III (Linear Imaging Self Scanning) bands 2 and 3. Therefore, using LISS-III satellite data, Equation (4) can be applied to monitor Secchi disk transparency. For the period before 2013, LISS-III data were employed for SDT quantification in the absence of Landsat-8 OLI data.

In this study, ground-observed data were interpolated to create two-dimensional images. Various interpolation approaches (Table 3) were tested, and the most effective one was selected. Eleven randomly selected points were used to assess both the absolute difference (AD) and the absolute percentage difference (APD) to determine the agreement between the observed and interpolated values. The AD and

APD values were calculated using Equations 5 and 6 (Melin et al. 2007):

$$AD = (1/N)\sum_{i=1}^{i=N}(|yi - xi|) \quad ...(5)$$

$$AD = 100 * (1/N)\sum_{i=1}^{i=N}\frac{(|yi - xi|)}{xi} \quad ...(6)$$

Where x represents the observed value, y is the interpolated value, and N is the number of points. Satellite data were employed to monitor the trophic status of the lake during the post-monsoon season from 2010 to 2019.

RESULTS AND DISCUSSION

The primary objective of this study was to monitor the trophic status of the lake using satellite data. Measurements of Secchi disk transparency (SDT), dissolved oxygen (DO), and pH were conducted during the post-monsoon season of 2019. DO, and pH are crucial water quality metrics routinely monitored to assess the health condition of water bodies (Boavida & Marques 1996, Mullins & Whisenant 2004, Parinet et al. 2004, Nayak et al. 2004, Riduan et al. 2009, Azary et al. 2010, Sharma et al. 2010). The field data were meticulously analyzed and processed using SURFER software. A concerted effort was made to identify the optimal interpolation method, and the statistical outcomes comparing various techniques are presented in Table 3. The optimal interpolation method was determined by assessing how well the interpolated values align with in-situ observations. The evaluation, based on in-situ observed SDT, is graphically represented in Fig. 4(a-k). Statistical comparisons of the absolute differences (AD) and absolute percentage differences (APD) between measured and extrapolated values at selected sites are detailed in Table 3. Upon an overall examination of shape and interpolated value range, the Kriging interpolation method emerged as the most effective. The AD and APD values of Kriging closely align with inverse distance to power, natural neighbor, and modified Shephard's method. However, values for inverse distance to power and modified Shephard's method fall outside the acceptable range, and the natural neighbor method produces an out-of-shape image, along with other approaches. Consequently, the Kriging interpolation method is employed for extrapolating field data in the present research.

Table 3: The different interpolation methods and values of AD and APD derived from the observed and interpolated values of SDT.

Sl. No.	Methods	AD	APD
(a)	Kriging	0.018873545	1.443803073
(b)	Inverse distance to power	0.027220545	2.329114213
(c)	Minimum curvature	0.033879364	2.743505355
(d)	Modified Shephards Method	0.019928455	1.569698211
(e)	Natural neighbour	0.024400000	1.913597509
(f)	Nearest neighbor	0.036363636	2.955635274
(g)	Polynomial regression	0.119352727	9.543133332
(h)	Radial basis function	0.035463818	2.725649744
(i)	Triangulation with linear interpolation	0.030948273	2.431568419
(j)	Moving average	0.126437182	10.11023505
(k)	Local polynomial	0.085441273	6.639062398

The dissolved oxygen (DO) and pH of water bodies exert a significant influence on the spatial and seasonal distribution of aquatic species, particularly fish. These parameters have direct or indirect effects on various crucial limnological characteristics, encompassing clarity, viscosity, total dissolved solids, and conductivity (Whitney 1942, Araoye 2009). pH, a critical parameter of water bodies, supports aquatic life within a specific range conducive to optimal growth and survival. Although every aquatic species exhibits a preferred pH range, the majority favor a pH range of 6.5 to 9.0 (US EPA 1986). Deviations from this range induce physiological stress, and extreme pH levels can lead to severe consequences, including mortality. The concentration of dissolved oxygen (DO) in a water body serves as a key indicator for biological livelihood and is essential for water quality assessment. Oxygen depletion negatively affects aquatic life, influencing their growth. Analyzing oxygen levels is crucial for understanding the health of aquatic ecosystems, revealing the extent to which water has been contaminated, lost organic substances, and undergone self-purification (Chapman & Kimstach 1996). As a result, measuring the DO of a water body is crucial for determining water quality because oxygen is involved in or influences virtually all chemical and biological processes. The significance of DO in the aquatic ecosystem has been examined by numerous researchers (Walker 1979, Carr & Neary 2006, Ashraf et al. 2010, Saluja & Garg 2017). It is noteworthy that this study does not intend to estimate additional water quality parameters, such as Total Suspended Matter (TSM), Chlorophyll, and Nutrients. Consequently, the analysis is confined to selected water quality parameters, and the kriging method is employed to create in-situ observed interpolated images of DO, pH, SDT, and Trophic State Index (TSI), as illustrated in Fig.5 (a-d). A detailed analysis of these water quality parameters is described below.

