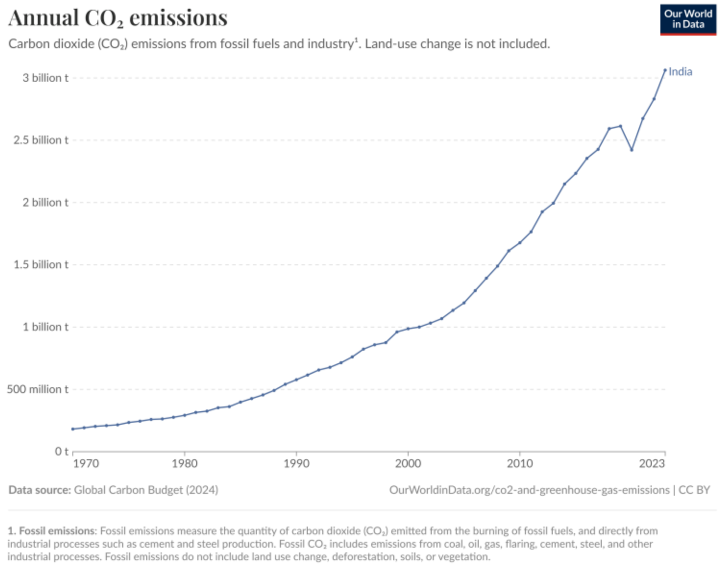
Estimating Carbon Sequestration In Urban Water Bodies Using Remote Sensing And Modeling Techniques

Guides:
Jay Shah and Tushar Bose

Presented by:
Ajay Patel (PGE23022)
Master of Geomatics
Faculty of Technology, CEPT University

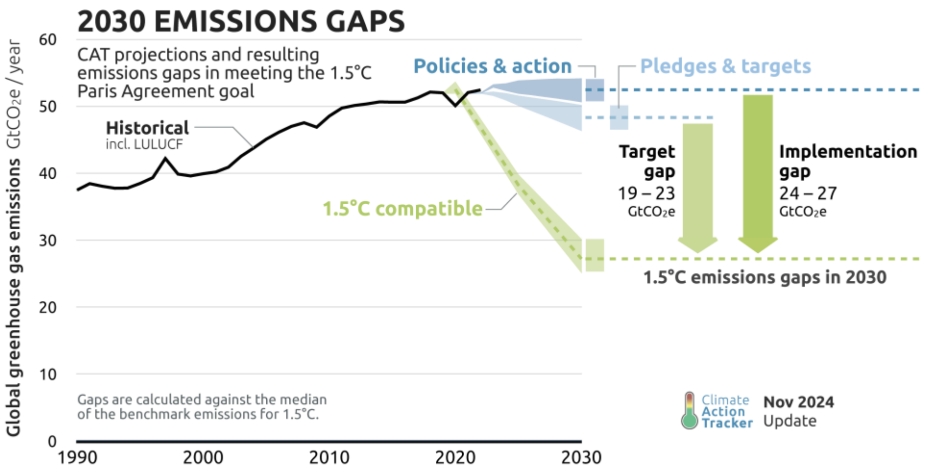
CWAS CENTER FOR WATER AND SANITATION
CRDF CEPT UNIVERSITY

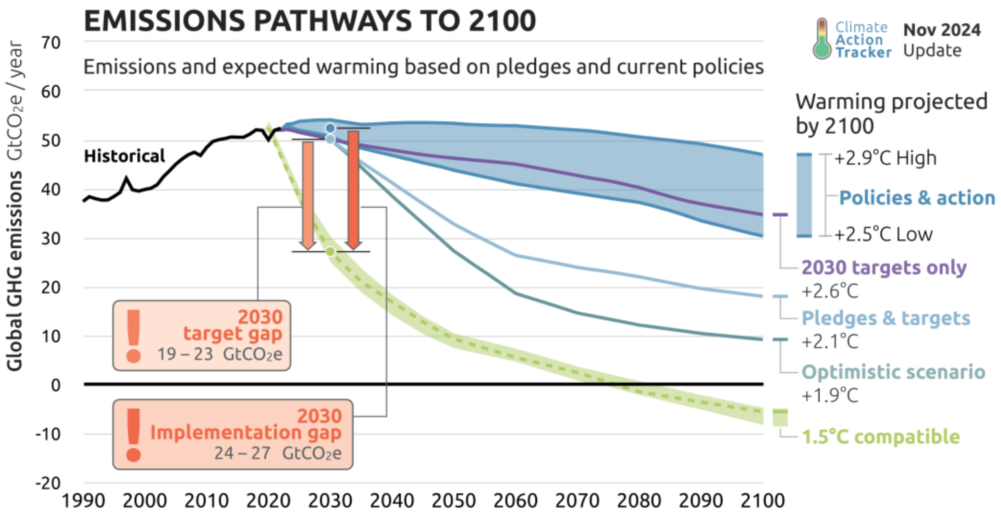
Background



Source:-https://ourworldindata.org/

Year	Value	Increase from Previous	Time Gap
1970	181.72 million t	–	–
1984	361.56 million t	~2×	14 years
1994	714.06 million t	~2×	10 years
2008	1.4 billion t	~2×	14 years
2023	3.06 billion t	~2.2×	15 years
2025*	**~3.4 billion t**		2 years

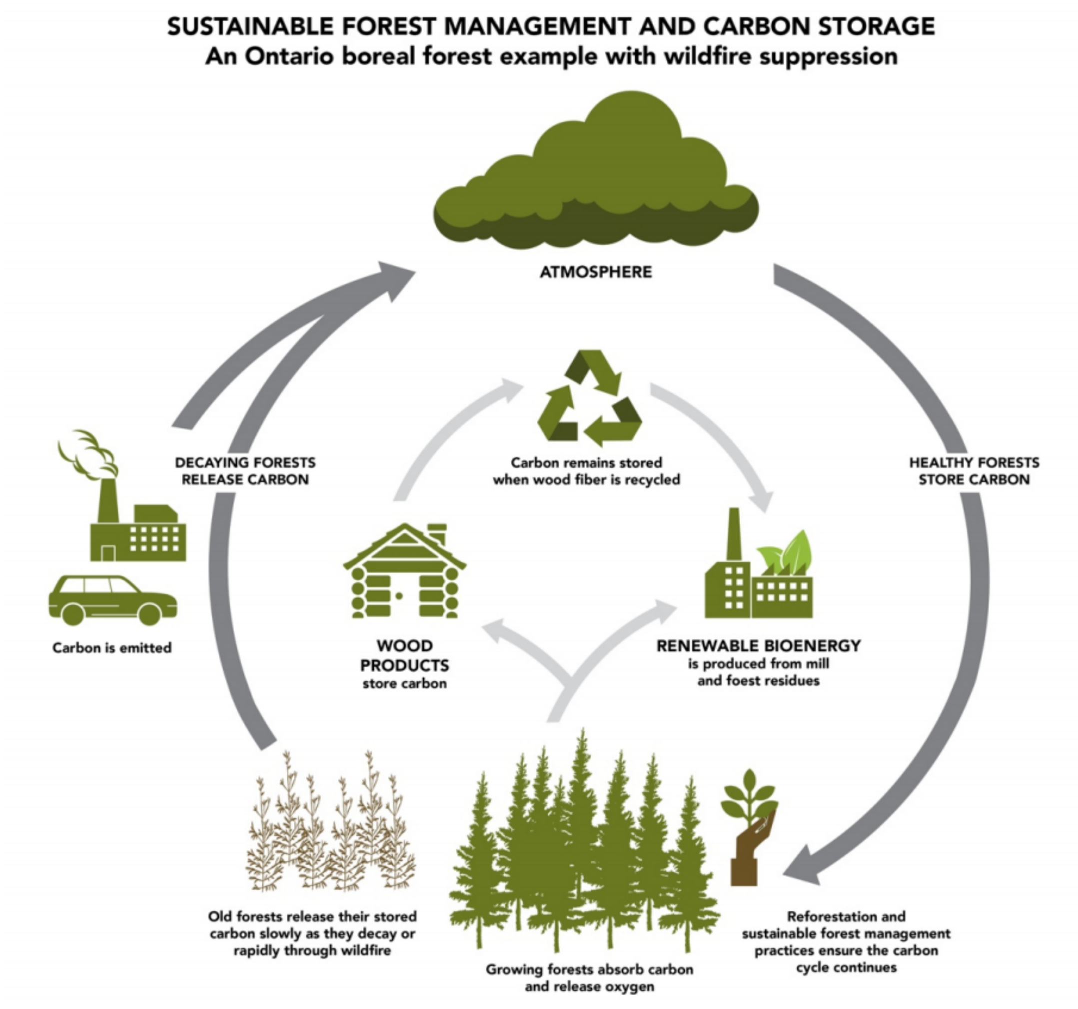




Source:https://climateactiontracker.org/

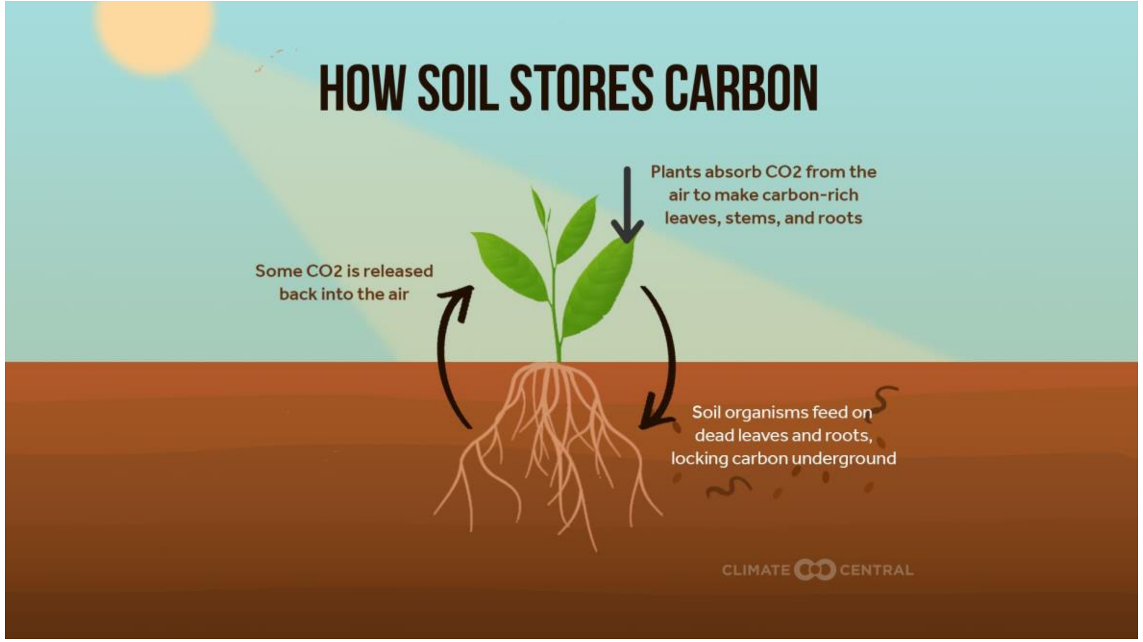
Types Carbon Sequestration Processes

➢ Forestry



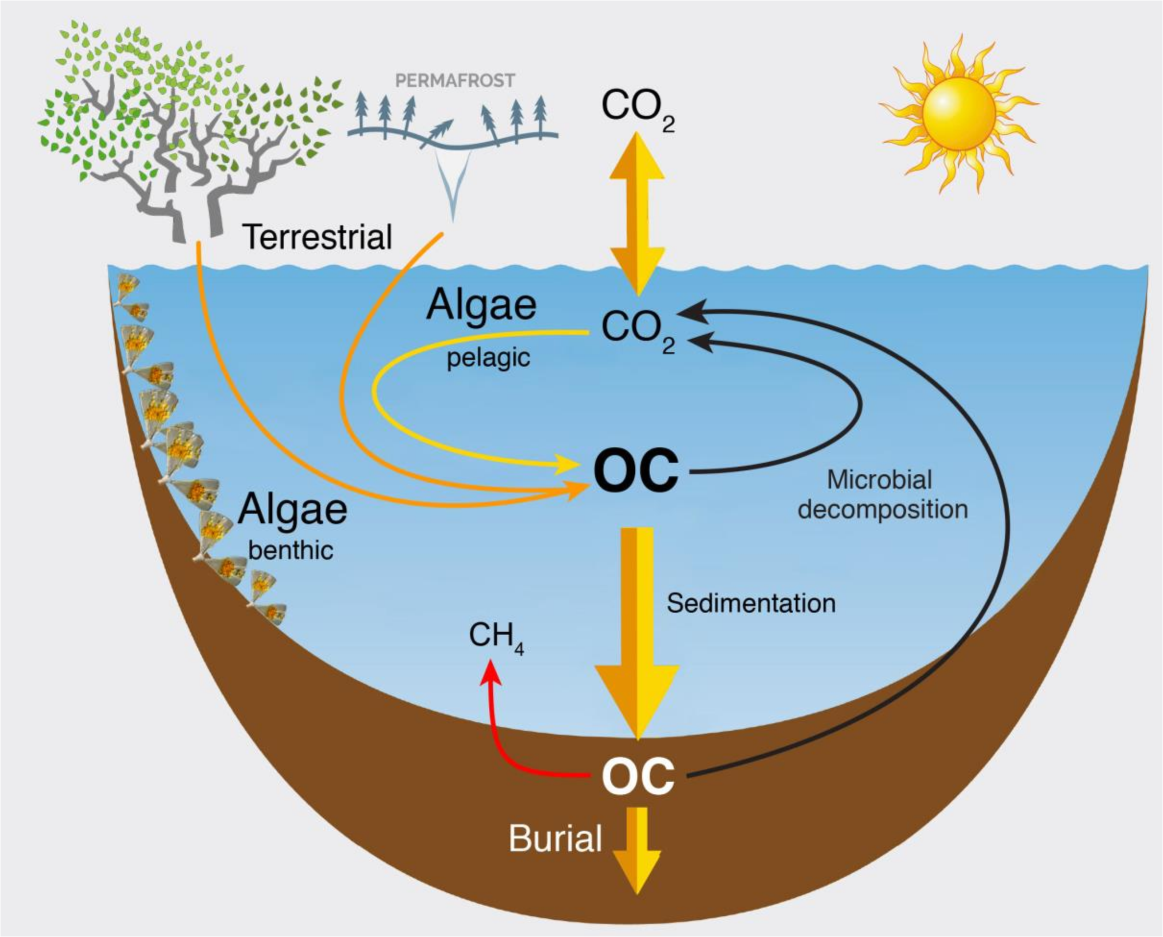
https://files.ontario.ca/mnrf-sustainable-forest-mgmt-carbon-storage.png

