From Sources to Sinks: Advancing Surface Water Management Through Satellite Remote Sensing

Shahzaib Khan

Doctoral Defense

Supervisory Committee

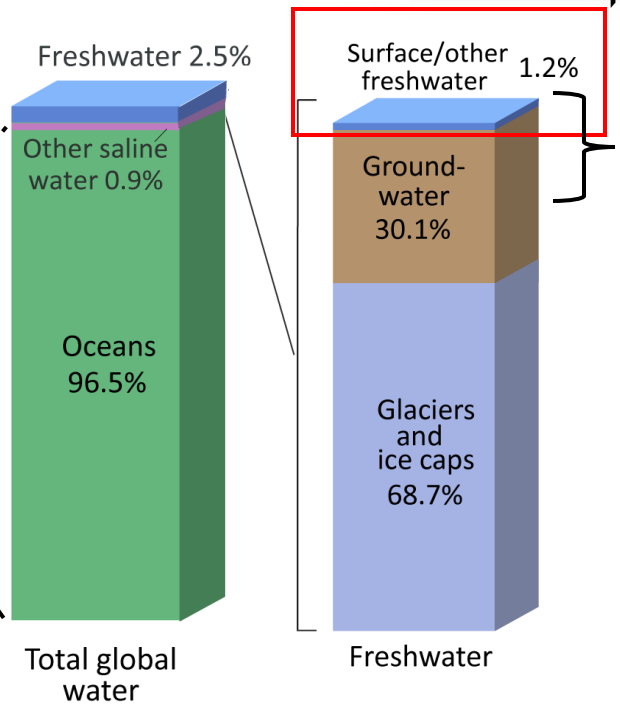
Faisal Hossain (Chair)
Erkan Istanbulloglu (Member)
Nicoleta Cristea (Member)
Katharine Huntington (GSR)