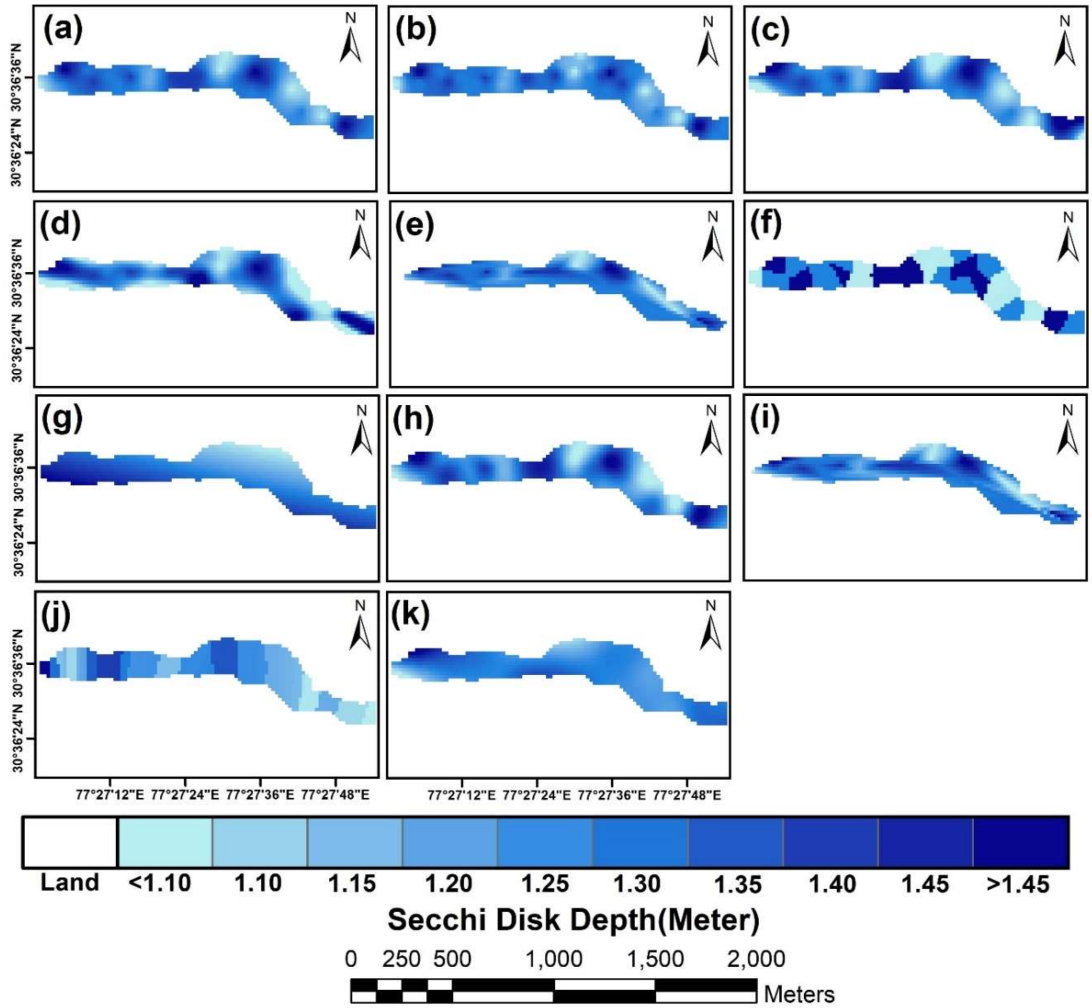

Fig. 4: The interpolated images of in-situ Secchi disk transparency data: (a) Kriging, (b) Inverse distance to power, (c) Minimum curvature Method, (d) Modified shepherds Method, (e) Natural Neighbor, (f) Nearest Neighbor, (g) Polynomial regression, (h) Radial Basis Function, (i) Triangulation with linear interpolation, (j) Moving Average and (k) Local Polynomial.