➢ Soil Carbon Storage



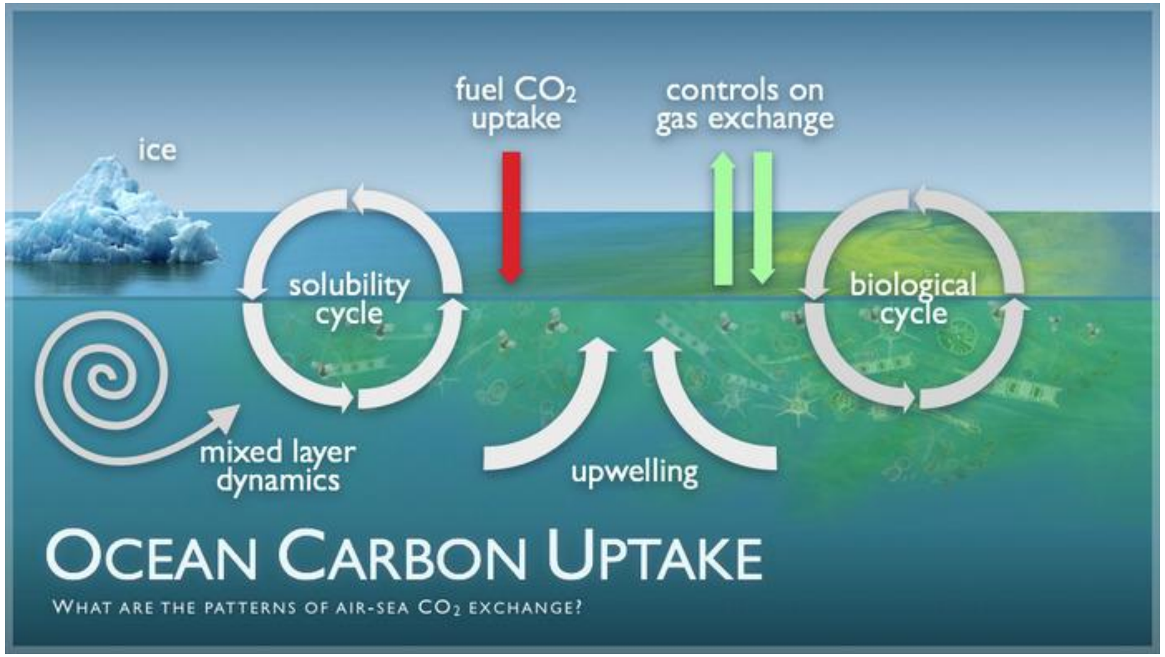
https://www.climatecentral.org/climate-matters/solutions-series-capturing-carbon-in-soil-2022

➢ Wetlands



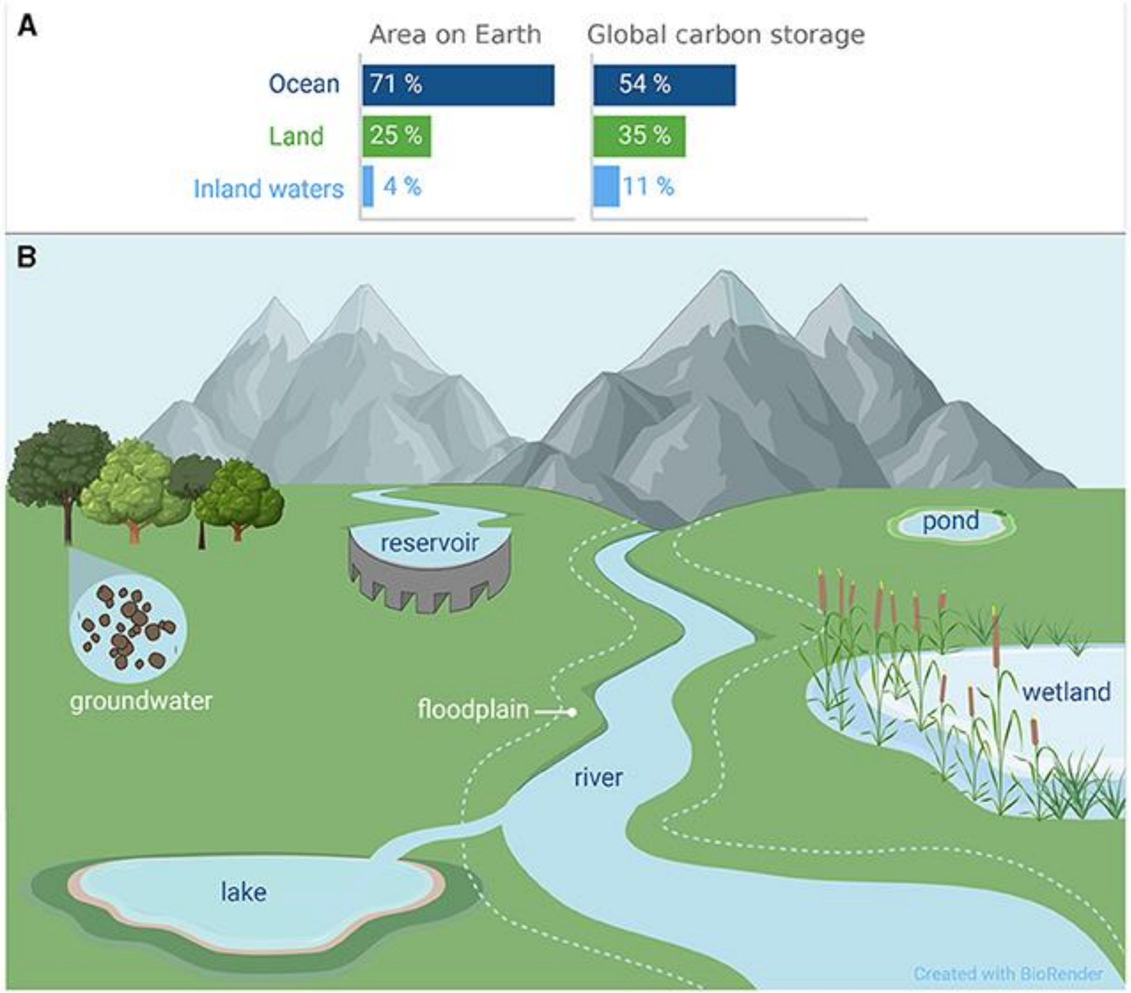
https://www.arcticcirc.net/research-interests/gudasz-lake-carbon-cycles

➢ Ocean Sequestration



https://emeraldreview.com/2022/10/the-ocean-and-carbon-sequestration-leveraging-the-oceans-carbon-capture-potential/

High Carbon Storage Efficiency in Lakes and Ponds



Franco-Cisterna B, Drost AM, van Santvoort V, Sarkis S and McGowan S (2024) Freshwater Ecosystems: Carbon Sequestration Champions. Front. Young Minds. 12:1302239. doi: 10.3389/frym.2024.1302239

Although inland waters cover only 4% of Earth's surface, they store 11% of global carbon, making them the most efficient carbon sinks per unit area, with a **carbon storage density** of **2.75%**, compared to 1.40% for land and 0.76% for oceans.

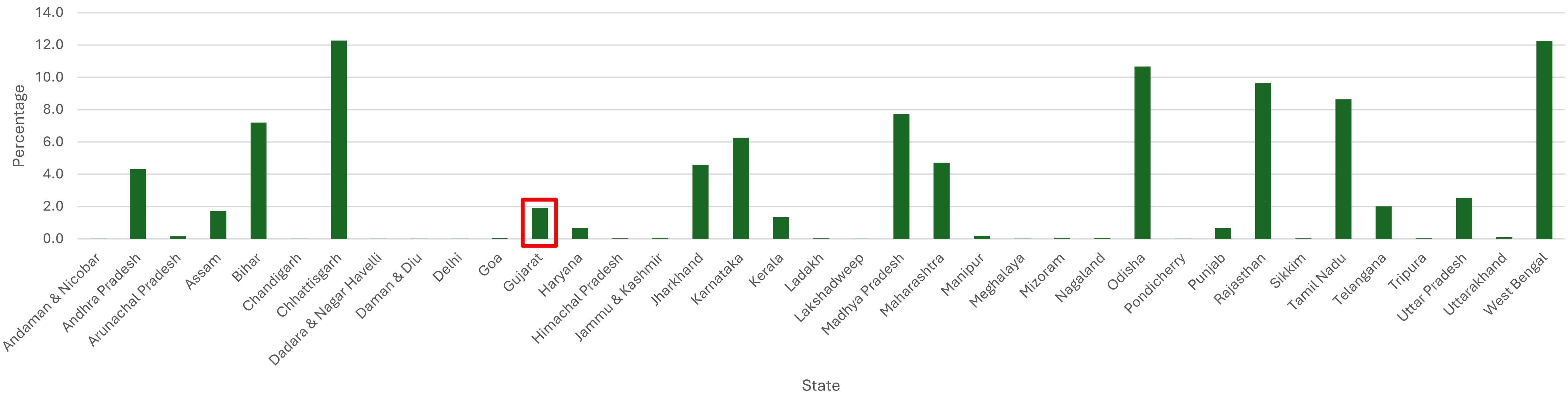
Lakes & ponds store large amounts of carbon despite their small area.

Algae & bacteria absorb CO_2 via photosynthesis.

“Lakes have a more significant potential for **carbon sequestration** per unit area (0.87 kgC·m−2·a−1) than the ocean and forest ecosystems. ”

Tian, Y., Zhao, Y., Zhang, X., Li, S., & Wu, H. (2023). Incorporating carbon sequestration into lake management: A potential perspective on climate change. Science of the Total Environment, 895, 164939.

Surface water bodies of India



State	Water bodies	Percentage
Gujarat	16,273	1.9%
Madhya Pradesh	65,940	7.7%
Maharashtra	40,106	4.7%
Rajasthan	82,075	9.6%

Total number of waterbodies: 8,51,121

- Gujarat's 1.91% share is lower compared to neighboring larger states.
- Despite being a semi-arid region, Gujarat holds a considerable number of water bodies.
- There's scope for improving water conservation, storage, and mapping strategies to boost sustainability.

Source: India Water Resources Information System

Need of the study

THE TIMES OF INDIA

City's wetlands disappearing at alarming rate

TNN | Nov 28, 2023, 08.28 AM IST

Ahmedabad: Considering the rate at which lakes and wetlands are disappearing in Ahmedabad, there are the obvious villains to blame — roads, property construction and civic amenities. The city's lakes have been degrading and disappearing at an alarming rate, according to a new study by researchers at Gujarat University's department of botany, bioinformatics and climate change impacts management.

The study conducted by Vishwa Kuchara, Charan Ronak, Archana Mankad and Hitesh Solanki examined 11 wetlands in the city and found that nearly 50% of them had shrunk in the past 23 years and 40% were redeveloped.

The number of lakes in the city plummeted from 603 in 1999, when the city area was 191 sq km to just 65 today, a decline of over 80%. In 2001, the number of lakes had reduced to 137, while in 2006, when the city area further expanded to 464 sq km, it dropped further to 122.

By 2017, according to a report prepared for Auda by Cept University, 65 lakes within Ahmedabad had garbage and building rubble and were choked with encroachments. A recent study conducted by the Bhaskaracharya Institute for Space Applications and Geoinformatics (BISAG) found that the lakes are shrinking at a decadal rate of 1.57 sq km.

"The number of lakes in the city has been constantly declining with the expanding municipal boundaries," observed a senior Ahmedabad Municipal Corporation (AMC) official in the Nort West Zone.

The Makarba lake has degraded by 14% in the past decade, according to a study conducted by Gujarat University.

Another example worth noting is the Vastrapur lake. More than two decades ago, it was visited by migratory birds.

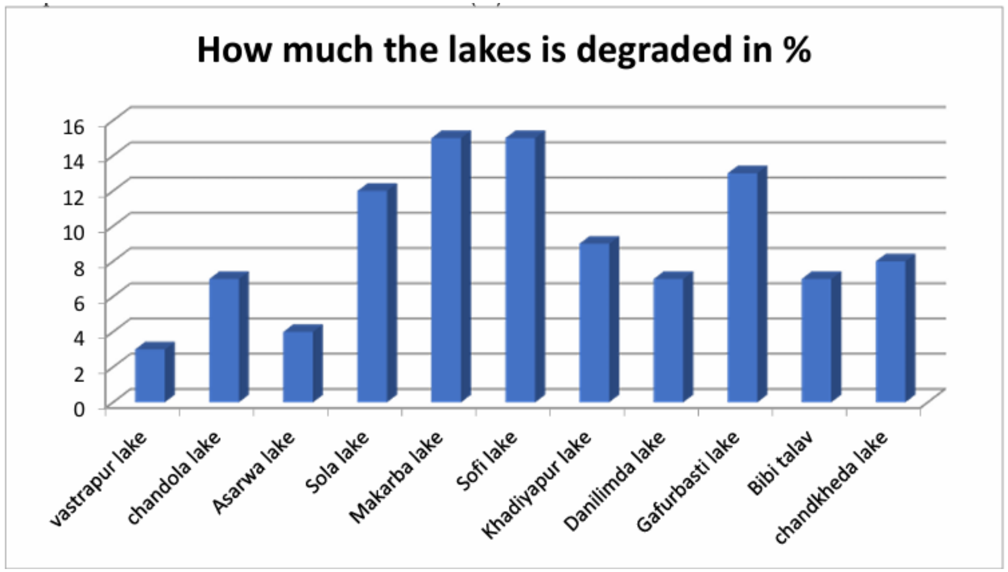
In those days, the lake's sub-catchment area was 11.52 lakh sq m. Large amounts of water seeped through large vacant surfaces, and natural drains fed the lake.