Earth's Water

A freeway sign in LA, California

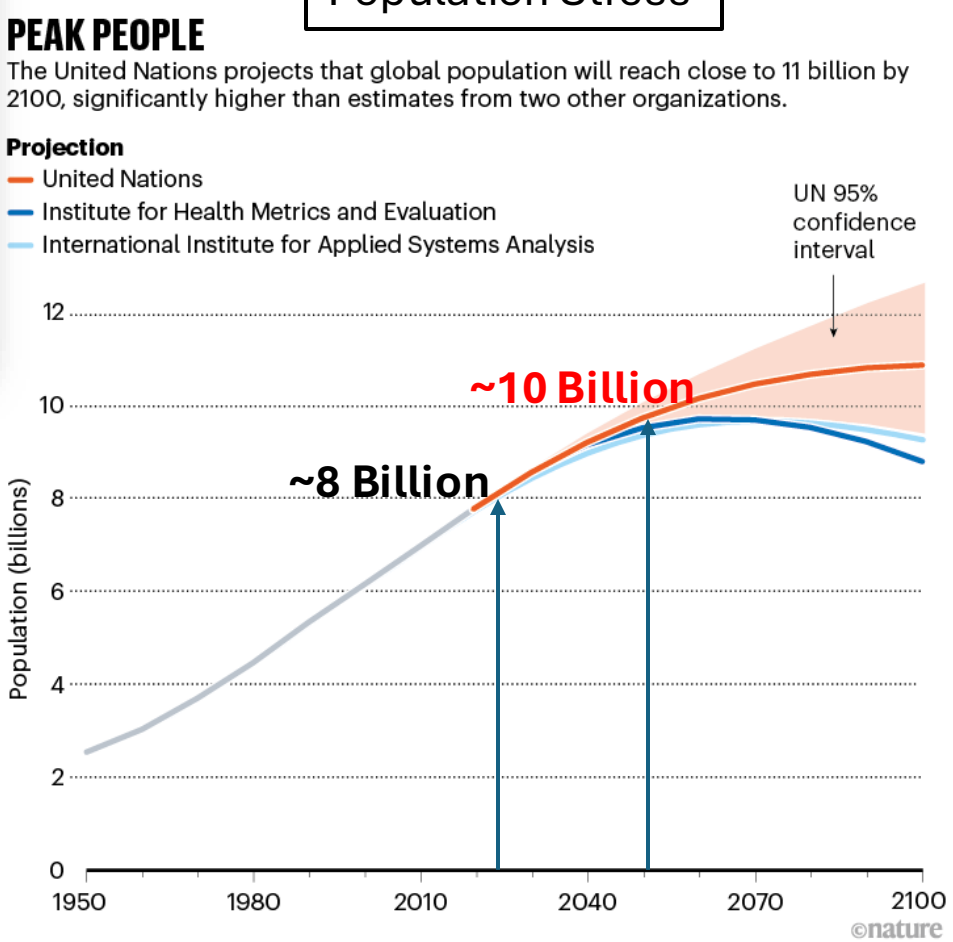
12News, Arizona

Around 70% Earth's surface is covered with water