Fig. 5(a) depicts varying DO concentrations across different areas of the lake during the post-monsoon season of 2019. Higher DO levels are observed in some pockets of the western part (9.47 mg.L^{-1}), south-western part (10.57 mg.L^{-1}), and central part (10.34 mg.L^{-1}) of the lake, while the lowest DO concentrations are found in the western part (7.42 mg.L^{-1}), eastern part (7.49 mg.L^{-1}), and central parts (6.87 mg.L^{-1}) of the lake. The range of DO values in the present study is from 6.67 to 10.57 mg.L^{-1}, with an average DO value of approximately 8.28 mg/L. The maximum concentration of DO is found in the southwestern part of the lake, attributed to clear water and minimal anthropogenic activity (Singh & Sharma 2012, Gupta et al. 2018, Kumar et al. 2019). Conversely, the minimum DO levels observed in the western, central, and eastern pockets of the lake may be attributed to weed growth and anthropogenic activities, leading to eutrophic conditions and resulting fish mortality in the lake (Das et al. 2001, 2008).

The pH of water serves as an indicator of its acidity or alkalinity, gauged through the concentration of hydrogen ions (H+) and hydroxyl ions (OH-) in water (Dhillon & Mishra, 2013). Our observations reveal that the entire lake water exhibits a slight acidity to alkalinity. Fig. 5(b) illustrates the spatiotemporal pattern of pH concentration across different locations during the post-monsoon season. In this study, the pH of lake water ranged from a maximum of 8.82 to a minimum of 6.98 in October, aligning closely with previous observations (Singh & Sharma 2012, Kumar et al. 2019). The average pH value during the post-monsoon season was 7.52. Some pockets in the western part (7.12), central part (6.98),

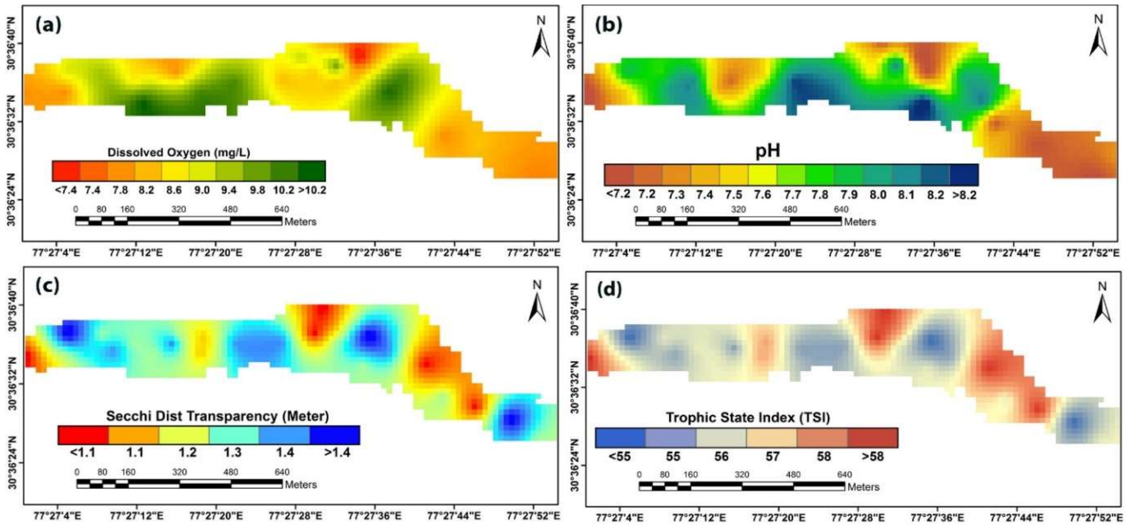

Fig. 5(a-d): Interpolated images of in-situ data (a) Secchi Disk Transparency (SDT), (b) DO, (c) pH and (d) Trophic State Index during October 2019.

and the entire eastern part (7.09) of the lake exhibited a lower pH concentration. The remaining areas of the lake displayed a large variation in pH (7.16 - 8.82), indicating an alkaline nature associated with the presence of submerged weeds. The uptake of carbon dioxide (CO_2) during photosynthesis by these weeds may contribute to increased alkalinity in the lake water (Suba Rao et al. 1981, Panda et al. 1989, 2008, Nayak et al. 2004). Conversely, low pH values suggest a slightly acidic character in different locations, potentially attributed to pollution, weed decay, and the decomposition of carbonaceous material from the deciduous forest around the lake/catchment (Singh & Sharma 2012).