By 2000, vacant land reduced to 32% and when Auda began lake development in 2002, the built zone covered 60% of the area.

Today only 9% of vacant land remains.

With the area of Ahmedabad city expanding to 503 sq km in 2020, there is mounting pressure for development that is likely to threaten the city's remaining lakes and small water canals, says a senior Auda official.

These precious waterbodies, located near Rancharda, Sanand Road, Shela and Ambli, face the imminent prospect of obliteration under the relentless expansion of TP roads.



Source: Google Earth

Source :Solanki[4], H. (2023). STATUS OF SELECTED WETLANDS IN AHMEDABAD.

Objectives

Identify water quality parameters that affect carbon sequestration or carbon emission potential of lakes

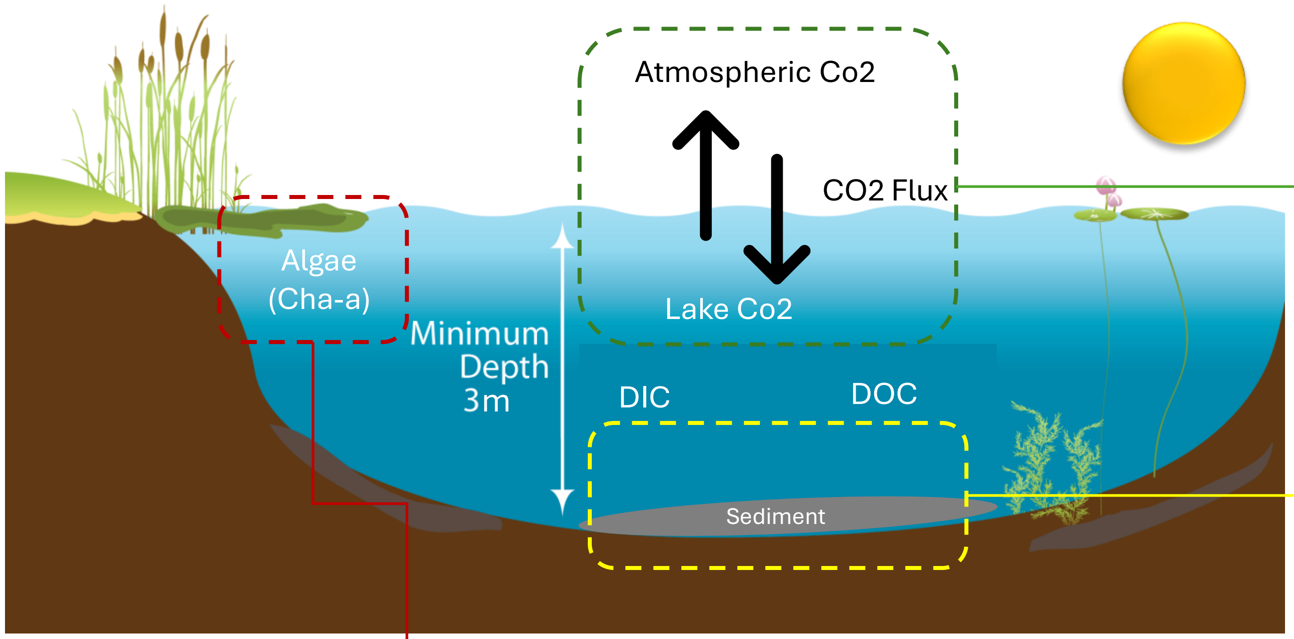
Assessment of water quality and carbon sequestration in stagnant water bodies through satellite imagery

Developing prediction models for carbon sequestration and water quality of lakes

Literature review

Carbon sequestration

Carbon sequestration is the process of capturing and storing atmospheric carbon dioxide in water.
It is one method of reducing the amount of carbon dioxide in the atmosphere with the goal of reducing global climate change. *Source: United States Geological Survey*



CO_2 Flux – The exchange of carbon dioxide (CO_2) between the lake and the atmosphere. Lakes can act as sources (releasing CO_2) or sinks (absorbing CO_2) depending on factors like respiration, photosynthesis, and organic matter decomposition.

Carbon Storage – The amount of carbon retained within the lake ecosystem, including dissolved inorganic carbon (DIC), dissolved organic carbon (DOC), and sediments. Some carbon is buried long-term in lake sediments.

Primary Productivity – The rate at which aquatic plants and phytoplankton produce organic matter via photosynthesis. It determines the lake's ability to sequester carbon and support higher trophic levels.

CO_2 Flux Calculation

$$FCO_2 = k * KH * (pCO2 - pCO2air)$$

k represents the gas transfer velocity (m d^{-1}), kH is Henry's constant, pCO2 is the partial pressure of CO_2 in the lake water (μatm), and pCO2air is the atmospheric CO_2 concentration (μatm)

$$\boldsymbol{k} = 0.251 * u^2 * \left(\frac{sc}{660}\right)^{-0.5}$$

Schmidt number (*Sc*)

$$\mathbf{SC} = 1911.1 - 118.11*T + 3.4527*T^2 - 0.04132*T^3$$

$$\mathbf{ln\ K1} = 2.83655 - 2307.1266/T - 1.5529413 \ln(T) + (-0.20760841 - 4.0484/T)S^{0.5} + 0.08468345*S - 0.00654208*S^{1.5}$$

$$\mathbf{ln\ K2} = -9.226508 - 3351.6106/T - 0.2005743 \ln(T) + (-0.106901773 - 23.9722/T)S^{0.5} + 0.1130822*S - 0.008469343*S^{1.5}$$

$$(\boldsymbol{H}^+) = 10^{-\rho H}$$

$$\alpha_0 = \left(1 + \frac{K_1}{[H^+]} + \frac{K_1 K_2}{[H^+]^2}\right)^{-1}$$

$$[H_2CO_3*] = \alpha 0 \cdot DIC$$

$$pCO_2^{\text{water}} = \frac{[H_2CO_3^*]}{K_H}$$

$$\boldsymbol{F} = FCO_2 * \text{area} * \text{days}$$

A positive FCO2 corresponds to CO_2 emission from water to the atmosphere, whereas a negative value indicates that carbon is absorbed in water. This distinction is crucial in understanding the role of urban lakes in either mitigating or contributing to atmospheric CO_2 levels

[1]Re-estimating China's lake CO2 flux considering spatiotemporal variability [2] High Emissions of Carbon Dioxide and Methane From the Coastal Baltic Sea at the End of a Summer Heat Wave [3] Relationship Between Wind Speed and Gas Exchange Over the Ocean [4] Thermodynamics of the carbon dioxide system in the oceans [5] AQUATIC CHEMISTRY

Carbon storage

This equation provides a bulk estimate of the amount of carbon present in the water body at a given time. It is important for understanding the lake's potential to act as a temporary or long-term carbon sink

SC =(DOC+DIC)* h* S

SC = The carbon sequestration of water body carbon storage

DOC = the concentration of dissolved organic carbon in water (mg/L)

DIC = the concentration of dissolved inorganic carbon in water (mg/L)

h = the depth of the lake(m)

S = the water area

Chen, B., Zhang, M., Yang, R., & Tang, W. (2023). Spatiotemporal variations in the carbon sequestration capacity of plateau lake wetlands regulated by land use control under policy guidance. *Land*, *12*(9), 1695.

Primary Productivity

Carbon Sequestration = Average Primary Productivity × Lake Area

$\mathbf{PP_{eu}} = 0.66125 \times P^{B}{}_{opt} \times (E_0 / (E_0 + 4.1)) \times Z_{eu} \times C_{opt} \times D_{irr}$

- PP_{eu} = Primary productivity in the euphotic zone (mg C m^2 d^1)
- $P^{B}{}_{opt}$ = Optimal photosynthetic rate per unit chlorophyll (mg C mg^1Chl-a h^1)
- E0 = Daily surface irradiance (mol photons m^{-2} d^{-1}), assumed between 20 and 23
- Zeu = Euphotic zone depth (m)
- Copt = Chlorophyll-a concentration in surface water (mg m^3)
- Dirr = Daily photoperiod in hours

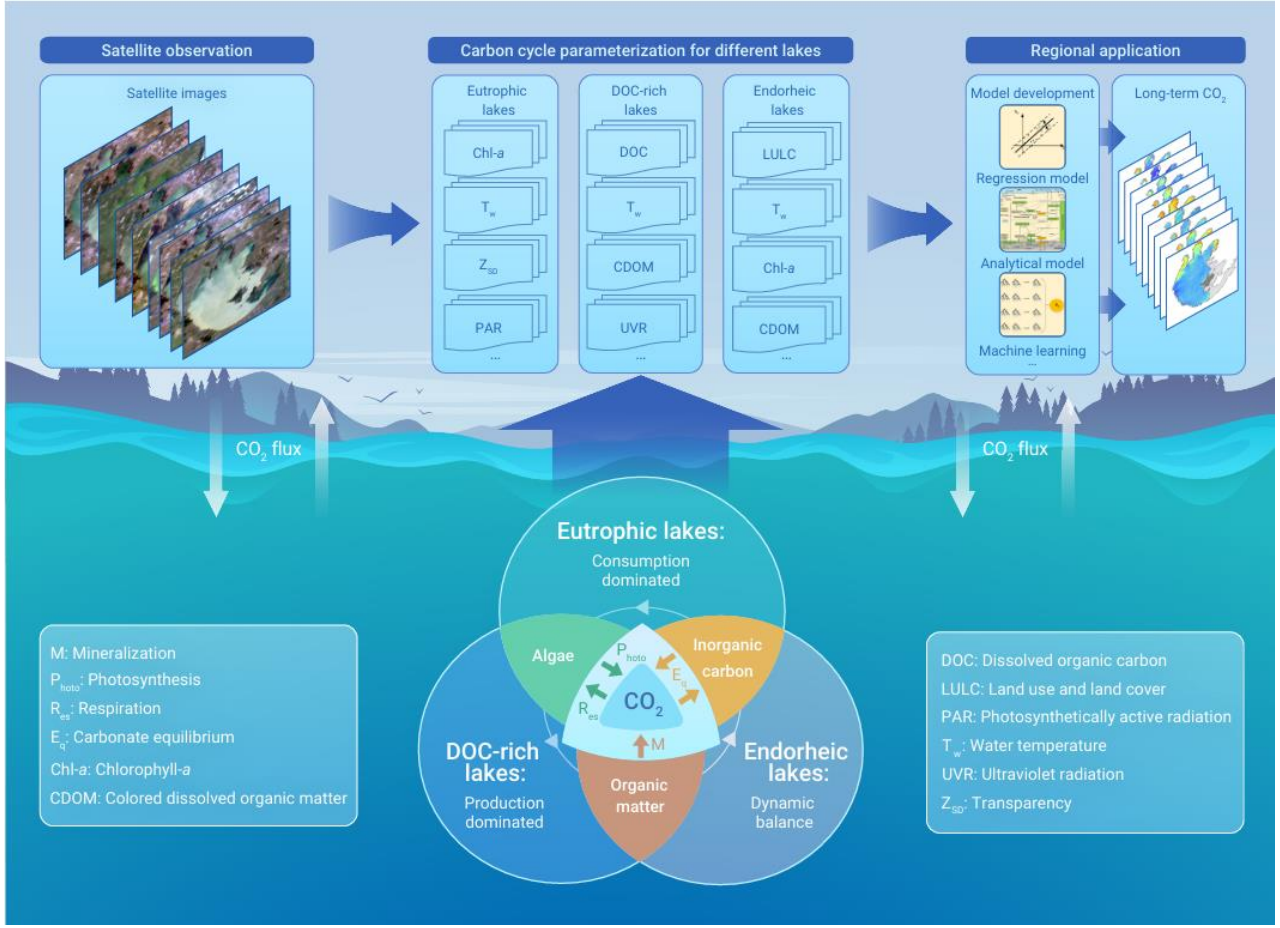
$\mathbf{P^{B}{}_{opt}} = 1.2956 + 2.749 \times 10^{-1}T + 6.17 \times 10^{-2}T^2 - 2.05 \times 10^{-2}T^3 + 2.462 \times 10^{-3}T^4 - 1.348 \times 10^{-4}T^5 + 3.4132 \times 10^{-5}T^6 - 3.27 \times 10^{-8}T^7$

Zeu = 1.7239 * SD + 0.1685

Tian, Y., Zhao, Y., Zhang, X., Li, S., & Wu, H. (2023). Incorporating carbon sequestration into lake management: A potential perspective on climate change. Science of the Total Environment, 895, 164939.

CO_2 calculation based on modelling technique

- **Satellite imagery** extracts lake parameters like chlorophyll-a, water temperature, transparency, and radiation levels.
- Lakes are classified into **eutrophic, DOC, and endorheic** based on their biogeochemical characteristics and carbon processes.
- **Carbon cycle parameters** vary for each lake type, including factors like dissolved organic carbon (DOC), CDOM, and land use (LULC).
- Advanced modeling techniques such as **regression, analytical models, and machine learning** are applied to estimate long-term **CO_2 fluxes**.
- The central carbon cycle includes processes like **photosynthesis, respiration, mineralization, and carbonate equilibrium**.
- This framework enables **regional CO_2 monitoring**, supporting climate impact assessments and sustainable lake management.



Duan, H., Xiao, Q., & Qi, T. (2023). Measuring lake carbon dioxide from space: Opportunities and challenges. *The Innovation Geoscience*, *1*(2), 100025.

Summary of literature review

- **Three main methods** to estimate carbon sequestration in lakes were identified:
- **CO_2 Flux Method** – Calculates the net exchange of CO_2 between the lake surface and atmosphere.
- **Carbon Storage Method** – Measures the amount of carbon stored in water and sediments.
- **Primary Productivity Method** – Estimates the amount of carbon fixed by aquatic plants and algae through photosynthesis.