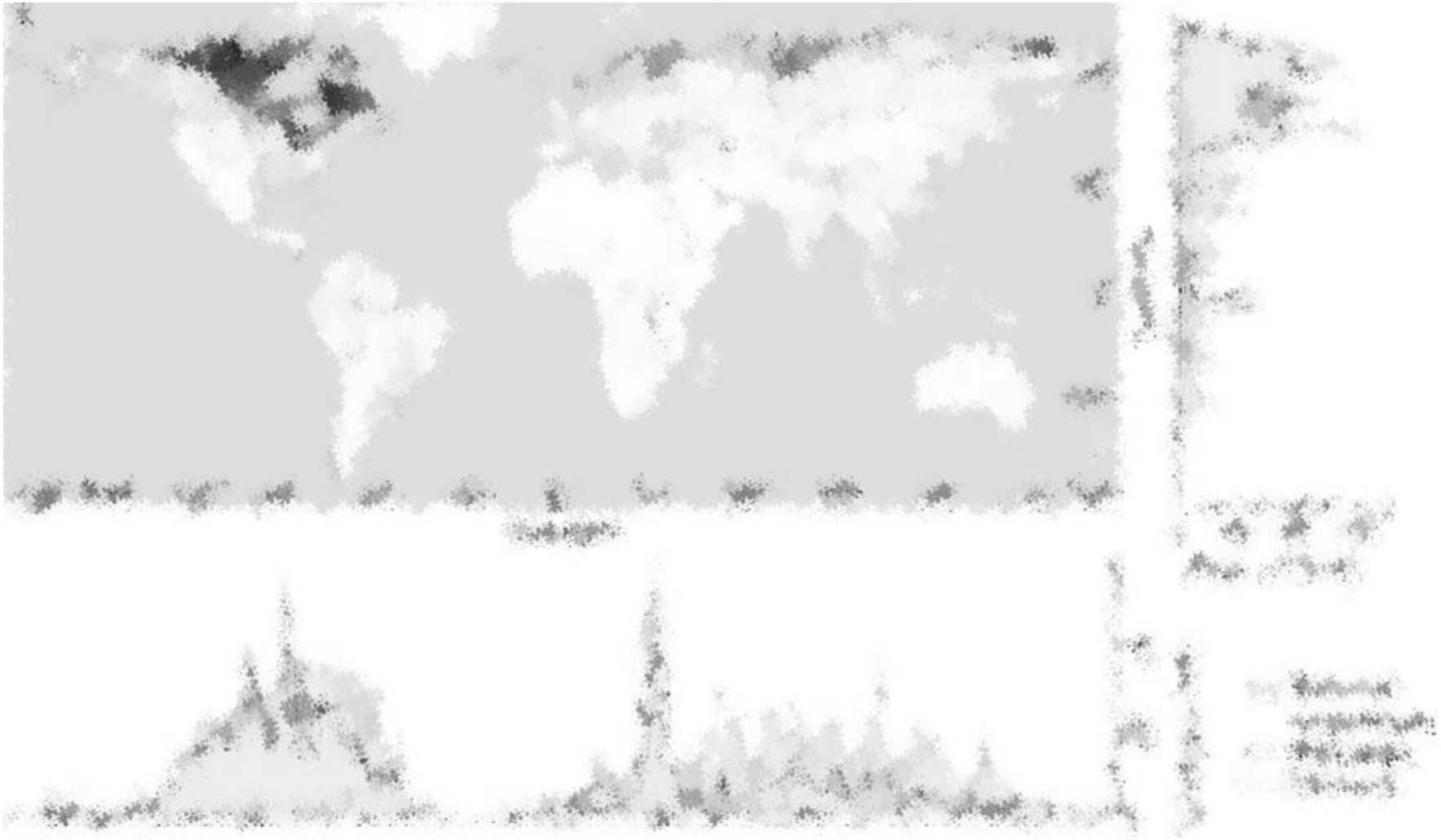
Stressed

Population Stress



Do we have enough water for human sustenance?

Earth's Surface Water - Known (L^2)