The spatiotemporal variability in Secchi disk transparency (SDT) during the post-monsoon season was analyzed. In-situ observed transparency ranged from 0.93 to 1.5 m, with an average transparency of 1.28 m. Fig. 5(c) illustrates that certain pockets of the eastern, western, and central parts of the lake displayed high transparency, with SDT measurements between 1.4 and 1.5 m, potentially due to minimal anthropogenic activity. However, pockets in the western and central parts exhibited low transparency (<1 m), indicating highly polluted water in terms of SDT. This could be associated with lower layers mixing with upper layers due to upwelling activities, human interference (boating, bathing), pollution, soil erosion, weed growth, and the influx of stream water from the surrounding drainage basin (Sehgal 1980, Das et al. 2001, 2008, Singh & Sharma 2012, Gupta et al. 2018). Some pockets in the eastern parts of the lake exhibited shallow depth, turbid water, and widespread weed growth, contributing to the overall low transparency. Notably, the eastern part of the lake near the Zoo area displayed maximum hydrophytes, indicating high productivity.

Renuka Lake exhibits signs of accelerated eutrophication due to human activities in the catchment area, resulting in high nutrient content and supporting rich biological diversity (Melkania 1988). The lake boasts a macro-phytic vegetation cover spanning approximately 39,969 square meters. A study by Singh & Mahajan (1987) identifies 42 different types of macrophytes, with Phragmites, Acorus, Typha, Carex, Pontederia, and Veronica being the most common. This abundance of macrophytic genera shows the high biological diversity of the lake. The nutrient concentration in the lake water shows an increasing trend, indicative of rising pollution, nutrient-rich water, and planktonic population. Given its status as a key indicator of lake health, regular monitoring of the Trophic State Index (TSI) is imperative.

TSI is measured using both in-situ observed SDT and Landsat-8 OLI satellite data, as depicted in Fig. 5(d). The majority of TSI values are highest in some pockets of the eastern part (58.46), central part (58.62), and western part (58.25) of the lake. However, except for these areas, minimum TSI values range from 54.15 to 54.45. The average in-situ observed TSI value for the lake is 56.38. Overall, the TSI values suggest that the lake water exhibits a eutrophic to hypereutrophic condition. A standard set by Caspers (1982) deems a lake hypereutrophic if its SDT values fall within the range of 0.7-1.5. Following this standard, the SDT values for Renuka Lake (0.93-1.5 m) from this study confirm its hypereutrophic condition. This finding is supported by a previous study by Kumar et al. (2019), which reported SDT values within the range of 0.9-1.14 m.

Various optical remote sensing satellite data, including Landsat-TM (Brezonik et al. 2005, Olmanson et al. 2008, Kulkarni 2011, Torbick et al. 2013), Landsat ETM (Allan et al. 2007, Mishra & Garg 2011), Landsat-8 OLI (Lim et al. 2015, Lee et al. 2016, Urbanski et al. 2016, Olmanson et al. 2016, Liu et al. 2019, Jally et al. 2020), LISS-III (Coskun et al. 2006, Sheela et al. 2011, Gholizadeh 2016), LISS-IV (Mobwoga et al. 2010), Sentinel-2 (Toming et al. 2016, Bonansea et al. 20219, Bhangale et al. 2020, Bresciani et al. 2019, Torres Bejarano et al. 2020, Sent at al. 2021), MODIS (Wu et al. 2009, Knight et al. 2012), MERIS (Giardino et al. 2014, Mohamed 2015), and Rapid Eye (Fritz et al. 2017, Mishra et al. 2018, Avdan et al. 2019, Cahalane et al. 2019), have been utilized for the study of water quality assessment and eutrophication of the lake.