- For each method, **standard formulas** were reviewed to quantify carbon sequestration accurately.

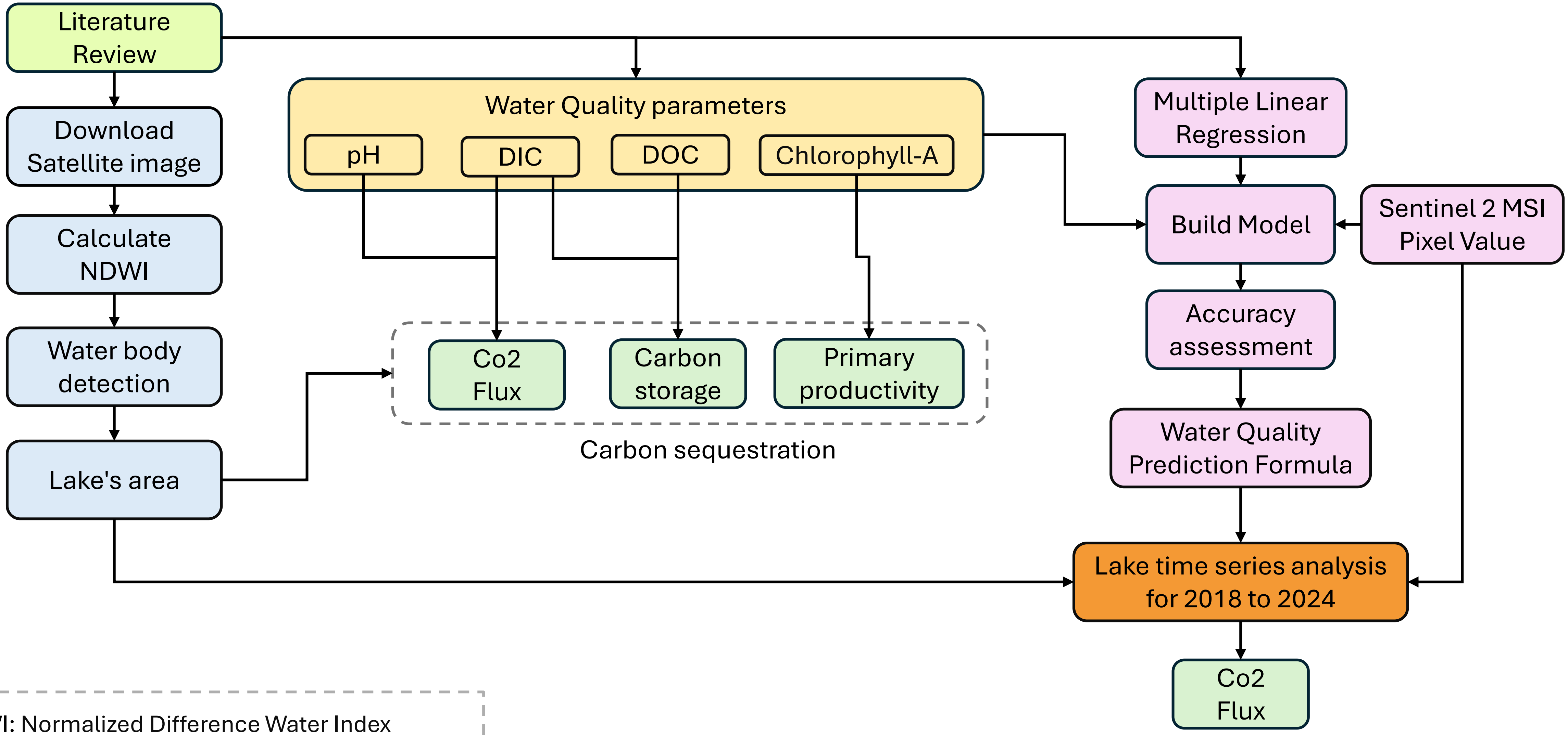
- **Satellite-based approach** is widely used for large-scale assessments, enabling:
- Detection of lake boundaries using **NDWI (Normalized Difference Water Index)** from **temporal remote sensing data**.
- Estimation of lake-specific parameters such as **chlorophyll-a, water temperature, DIC, and transparency**.

- Different lake types (eutrophic, DOC, and endorheic) were studied, each showing unique **carbon dynamics and influencing factors**.
- Various **modeling techniques** (e.g., regression, analytical models, machine learning) are applied to:
- Predict **long-term CO_2 fluxes**.
- Support **regional carbon budget estimation** and **climate policy planning**.

Required Datasets and Data Sources

No.	Step	Data source	Tool/Software Used
1	Water Body Identification	Sentinel-2 MSI satellite imagery (10m resolution)	ArcGIS Pro, Google Earth Engine (GEE)
2	Lab Testing of Water Samples	Certified laboratory analysis of water samples	Laboratory Analysis
3	Band Value Extraction	Extract Sentinel-2 band values for the exact pixel location of each water sample	Google Earth Engine (GEE)

Methodology



NDWI: Normalized Difference Water Index

DIC: Dissolved inorganic carbon

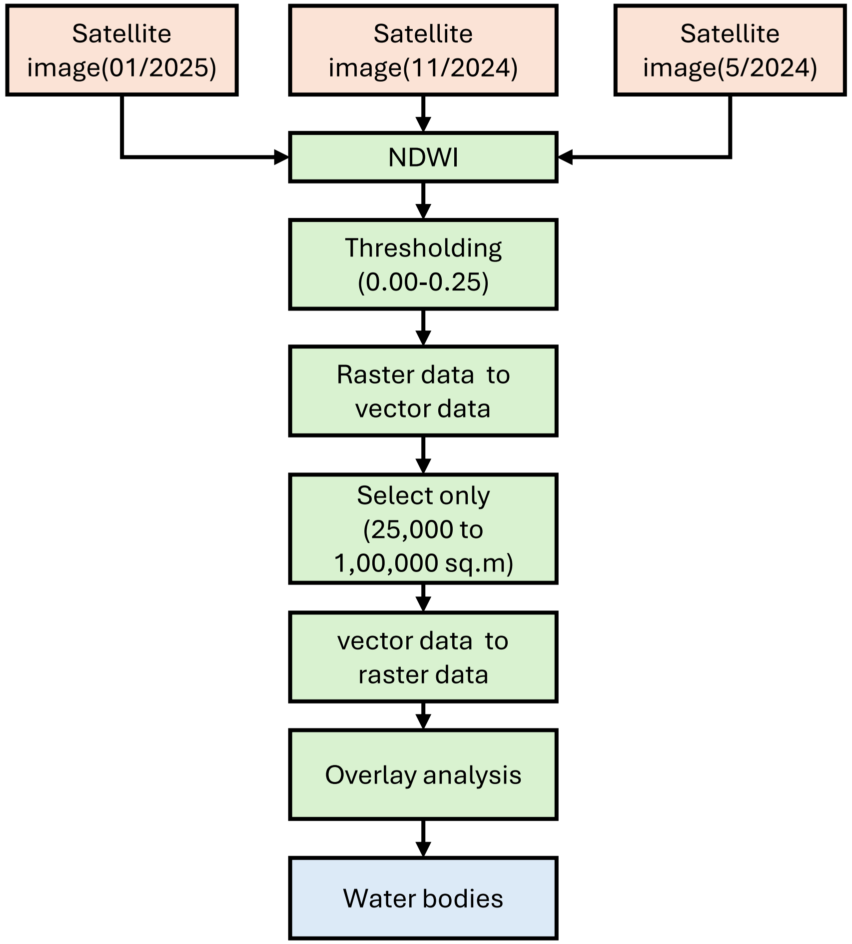
DOC: Dissolved organic carbon

Note: Water quality data given by CWAS

Sentinel 2 Pixel value is obtained from GEE

Stagnant Water Bodies Detect

Methodology of water bodies detection

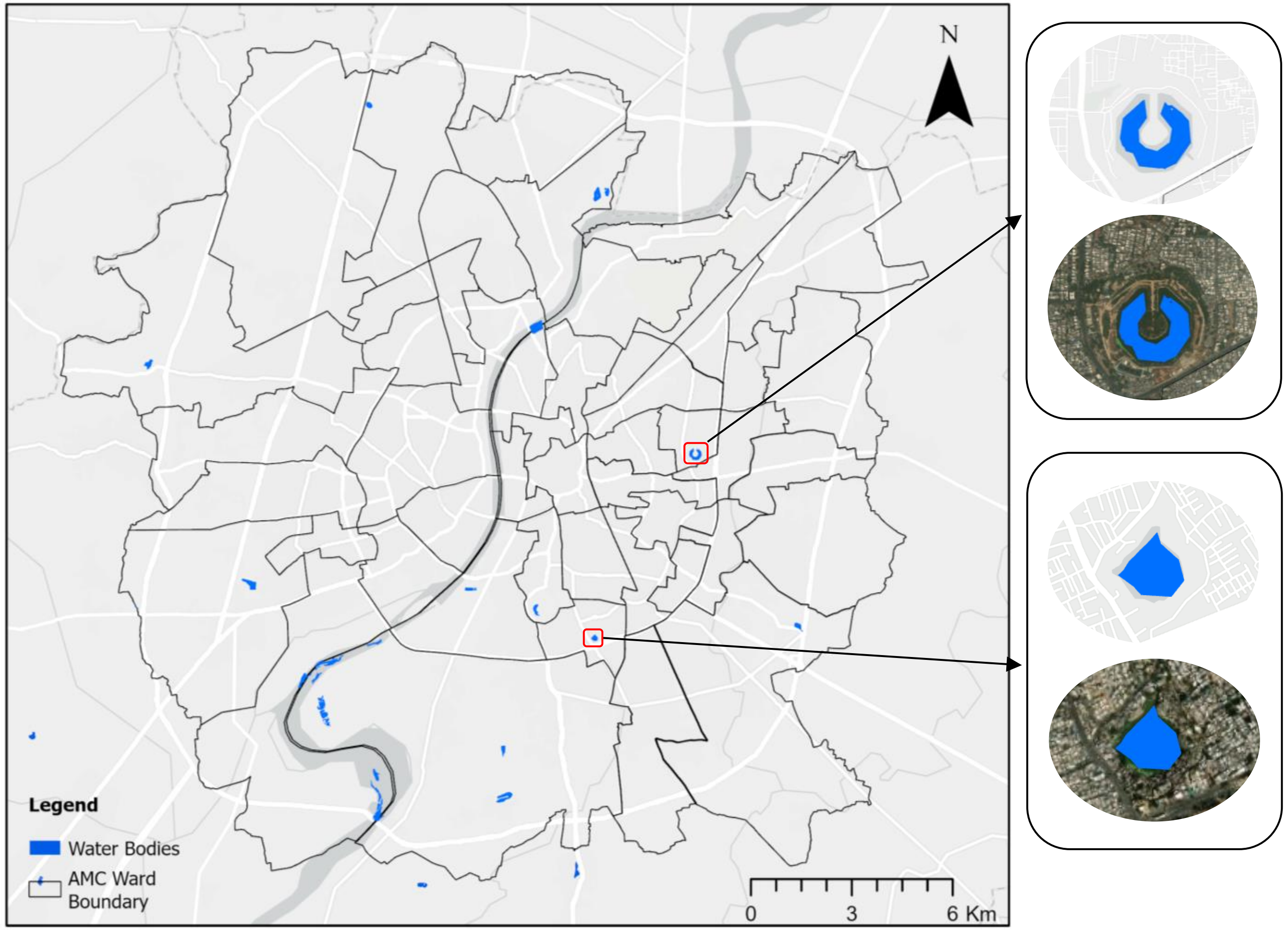


Sentinel-2 MSI (10m)
NDWI = (B3 - B8) / (B3 + B8)

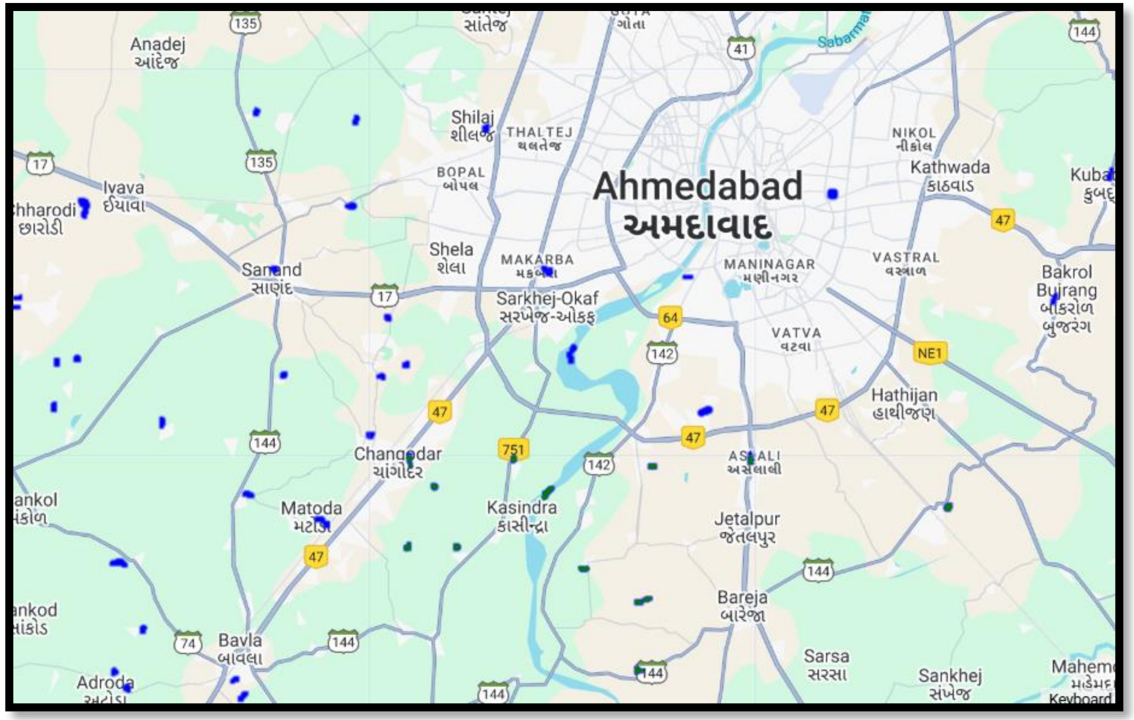
- Input data
- Processing
- Output

Water bodies detection using ArcGIS Pro

Ahmedabad Lakes



Water bodies detection using Google Earth Engine



Using Google Earth Engine and Sentinel-2 data, approximately **130 water bodies** were identified through NDWI index analysis for the Ahmedabad District.