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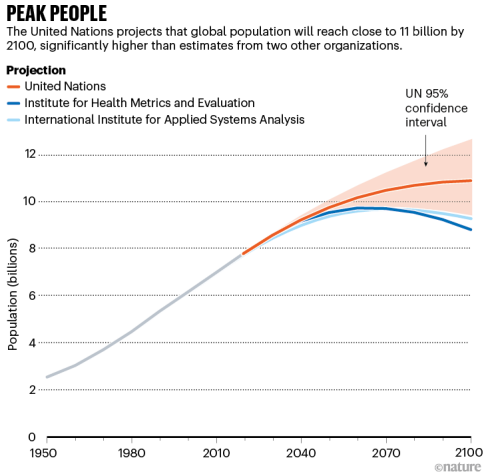
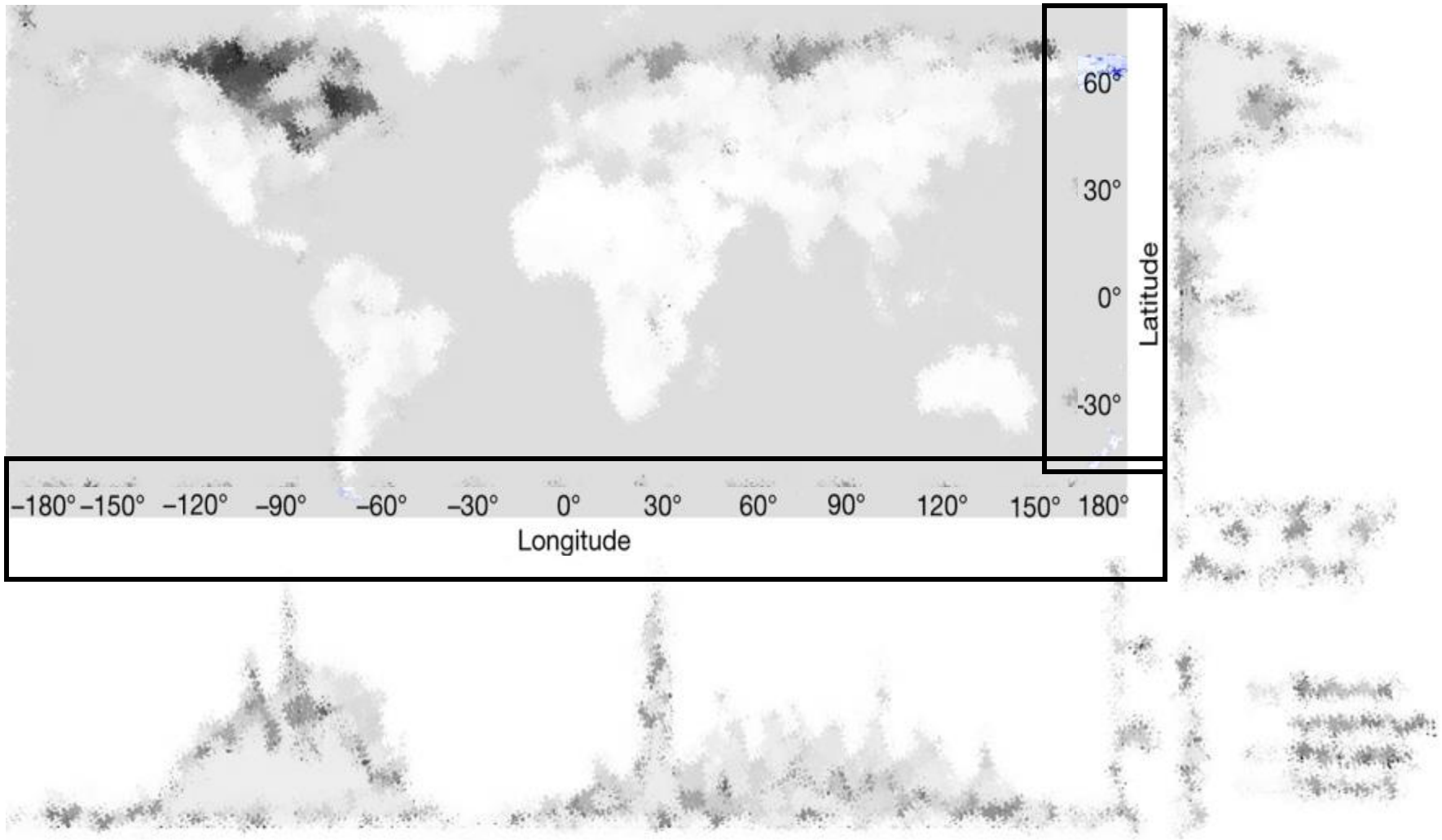