Landsat-8 and LISS-III satellite data were employed to monitor changes in the lake's trophic status during the post-monsoon period of 2010-19. The trophic status was analyzed annually, revealing distinct patterns (Fig. 6(a-j)). In 2010, certain areas in the western, central, and eastern parts of the lake exhibited high Trophic State Index (TSI) values, indicating eutrophic to hypereutrophic conditions. The southwestern and central parts transitioned from oligotrophic to mesotrophic. Similar patterns persisted in 2011-12 (Fig. 6(b, c)), and 2013 saw high TSI values in specific pockets of the lake, with the remaining areas demonstrating oligotrophic to mesotrophic conditions. The years 2014-15 (Fig. 6(e, f)) showed high TSI values in the entire eastern part and some western pockets, while the central and southwest parts indicated mesotrophic to eutrophic conditions. In 2016-17 (Fig. 6(g, h)), the central and southwest parts exhibited mesotrophic conditions, whereas the western and eastern parts displayed high TSI values. In 2018 (Fig.

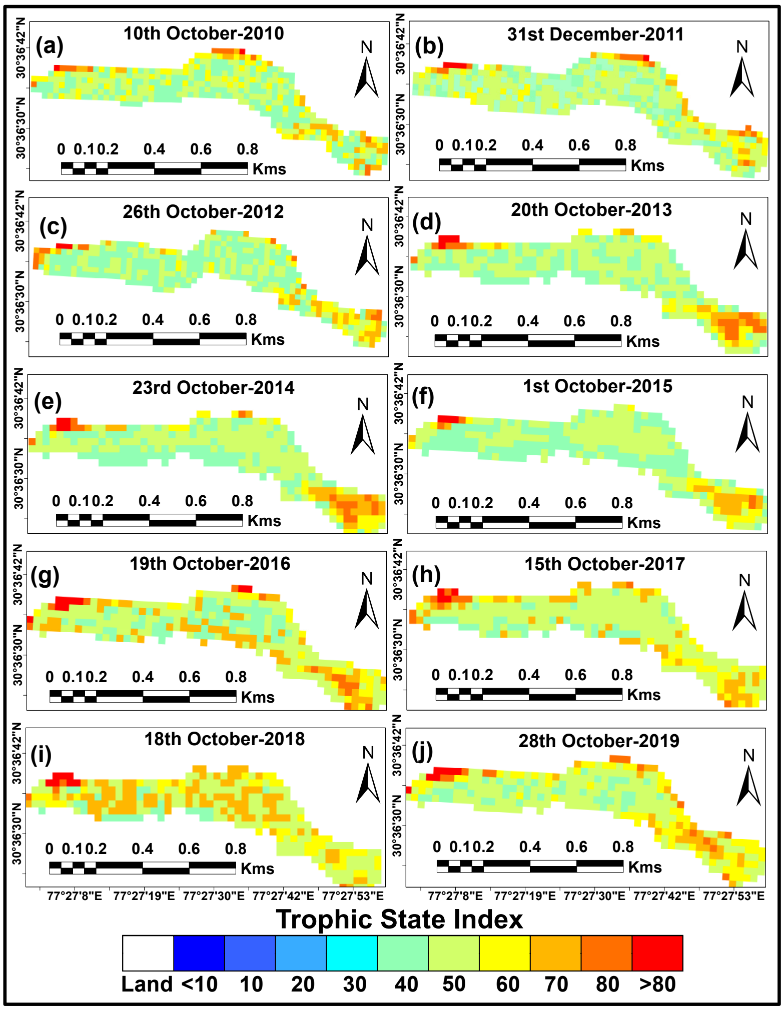

Fig. 6(a-j): TSI images derived from Landsat-8 OLI and LISS-III for 2010 to 2019.

6(i)), a substantial area of the lake showed high TSI values (hypereutrophic condition), except for some central pockets. 2019 (Fig. 6(j)) exhibited TSI patterns similar to 2017 (Fig. 6(h)).

Tourist-generated garbage and sewage seepage, contributing to macrophyte growth, especially in the lake's extreme west where tourist facilities are located, may explain the high trophic status observed during different years (Sehgal 1980, Das et al. 2001, 2008, Singh & Sharma 2012, Gupta et al. 2018, Kumar et al. 2019). The decrease in lake water transparency during winter months may result from the mixing of lower and upper layers due to upwelling activity (Sehgal 1980, Gupta et al. 2018). Human activities like grazing and road construction accelerate silt flow into the lake, as determined at 3.3 mm/year using the Pb210 isotope method (Das & Kaur 2001). Despite this, some pockets in the central and southwest areas showed fairly clear water (mesotrophic) in 2019, possibly due to conservation efforts by the lake development authority, including regular cleaning of weeds and hydrophytes.