•**Manual Method**: Involves downloading satellite images and processing them in **ArcGIS Pro** to compute **NDWI** and extract lake boundaries manually.

- This process is **time-consuming, repetitive**, and less efficient for **temporal analysis**.

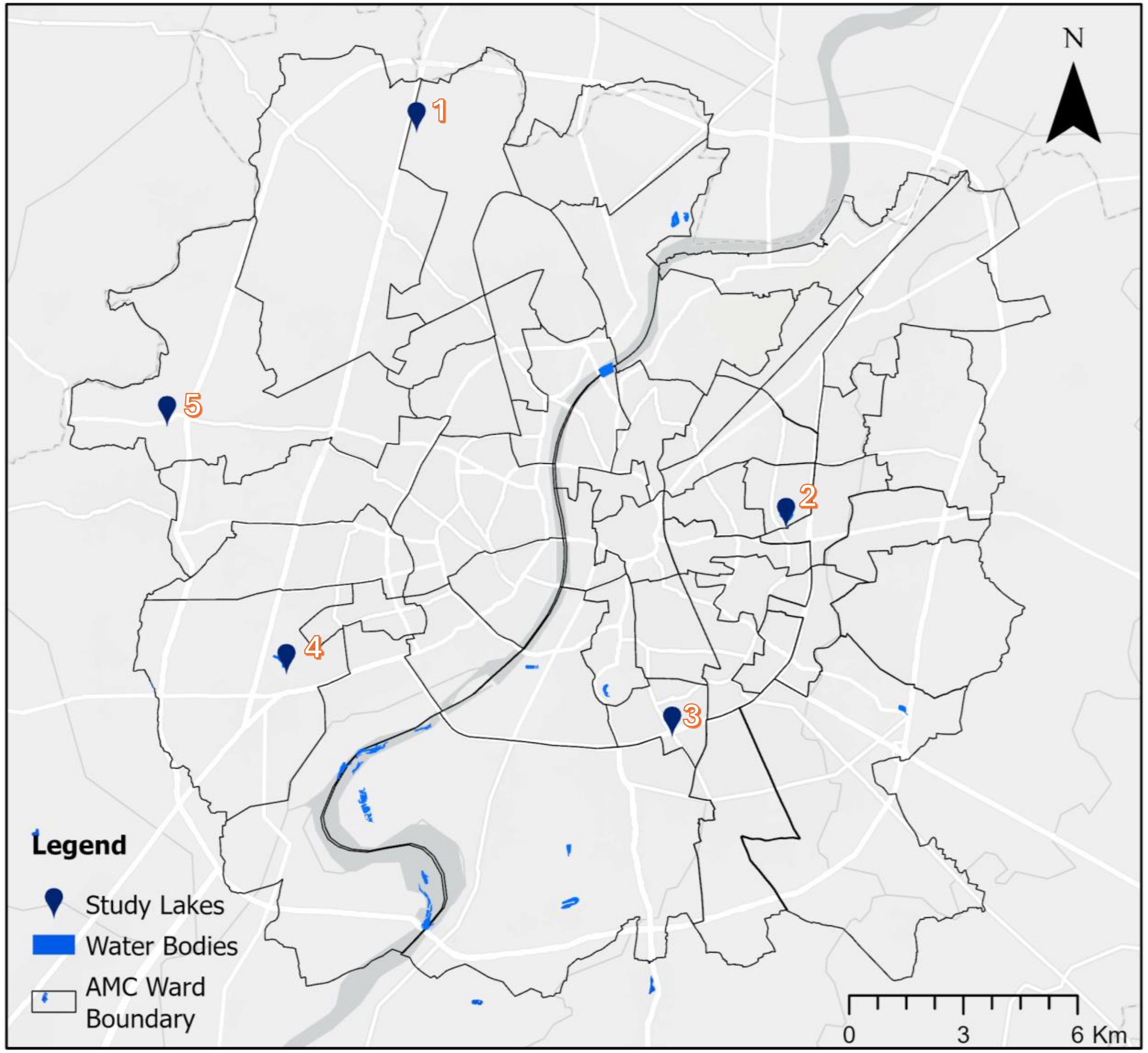
•**Google Earth Engine (GEE) Method**: Enables **cloud-based processing** of large-scale temporal satellite data (e.g., Sentinel-2) and automatic NDWI calculation.

- Offers **fast, accurate**, and **scalable** lake area extraction across multiple timeframes.

Conclusion: Due to its **efficiency and reliability**, the **GEE method was adopted** in this study for calculating lake area and monitoring temporal changes.

Selected Lakes for Calculation of Carbon Sequestration

[1] Chharodi Lake



[2] Malek Saban Lake

[5] Shilaj Lake

[3] Isanpur Lake

[4] Makarba Lake

Source: Google Earth Pro

Calculation of Carbon Sequestration based on ground truth data

Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**	**Column 7**	**Column 8**	**Column 9**
Lake Name	PH	Temperature C°	Salinity mg/L	Chlorophyll-A µg/L	DOC mg/L	DIC mg/L	Area m^2	Depth m
Chharodi Lake	9.5	28	0.4536	5.1	12	60	25502.9	3.9
Makrba Lake	9.1	27	0.432	5.1	6.1	48	63606.8	10.8
Shilaj Lake	9.3	29	0.2898	17	5.8	35	39412.7	6.5
Isanpur Lake	9.3	28	0.1872	-	5.9	47	27115.4	-
Malek Saban	9.1	29	0.1764	-	5.3	60	70294.8	7.8

Column 1:- Selected Lakes for carbon sequestration calculation
Columns 2 to 7:- Water quality parameters (Ground measurements)
Column 8:- Lake area based on the GEE method
Column 9:- Lake depth

CO_2 Flux Calculation

Example of Chharodi Lake

Data Required: pH-9.5, Temperature- 28°C, Salinity- 0.4536 ppt, DIC- 60 mg/L, wind speed(u)- 3.5 m/s, K_H = 0.03356, $_pCO^2$ air – 0.000355 atm

SC = 1911.1 – 118.11*T + 3.4527*T^2 - 0.04132*T^3

= 1911.1 – 118.11*28 + 3.4527*$(28)^2$ - 0.04132*$(28)^3$

SC = **403.88**

$$k = 0.251 * u^2 * \left(\frac{sc}{660}\right)^{-0.5}$$

$$k = 0.251 * 3.5^2 * \left(\frac{403.88}{660}\right)^{-0.5}$$

k = 3.90

$$(H^+) = 10^{-pH}$$

= $10^{-9.5}$

$(\boldsymbol{H^+})$ = **3.16 x 10^{-10} mol/l**

Temperature = 301.15 K

ln K1 = 2.83655 - 2307.1266/T - 1.5529413 In (T) + (-0.20760841 - 4.0484/T) *$S^{0.5}$ + 0.08468345*S - 0.00654208*$S^{1.5}$

= 2.83655 - 2307.1266/301.15 - 1.5529413 In (301.15) + (-0.20760841 - 4.0484/301.15) *$0.4536^{0.5}$ + 0.08468345*0.4536 - 0.00654208*$0.4536^{1.5}$

K1 = 1.03 x 10^{-6}

ln K2 = -9.226508 - 3351.6106/T - 0.2005743 In (T) + (-0.106901773 - 23.9722/T) *$S^{0.5}$ + 0.1130822*S - 0.008469343*$S^{1.5}$

= -9.226508 - 3351.6106/301.15 - 0.2005743 In (301.15) + (-0.106901773 - 23.9722/301.15) *$0.4536^{0.5}$ + 0.1130822*0.4536 - 0.008469343*$0.4536^{1.5}$

K2 = 4.73 x 10^{-10}

$\alpha 0 = [1+(K1/[H^+]) + (K1K2/[H^+]^2)]^{-1}$

$= [1+(1.03 \times 10^{-6}/3.16 \times 10^{-10}) + (1.03 \times 10^{-6})(4.73 \times 10^{-10})/(3.16 \times 10^{-10})^2)]^{-1}$

=**0.00012**

CO_2 Flux Calculation

DIC = 0.005 mol/l

$[H_2CO_3] = \alpha 0 \cdot DIC$

$= 0.00012 \times 0.005 =$ **$[H_2CO_3] = 6.12 \times 10^{-7}$**

${}_PCO_2^{water} = [H_2CO_3] / K_H$

$= 6.12 \times 10^{-7} / 0.03356$

$= 1.82 \times 10^{-5}$ atm

$FCO_2 = k * K_H * (pCO_2 - pCO_2air)$

$= 3.93 * 0.03356 * (1.82 \times 10^{-5} – 0.000355)$

$= - 4.44 \times 10^{-5}$ mol/m^2/day

F= FCO_2 *Lake area * days in Year

$= - 4.44 \times 10^{-5} * 25502.9 * 365$

= - 413.51 mol/year

CO_2 Flux = - 4962.33 gC/year

Carbon Storage Calculation

Example of Chharodi Lake

Data Required: DOC – 12 mg/L, DIC – 60 mg/L, h–3.9 m, S - 25502.9 m^2

SC =(DOC+DIC) * h* S

= (12 + 60) * 3.9 * 25502.9

= 7161214.32 mg/L

= 7161.21 gC

Primary Productivity Calculation

Example of Chharodi Lake

Data Required: Temperature – 28 °C, Chlorophyll-a – 5.1 mg/m^3, E_0 – 21, SD – 0.34m, Dirr – 12 hr

$P^B{}_{opt}$ = 1.2956 + 2.749 × 10^{-1}T + 6.17 × 10^{-2}T^2 − 2.05 × 10^{-2}T^3 + 2.462 × 10^{-3}T^4 − 1.348 × 10^{-4}T^5 + 3.4132 × 10^{-5}T^6 − 3.27 × 10^{-8}T^7

= 1.2956 + 2.749 × 10^{-1}(28) + 6.17 × 10^{-2}(28)^2 − 2.05 × 10^{-2}(28)^3 + 2.462 × 10^{-3}(28)^4 − 1.348 × 10^{-4}(28)^5+ 3.4132 × 10^{-5}(28)^6 − 3.27 × 10^{-8}(28)^7

$P^B{}_{opt}$= 14807.33

Zeu = 1.7239 * SD + 0.1685

= 1.7239 * 0.34 + 0.1685

= 0.754 m

PP_{eu} = 0.66125 × $P^B{}_{opt}$ × (E_0 / (E_0 + 4.1)) × Z_{eu} × C_{opt} × D_{irr}

= 0.66125 × 14807.33× (21 / (21+ 4.1)) × 0.754 × 5.1 × 12

= **378330.52 mgC/m2/day**

Carbon Sequestration = Average Primary Productivity × Lake Area

= 378330.52 x 25502.9

= 9648525495 mgC/ day

= 9648.52 gC/day

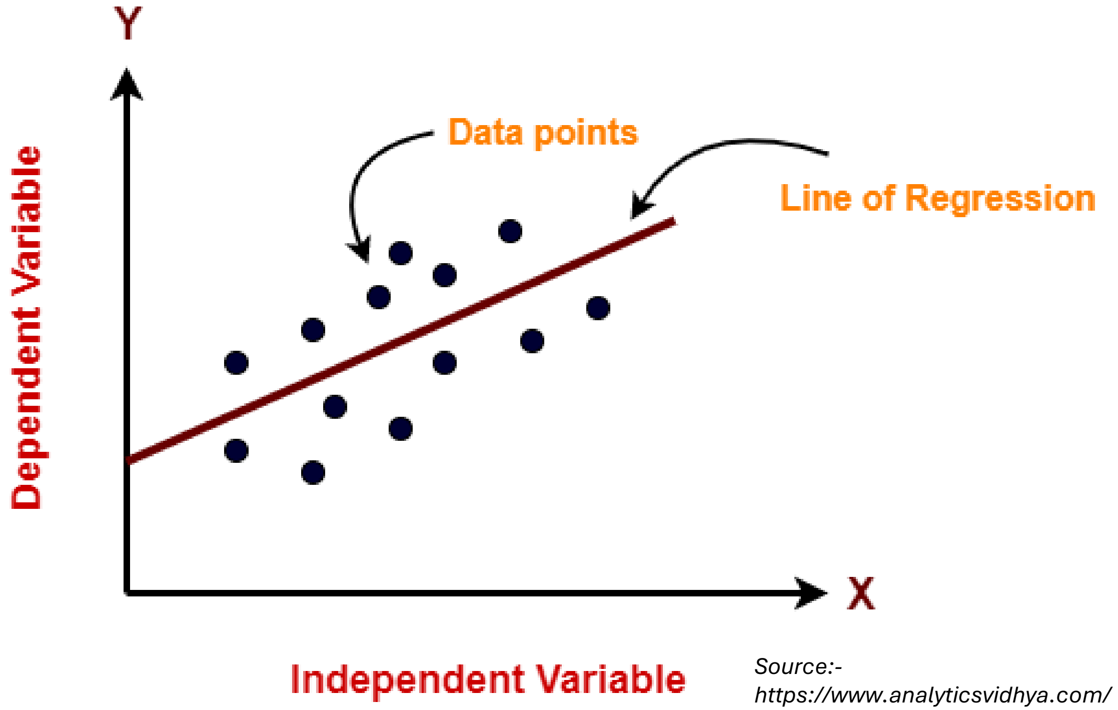
Calculation of Carbon Sequestration

Lake Name	Co2 Flux gC/year	Carbon storage gC	Primary productivity gC/day
Chharodi Lake	-4962.33	7161.21	9648.52
Makrba Lake	-10627.3	37164.18	22442.92
Shilaj Lake	-7801.33	10452.24	64149.61
Isanpur Lake	-5113.15	-	-
Malek Saban	-11938.4	35803.95	-

Due to the absence of this critical water quality parameter, carbon sequestration could not be calculated for these two lakes

Multiple Linear Regression

Multiple Linear Regression is a statistical method used to model the relationship between one **dependent variable** and **two or more independent variables**.