Earth's Surface Water - Known (L^2)

Where do we have surface water?



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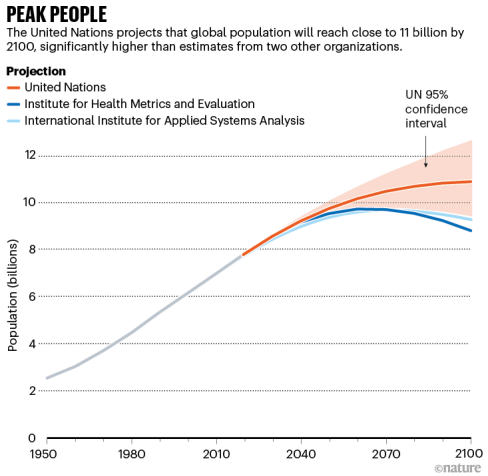
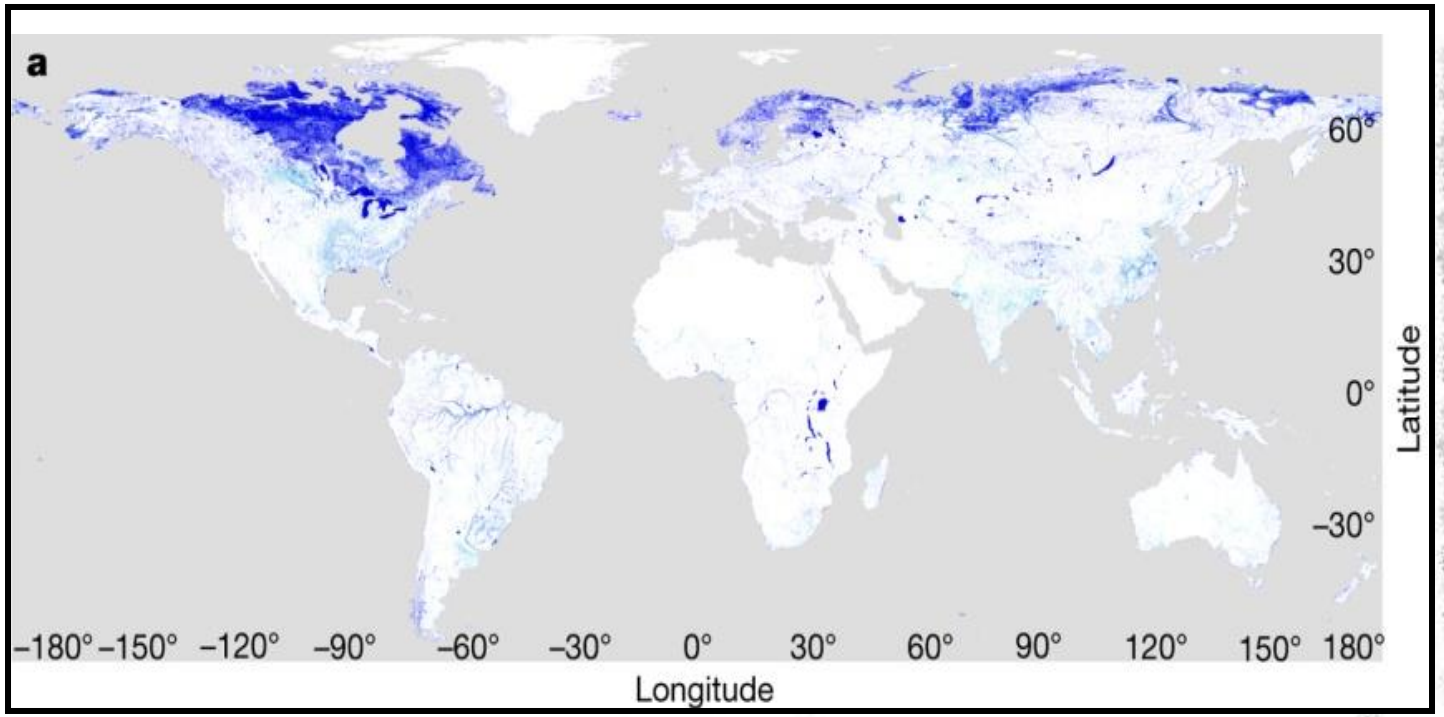


Earth's Surface Water - Known (L^2)

Where do we have surface water?

What area is covered with water (L^2)?