To understand the increasing impact of TSI values in the lake, TSI derived from satellite data and Secchi disk transparency (SDT) are presented in Fig. 7 and Fig. 8. Fig.7 illustrates the average TSI values exhibiting an initial increase followed by a decrease with slight fluctuations in SDT values. The lowest average TSI values were observed in 2015 and 2017. Conversely, Fig.8 depicts a decreasing to increasing trend in SDT values from 2010 to 2019. The

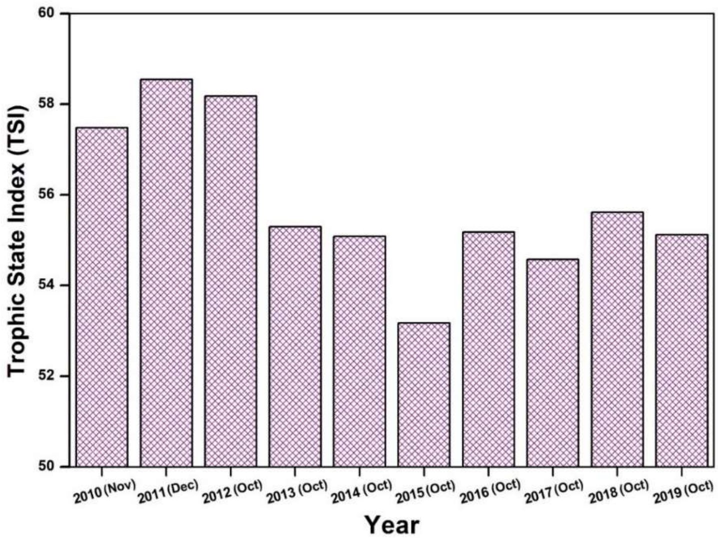

Fig. 7: Comparison of average TSI from Landsat-8 OLI and LISS-III during 2010-19.

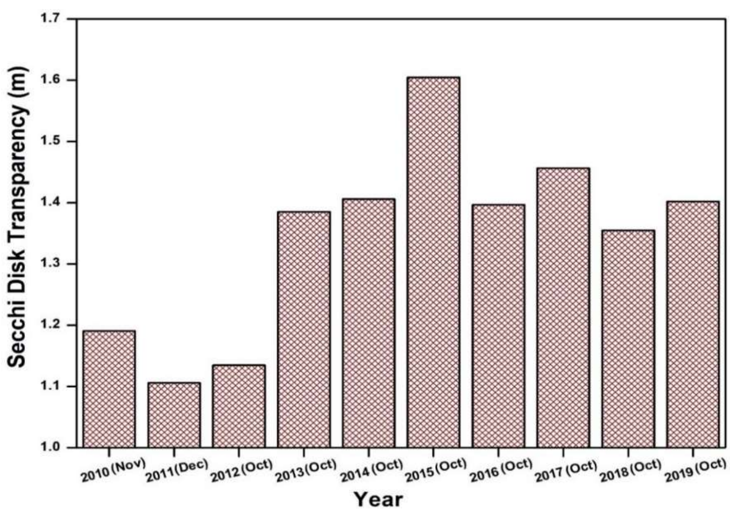

Fig. 8: Comparison of average SDT (m) from Landsat-8 OLI and LISS-III during 2010-19.

minimum transparency was observed in 2010-12. High TSI values leading to substantial development of algae, weeds, and hydrophytes, coupled with a decline in lake transparency, underscore the lake's extreme nutrient richness, impacting its clarity. Table 1 presents in-situ observations, indicating the disappearance of the Secchi disc at a depth of less than 1 meter in certain locations. A comparison of the mean TSI value derived from in-situ measurements with that from satellite observations for 2019 shows a close correspondence, with a difference of only 1.25%. The analysis of Fig. 7 and 8 reveals that the average in-situ measured TSI pattern aligns consistently with TSI values estimated from Landsat-8 OLI and LISS-III.