Source:- https://www.analyticsvidhya.com/

Equation Format

- $Y=\beta 0+\beta 1X1+\beta 2X2+...+\beta nXn+\epsilon$
- Y: Dependent variable (e.g., carbon-related parameter)
- X_1, X_2...: Independent variables (e.g., band values, weather data)
- β: Coefficients, ε: Error term

Advantages

Easy to implement
Good interpretability
Useful baseline for model comparison

https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-linear-regression/

❖ R2 (coefficient of determination)

R^2 measures how well the independent variables explain the variability of the dependent variable.

$0 \le R2 \le 1$

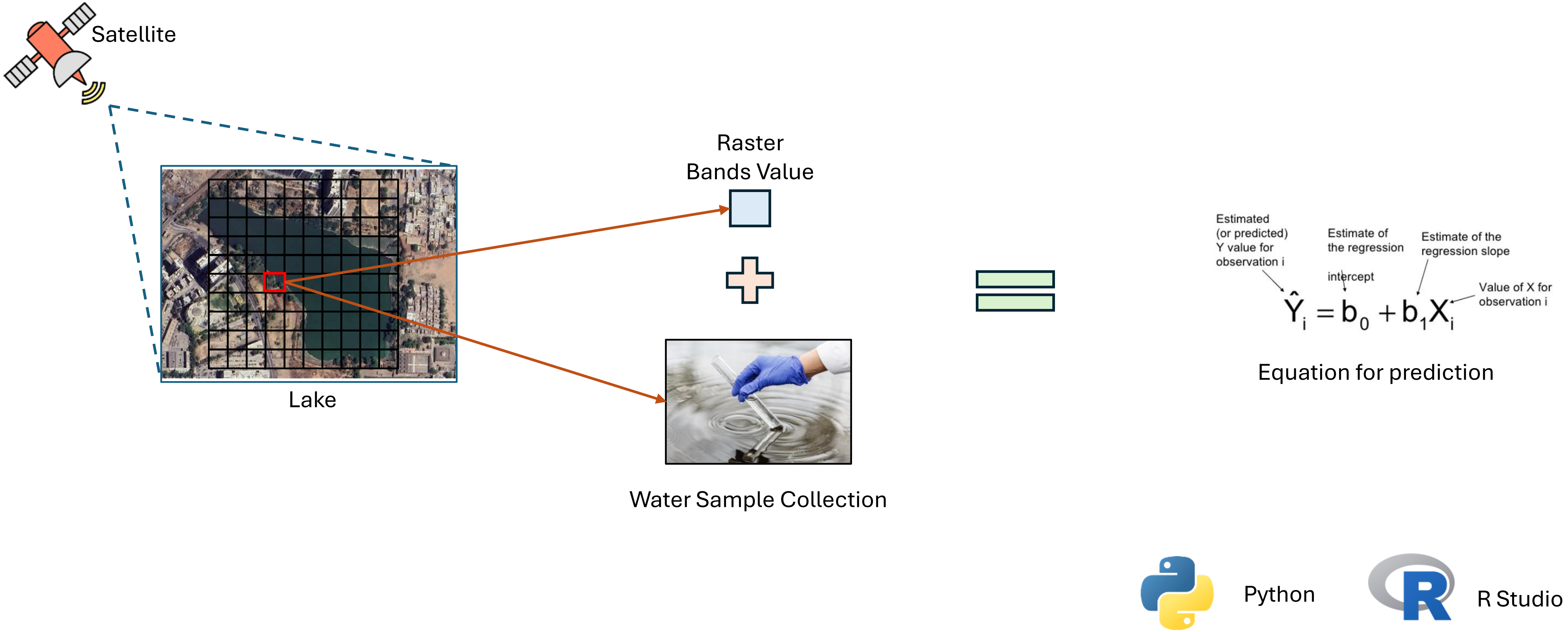
- **R^2 = 1**: Perfect prediction (all data points fit the model exactly)
- **R^2 = 0**: Model explains none of the variability

Higher R^2 = Better model performance

Water quality parameters	Equation	R2	Adj.R2
PH	6.15 +(0.00094 * WVP)+(0.00393 * B3)+(-0.000712 * B11) + (0.00086 * B1) +(0.108 * TCI_B) + (-0.014 * B2)	0.52	0.41
DIC	82.56+(-0.281 * AOT)+(0.0219 * WVP)+(-0.0344 * B11) + (0.0232 * B12)	0.94	0.93
COD	198.78+(-0.210* B8A)+(0.114 * B7)+(-0.473 * AOT) + (0.077 * B6)	0.58	0.50
Turbidity	164.64 +(-0.49759 * AOT)+(0.39329 * B7)+(-0.39857 * B8A)	0.56	0.51

A model was built to predict water quality parameters using **only 32 data points** for training and testing, which resulted in low accuracy.

Technique to build a water quality parameter prediction equation



Data set for modelling

Independent variable

Dependent variable

	B1	B2	B3	B4	B5	B6	B7	B8	B8A	B9	B11	B12	AOT	WVP	SCL	TCI_R	TCI_G	TCI_B	Dissolved.Inorganic.Carbon
1	614	833	1122	1066	1722	2477	2687	2710	2635	2782	2015	1273	238	1243	5	110	114	85	3.240
2	434	590	794	784	898	1000	1027	1157	949	799	920	673	234	378	5	81	81	59	3.350
3	405	506	814	542	1111	2982	3819	3700	3492	2692	1522	895	168	2080	4	57	83	52	49.000
4	239	564	888	680	1271	2177	2313	3311	2503	1346	1304	780	168	1681	4	72	90	58	51.000
5	639	1236	1650	2070	2060	2322	2492	3189	2603	2563	2693	2431	168	1915	5	212	169	125	44.000
6	438	1224	1768	2282	2759	2808	2859	2813	2828	2013	3722	3843	168	1980	5	229	179	129	41.000
7	354	720	1126	894	1187	1927	2435	3465	1786	994	1032	663	168	1497	5	91	114	75	57.000
8	709	1036	1362	1640	1660	2112	2428	2696	2038	2315	1921	1576	168	1990	5	168	139	104	59.000
9	555	835	1184	1274	1449	1714	1830	2083	1616	2296	1482	1351	168	1458	5	131	121	87	48.000
10	358	628	966	774	1435	1963	2076	1773	1795	1094	1225	998	168	1717	5	80	99	62	47.000
11	373	574	838	738	1189	1587	1948	1804	1836	948	1362	1163	168	1673	5	75	87	58	53.000
12	738	601	884	928	1495	1717	1689	1278	1686	2046	1891	1860	168	1727	5	101	91	60	53.000
13	459	527	874	592	1418	3585	3877	4157	4128	2624	1631	909	300	1772	4	62	90	53	5.886
14	334	580	914	744	1523	2481	2691	3596	2625	1524	1388	823	300	1526	4	78	94	60	6.003
15	396	666	1058	876	1471	3002	2798	3536	2606	1840	1129	781	300	1738	4	90	107	71	5.562
16	615	932	1294	1384	1907	2026	1890	2380	1795	2098	1800	1280	300	1785	5	140	133	95	5.051

Python Language Script(MLR)

```python
import numpy as np
import pandas as pd
from sklearn import linear_model
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
import matplotlib.pyplot as plt
import statsmodels.api as sm
```

```python
data = pd.read_csv("D:/ADI_data/ADI.csv")
```

```python
data_cleaned = data.dropna(subset=['Dissolved Inorganic Carbon'])
```

```python
band_columns = ['B1', 'B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B8', 'B8A', 'B9', 'B11', 'B12','AOT','WVP','SCL','TCI_R','TCI_G','TCI_B']
X = data_cleaned[band_columns]
y = data_cleaned['Dissolved Inorganic Carbon']
```

```python
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=34)
```

```python
model=linear_model.LinearRegression()
model.fit(X,y)
```

```
▾ LinearRegression
LinearRegression()
```

```python
abc=sm.add_constant(X)
abc1=sm.OLS(y,abc)
abc2=abc1.fit()
abc2.summary()
```

OLS Regression Results

Dep. Variable:	Dissolved Inorganic Carbon	**R-squared:**	0.972
Model:	OLS	**Adj. R-squared:**	0.933
Method:	Least Squares	**F-statistic:**	25.02
Date:	Sun, 06 Apr 2025	**Prob (F-statistic):**	2.98e-07
Time:	16:08:22	**Log-Likelihood:**	-88.421
No. Observations:	32	**AIC:**	214.8
Df Residuals:	13	**BIC:**	242.7
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	41.6753	40.978	1.017	0.328	-46.852	130.203
B1	-0.0321	0.019	-1.688	0.115	-0.073	0.009
B2	0.0952	0.107	0.893	0.388	-0.135	0.325
B3	0.1454	0.140	1.035	0.319	-0.158	0.449
B4	-0.2412	0.122	-1.982	0.069	-0.504	0.022
B5	0.0023	0.012	0.185	0.856	-0.024	0.029
B6	-0.0169	0.014	-1.195	0.254	-0.047	0.014
B7	0.0065	0.010	0.645	0.530	-0.015	0.028
B8	0.0012	0.005	0.228	0.824	-0.010	0.012
B8A	0.0056	0.013	0.445	0.664	-0.022	0.033
B9	0.0037	0.004	0.834	0.420	-0.006	0.013
B11	-0.0413	0.016	-2.506	0.026	-0.077	-0.006
B12	0.0274	0.012	2.303	0.038	0.002	0.053
AOT	-0.2409	0.027	-8.907	0.000	-0.299	-0.183
WVP	0.0258	0.005	4.959	0.000	0.015	0.037
SCL	5.1343	8.309	0.618	0.547	-12.816	23.084
TCI_R	2.3657	1.185	1.996	0.067	-0.194	4.926
TCI_G	-1.3151	1.533	-0.858	0.407	-4.627	1.997
TCI_B	-0.8708	0.947	-0.920	0.375	-2.917	1.175

Omnibus:	0.569	**Durbin-Watson:**	1.762
Prob(Omnibus):	0.752	**Jarque-Bera (JB):**	0.674
Skew:	-0.176	**Prob(JB):**	0.714
Kurtosis:	2.382	**Cond. No.**	2.48e+05

```python
import math
import numpy as np

# Predictions
y_pred = model.predict(X)

# --- Manual R² Calculation (Pearson) ---
sum_y = y.sum()                          # Sum of actual y (PH)
sum_y_pred = y_pred.sum()                # Sum of predicted y
sum_yy_pred = (y * y_pred).sum()         # Sum of (y * y_pred)
sum_y2 = (y**2).sum()                    # Sum of y²
sum_y_pred2 = (y_pred**2).sum()          # Sum of y_pred²
n = len(y)                               # Number of samples

# Pearson correlation coefficient (r)
numerator = (n * sum_yy_pred) - (sum_y * sum_y_pred)
denominator = math.sqrt((n * sum_y2 - sum_y**2) * (n * sum_y_pred2 - sum_y_pred**2))
r = numerator / denominator

# R-squared (R²)
r2 = r ** 2
print(f"R² (Manual - Pearson Method) = {r2:.6f}")

# --- Manual Adjusted R² Calculation ---
p = X.shape[1]  # Number of features
adj_r2 = 1 - ((1 - r2) * (n - 1) / (n - p - 1))
print(f"Adjusted R² (Manual) = {adj_r2:.6f}")
```

```
R² (Manual - Pearson Method) = 0.971941
Adjusted R² (Manual) = 0.933090
```

Python Language Script(CNN)

```python
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout, BatchNormalization,GlobalAveragePooling1D
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
import matplotlib.pyplot as plt
from permetrics.regression import RegressionMetric
```

```python
data = pd.read_csv("D:/ADI_data/ADI.csv")
band_columns = ['B1', 'B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B8', 'B8A', 'B9', 'B11', 'B12','AOT','WVP','SCL','TCI_R','TCI_G','TCI_B']
X = data[band_columns].values
y = data['PH'].values
```

```python
X = X.reshape(X.shape[0], X.shape[1], 1)
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=30)
```

```python
scaler = StandardScaler()
X_train_reshaped = X_train.reshape(X_train.shape[0], -1)
X_test_reshaped = X_test.reshape(X_test.shape[0], -1)
scaler.fit(X_train_reshaped)
```

```
▾ StandardScaler
StandardScaler()
```

```python
X_train_scaled = scaler.transform(X_train_reshaped).reshape(X_train.shape)
X_test_scaled = scaler.transform(X_test_reshaped).reshape(X_test.shape)
```

```python
model = Sequential([
    Conv1D(filters=32, kernel_size=1, activation='relu', padding='same', input_shape=(X_train.shape[1], 1)),
    BatchNormalization(),
    Conv1D(filters=32, kernel_size=1, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling1D(pool_size=2),

    Conv1D(filters=64, kernel_size=1, activation='relu', padding='same'),
    BatchNormalization(),
    Conv1D(filters=64, kernel_size=1, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling1D(pool_size=2),

    Conv1D(filters=128, kernel_size=1, activation='relu', padding='same'),
    BatchNormalization(),
    GlobalAveragePooling1D(),  # Replaces Flatten() for variable length

    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(1,activation='linear')  # Output layer for regression
])
```

```python
optimizer = Adam(learning_rate=0.006)
model.compile(optimizer=optimizer, loss='mse', metrics=['mae'])
```

```python
model.summary()
```

```python
history = model.fit(
    X_train_scaled, y_train,
    validation_split=0.20,
    epochs=200,
    batch_size=16,
    # callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 2s 178ms/step - loss: 80.9593 - mae: 8.9508 - val_loss: 72.7461 - val_mae: 8.5186
Epoch 2/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 40.5527 - mae: 6.2550 - val_loss: 64.4019 - val_mae: 8.0142
Epoch 3/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 8.1267 - mae: 2.4333 - val_loss: 52.9595 - val_mae: 7.2646
Epoch 4/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 14.6374 - mae: 3.0254 - val_loss: 50.0031 - val_mae: 7.0579
Epoch 5/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 10.7932 - mae: 2.8469 - val_loss: 52.7267 - val_mae: 7.2478
Epoch 6/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 2.8723 - mae: 1.5166 - val_loss: 53.0420 - val_mae: 7.2679
Epoch 7/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 3.2744 - mae: 1.6342 - val_loss: 50.6353 - val_mae: 7.0999
Epoch 8/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 1.7955 - mae: 1.0704 - val_loss: 46.8484 - val_mae: 6.8287
Epoch 9/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 3.1611 - mae: 1.3466 - val_loss: 42.8836 - val_mae: 6.5323
Epoch 10/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 3.6014 - mae: 1.6320 - val_loss: 39.5976 - val_mae: 6.2772
Epoch 11/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 4.7814 - mae: 1.7271 - val_loss: 37.8605 - val_mae: 6.1355
Epoch 12/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 3.0260 - mae: 1.4153 - val_loss: 37.6164 - val_mae: 6.1141
Epoch 13/200
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 1.6443 - mae: 1.0137 - val_loss: 37.0969 - val_mae: 6.0697
Epoch 14/200
```

```python
y_train_pred = model.predict(X_train_scaled).flatten()
y_test_pred = model.predict(X_test_scaled).flatten()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 114ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 116ms/step
```

```python
sum_x = y_train.sum()
sum_y = y_train_pred.sum()
sum_xy = (y_train * y_train_pred).sum()
sum_x2 = (y_train**2).sum()
sum_y2 = (y_train_pred**2).sum()

n = len(y_train)

numerator = (n * sum_xy) - (sum_x * sum_y)
denominator = math.sqrt((n * sum_x2 - sum_x**2) * (n * sum_y2 - sum_y**2))

r = numerator / denominator
R2 = r*r
print(f"Pearson correlation coefficient (r) = {r:.6f}")
print(f"R-squared (R2) = {R2:.6f}")
```

```
Pearson correlation coefficient (r) = 0.525343
R-squared (R2) = 0.275985
```

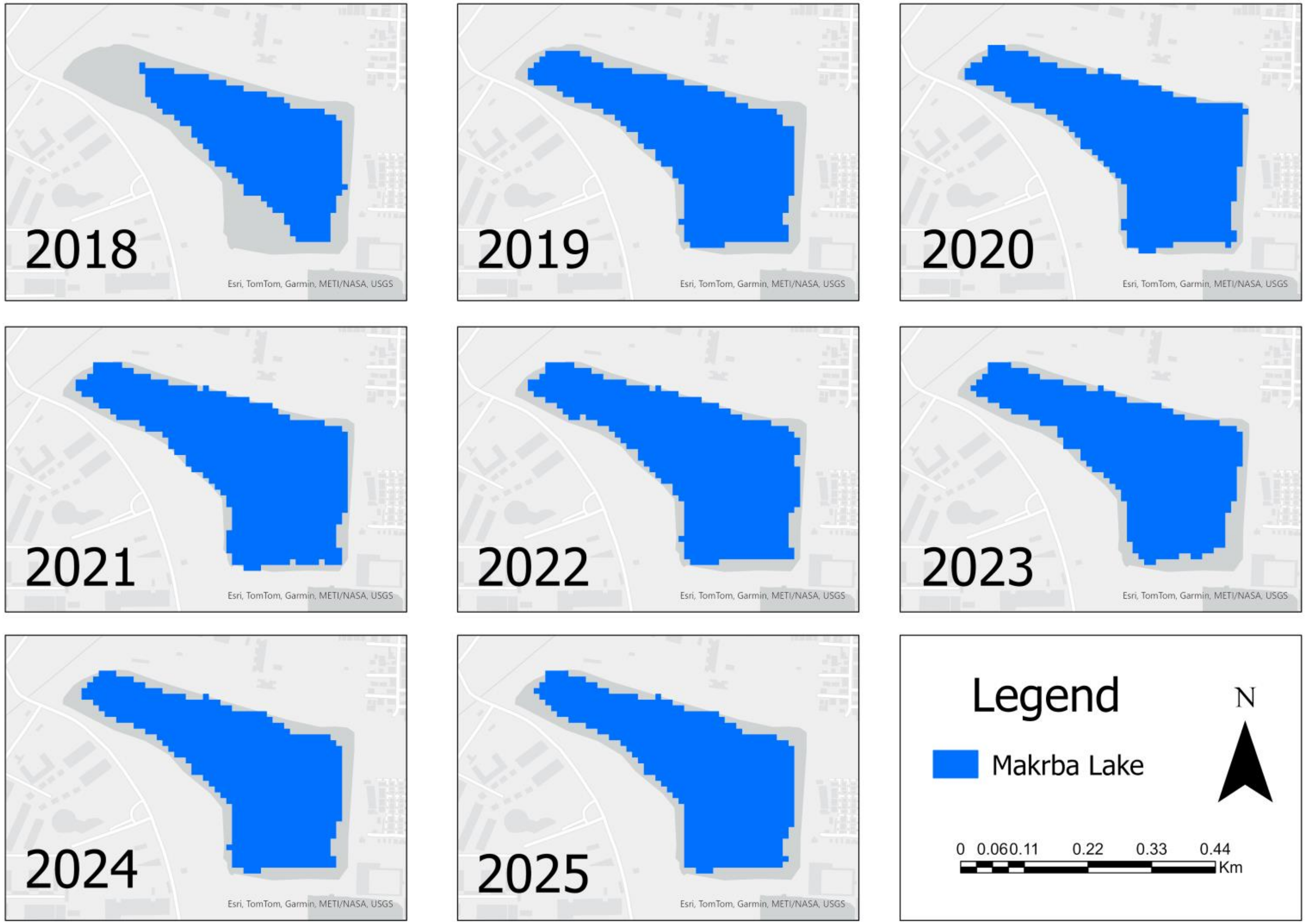
CNN:-Convolutional Neural Networks

R Language Script

```r
setwd("D:/ADI_data/")

Data = read.csv("ADI.csv")

Data2 = Data[,c(4:21,38)]

Data3=na.omit(Data2)

library("olsrr")

model = lm(Dissolved.Inorganic.Carbon~ .+B1, data = Data3)

a = ols_step_forward_p(model)

a

model2 = lm(Dissolved.Inorganic.Carbon~AOT+WVP+B11+B12, data = Data3)

summary(model2)
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 82.563546   7.589897  10.878 2.26e-11 ***
AOT         -0.281761   0.016384 -17.198 4.50e-16 ***
WVP          0.021946   0.003938   5.573 6.57e-06 ***
B11         -0.034469   0.006547  -5.265 1.50e-05 ***
B12          0.023283   0.005628   4.137 0.000308 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.83 on 27 degrees of freedom
Multiple R-squared:  0.9453,	Adjusted R-squared:  0.9372
F-statistic: 116.6 on 4 and 27 DF,  p-value: < 2.2e-16
```

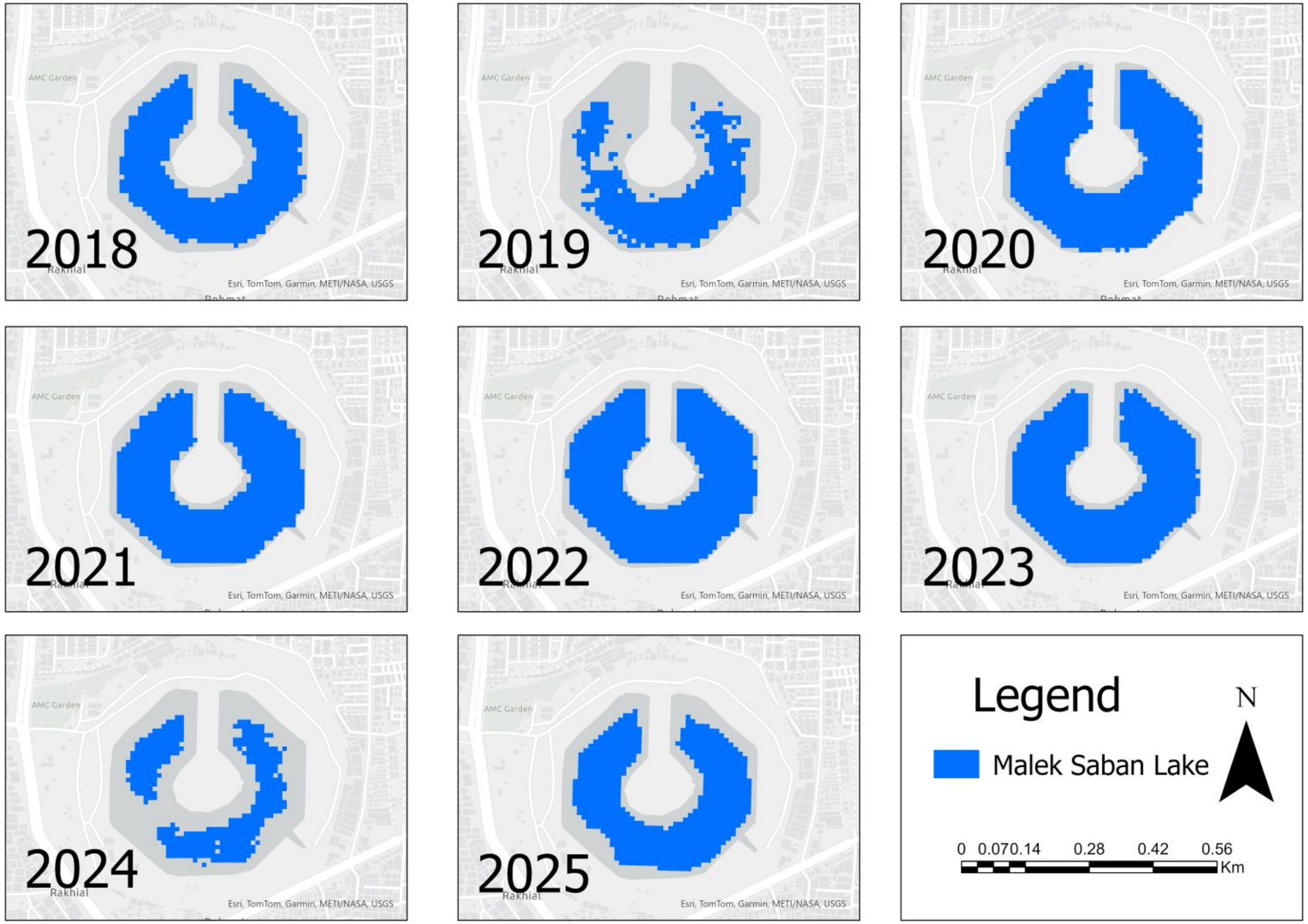
Makrba lake time series for 2018 to 2025



Year	Area (m^2)	CO2 Flux(gC/year)
2018	48,835.95	53759.24
2019	65,969.77	-9819.17
2020	72,200.23	-5501.71
2021	73,574.62	-7161.03
2022	70,184.49	-5892.49
2023	65,969.73	-9294.5
2024	65,420.01	-7330.7
2025	63606.8	-10627.3

- **2018** shows **high positive CO_2 flux**, indicating strong carbon release
- From **2019 to 2025**, all values are **negative**, showing that the water bodies acted as **carbon sinks**.
- The **area increased from 2018 to 2021**, peaking in 2021, then slightly declined.
- **CO_2 absorption (negative flux)** was **highest in 2025**, suggesting better sequestration or updated ground truth accuracy.

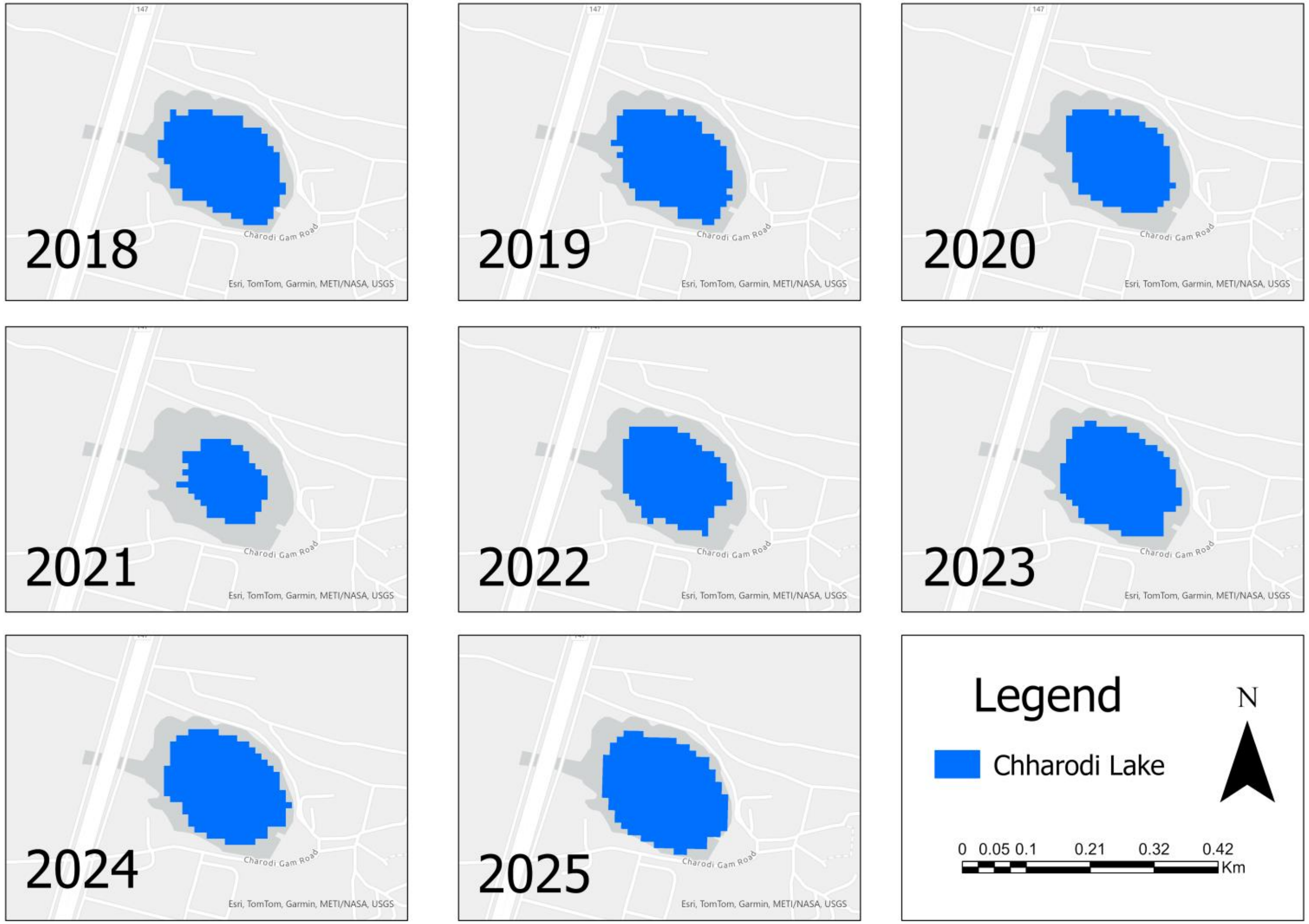
Malek Saban lake time series for 2018 to 2025