This study, while providing valuable insights into the trophic state of Renuka Lake, exhibits certain limitations that call for further exploration. Firstly, the focus on key water quality parameters, such as SDT, pH, and DO, leaves room for additional investigation into other critical contributors to the lake's overall health, including nutrient concentrations, chlorophyll, and pollutants. Expanding the scope to encompass a broader array of water quality parameters would enrich the study's comprehensiveness. Secondly, the paper briefly addresses post-monsoon season data, hinting at potential seasonal variability in water quality. A more thorough exploration of seasonal dynamics throughout the year could enhance our understanding of the lake's trophic state fluctuations and provide a more nuanced portrayal of its trophic status. Additionally, investigating the specific sources and relative impacts of anthropogenic activities, such as tourism and sewage, would contribute depth to the study. Furthermore, the research could further advance by exploring the integration of diverse data sources beyond Landsat-8 OLI, such as UAVs or high-resolution satellite imagery, to augment the accuracy and resolution of findings and a focus on long-term trends and predictive modeling could elevate the precision and forecasting capability of future assessments.

CONCLUSION

In this study, we have demonstrated the utility of remote sensing satellite data in enhancing lake research and monitoring, specifically focusing on crucial water quality metrics, trophic status, and water transparency. The *in-situ* measured Secchi Disk Transparency (SDT) indicates that the water quality of the entire Renuka Lake is within the eutrophic to hypereutrophic range. Trophic status is particularly pronounced in certain areas of the extreme western, central, and eastern parts of the lake, primarily attributed to their proximity to hotels, temples, and bathing Ghats, where human activities and pollution reach maximum levels. Factors such as upwelling, agricultural runoff, weed growth, drainage influx, and siltation from surrounding drainage basins contribute significantly to the increasing Trophic State Index (TSI) in Renuka Lake. Conversely, the central portion of the lake, where TSI is the lowest, exhibits relative clarity and greater depth due to minimal siltation and reduced human activity. The analysis of satellite data over the past decade unequivocally indicates that Renuka Lake has been consistently in a eutrophic to hypereutrophic condition, confirming the deterioration in water quality, as corroborated by TSI from ground observations. The Secchi disc transparency test emerges as a quick, easy, and accurate method for determining the trophic state of the lake. Notably, rigging interpolation stands out as a superior technique for generating water quality maps from in-situ data compared to alternative approaches.

The current pH and dissolved oxygen (DO) levels in Renuka Lake suggest favorable water quality conditions for aquatic life. However, to establish a comprehensive database and unravel the intricate relationships between physical, chemical, and biological processes in the lake, ongoing extensive monitoring programs are imperative. These programs should be implemented as part of an integrated development strategy aimed at safeguarding the wetland ecosystem from siltation, eutrophication, floodwater influx, and preserving aquatic life. Furthermore, afforestation initiatives in the lake's vicinity can effectively mitigate siltation and curb rapid soil erosion. Protective measures for the smallest Ramsar Wetland Ecosystem in the Shiwalik Range of the Lower Himalaya must include a complete prohibition on discarding household waste into the lake, regular cleaning of emergent and submerged aquatic weeds to reduce nutrient levels, and routine monitoring of water quality parameters to assess pollution. Thus, the consistent monitoring of water quality, both through in-situ observations and satellite data, is crucial for assessing and preserving the trophic status of the lake and safeguarding its Ramsar site wetland designation.

For an effective lake hydrological environment monitoring, the extensive utilization of continuous time-series satellite data, coupled with field-observed water quality data, proves beneficial. Landsat-8 OLI data, with its spatial, spectral, and radiometric resolutions, can intricately retrieve water quality indicators such as SDT and TSI. Recognizing the constraints of Landsat-8 OLI's 16-day revisit time and frequent cloud obscuration, incorporating other high-temporal-resolution satellite data sources like MODIS, Sentinel-2A, Rapid-Eye, and NOAA AVHRR can offer valuable insights into long-term trends in water quality metrics. The integration of field observations and remote sensing data becomes a valuable resource for limnologists and lake management authorities. Future research endeavors should delve into assessing the mechanisms essential for protecting Renuka Wetland from rapid eutrophication. Embracing readily accessible and upcoming satellite data, adhering to open access and public data policies, leveraging existing algorithms, and employing open-source data will undoubtedly enhance the efficacy of remote sensing applications in lake research.

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