Year	Area (m^2)	CO2 Flux(gC/year)
2018	73294.08	288303.94
2019	50656.91	-7450.87
2020	98290.58	8522.41
2021	92702.79	2476.73
2022	96916.51	-10884.22
2023	90595.91	-6311.80
2024	40855.19	-1396.03
2025	70294.8	-11938.4

- **2018** had the **highest CO_2 release** in a large area, indicating a strong carbon source that year.
- From **2019 onward**, there was a **shift to negative CO_2 flux** in most years, suggesting that the area acted more as a **carbon sink**.
- **2022 and 2025** recorded the **highest CO_2 absorption,** marking strong carbon sequestration.
- The **area fluctuated** significantly year to year, but **larger area did not always correlate with higher flux**, suggesting influence from other factors like water quality or temperature.

Chharodi Lake time series for 2018 to 2025



Year	Area (m^2)	CO2 Flux(gC/year)
2018	25448.04	271086.04
2019	24074.94	-3425.22
2020	21603.36	-1904.99
2021	13090.18	776.73
2022	21145.67	-1708.28
2023	25081.88	-3507.12
2024	25722.65	-889.81
2025	25502.9	-4962.33

•**2018** shows an **extremely high CO_2 emission**, indicating a strong carbon source.

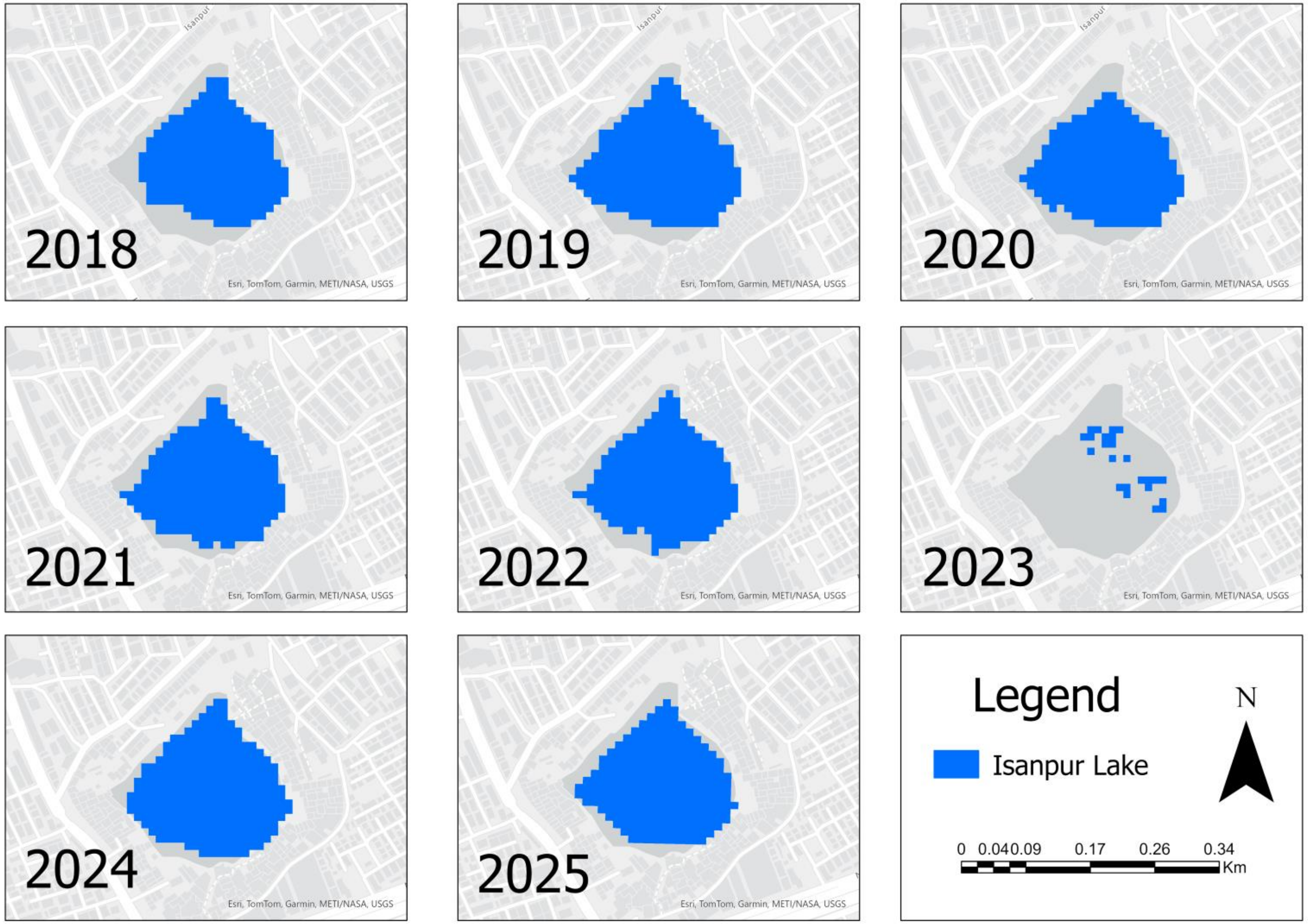
•From **2019 onwards**, CO_2 flux becomes **mostly negative**, meaning the area starts acting as a **carbon sink**.

•**2021** is the only year with a **slight positive flux**, but it's very low compared to 2018.

•**2025** shows the **highest carbon absorption** among all years, with a flux of **-4962.33 gC/year**.

•The **area remains relatively stable** after 2020, but **CO_2 flux varies**,

Isanpur Lake time series for 2018 to 2025



Year	Area (m^2)	CO2 Flux(gC/year)
2018	23733.66	68010.14
2019	25841.29	-3830.41
2020	23367.13	9520.99
2021	27004.53	-676.99
2022	25932.93	8802.95
2023	2199.26	-320.64
2024	28865.27	-3277.37
2025	27115.4	-5113.15

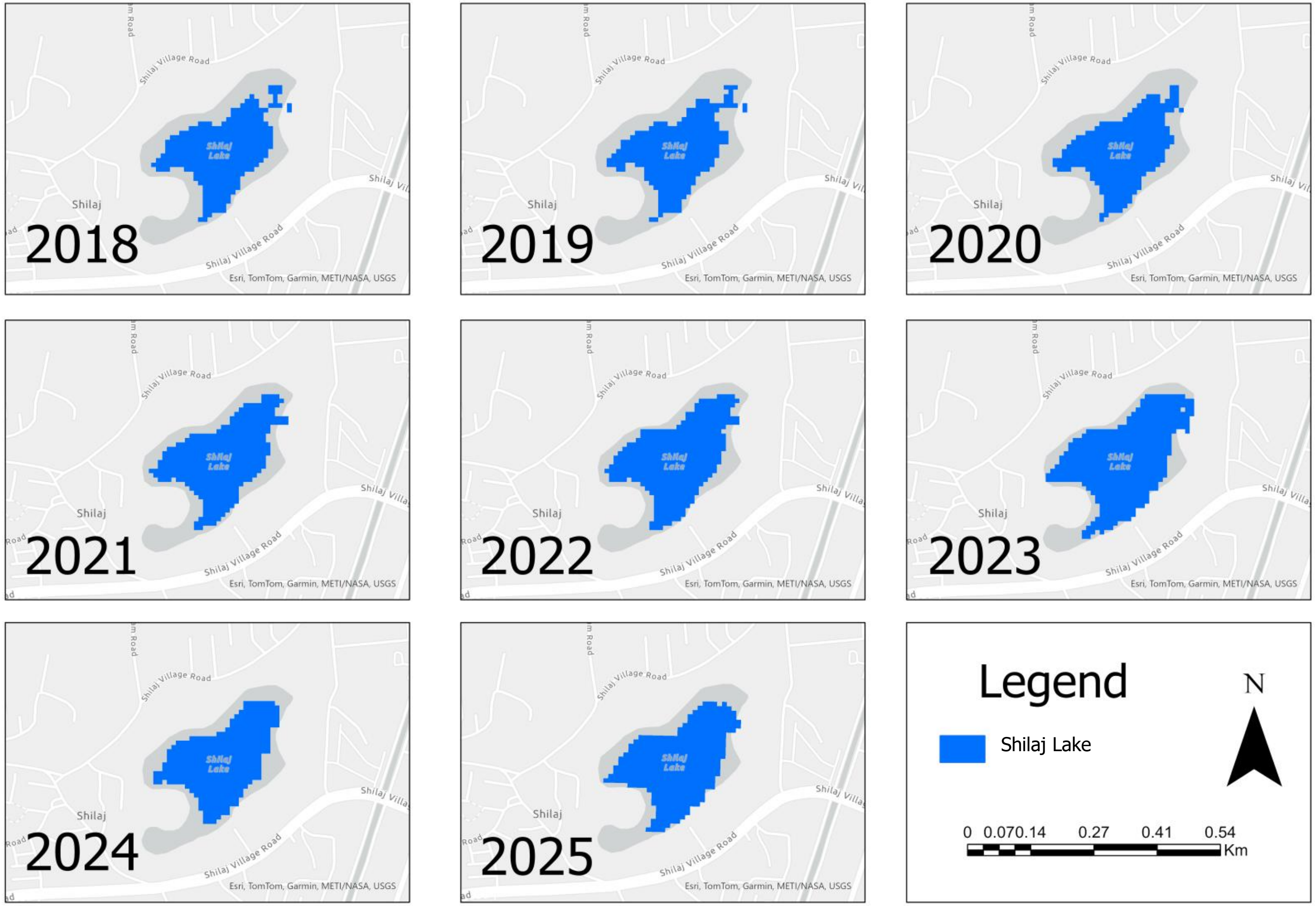
•**2018** recorded the **highest CO_2 emission**.

•**2019, 2021, 2023, 2024, and 2025** show **negative CO_2 flux**, meaning the area acted as a **carbon sink** in those years.

•**2020 and 2022** again show **positive flux**, but much lower than 2018, suggesting an occasional return to carbon source behavior.

•The **area remains fairly consistent**, except for **2023**, where it drastically drops to **2,199.26 m^2**, possibly due to dry-up or data anomaly.

Shilaj Lake time series for 2018 to 2025



Year	Area (m^2)	CO2 Flux(gC/year)
2018	31413.68	77581.36
2019	30314.66	-3929.44
2020	31871.61	10392.34
2021	37183.52	-2205.01
2022	40114.24	5264.03
2023	46708.37	-6893.31
2024	35901.33	-3828.04
2025	39412.7	-7801.33

- **2018** shows the **highest CO_2 emission**
- 2019, 2021, 2023, 2024, and 2025 show **negative CO_2 flux**, meaning the area functioned as a **carbon sink** in those years.
- The area size gradually **increases from 2018 to 2023**, peaking at 46,708.37 m^2 in 2023, followed by a slight drop in 2024.

One-at-a-time (OAT) Sensitivity Analysis

	-20%	-15%	-10%	-5%	0	+5%	+10%	+15%	+20%
pH	-1025.18	-332.89	-97.61	-21.47	-	4.588	5.311	5.4	5.541
T	-12.49	-9.61	-6.6	-3.44	-	3.86	8.36	13.79	20.63
DIC	1.08	0.81	0.54	0.27	-	-0.27	-0.54	-0.81	-1.08
Wind speed	-36	-27.75	-18.99	-9.75	-	10.25	21	32.25	44

pH has the **strongest impact,** even small decreases cause a large drop in CO_2 sequestration. **Wind speed** increases CO_2 flux significantly, more wind leads to more sequestration. **DIC** shows less DIC, more sequestration. **Overall**, **pH and wind speed** are the most sensitive factors influencing carbon sequestration in water bodies

Conclusion

- Most lakes showed **positive CO_2 flux (emission)** in 2018 but gradually shifted to **negative values**, indicating **increasing carbon sequestration** over time.
- From 2019 onwards, several lakes consistently recorded **negative flux values**, reflecting improved conditions for **carbon uptake**. While sequestration **generally improved**, fluctuations across years indicate the influence of environmental factors and lake health dynamics.
- Larger surface area doesn't always mean higher sequestration. For example, in some years, smaller areas show better performance, implying that the **quality of water parameters** (like pH, DIC, temp) plays a bigger role than area alone.
- A small decrease in **pH results in a large drop in CO_2 flux**, making **acidification a major threat** to carbon sequestration efficiency.
- Across all locations, **2018 consistently records the highest positive CO_2 flux**, indicating carbon emission.
- The **limited dataset of only 32 sample points** constrains the model's performance and generalization ability. The current accuracy is suboptimal due to this **data sparsity**.
- **Future studies should focus on collecting more sample data** across seasons and spatial locations to enhance model training.

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