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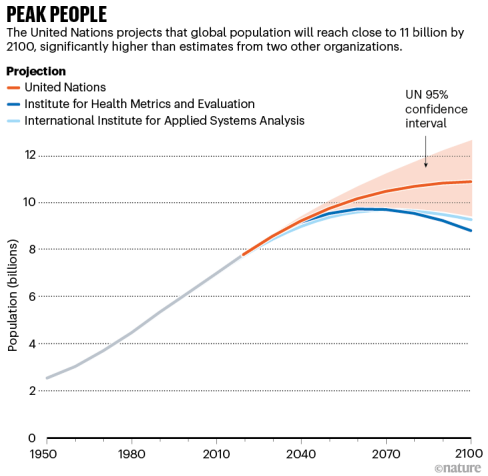
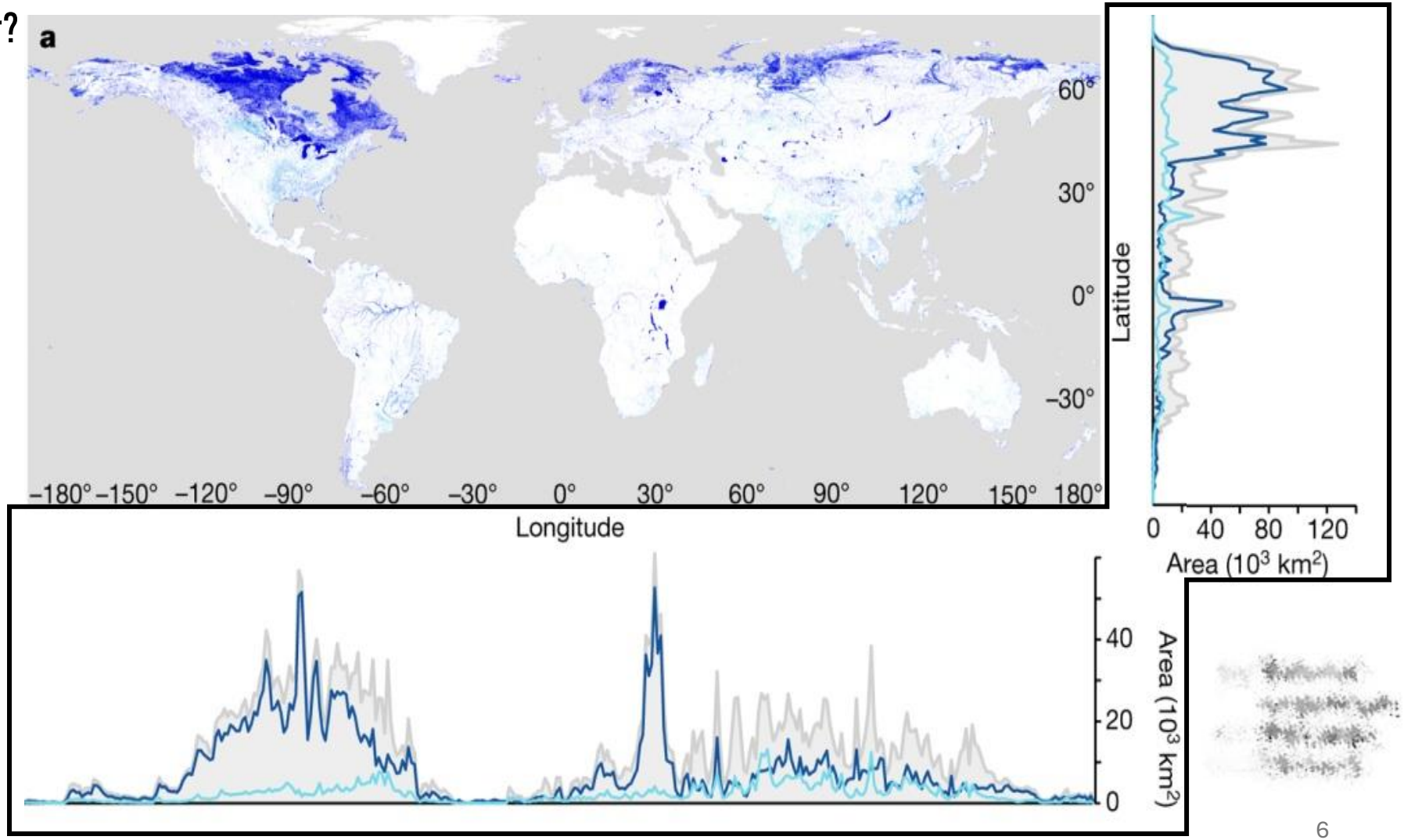


Earth's Surface Water - Known (L^2)

Where do we have surface water?

What area is covered with water (L^2)?

How L^2 is spatially distributed?



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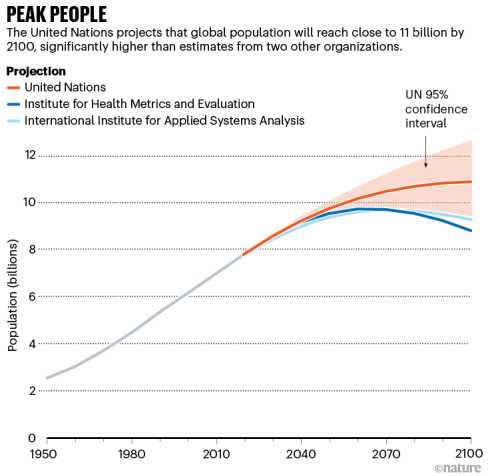


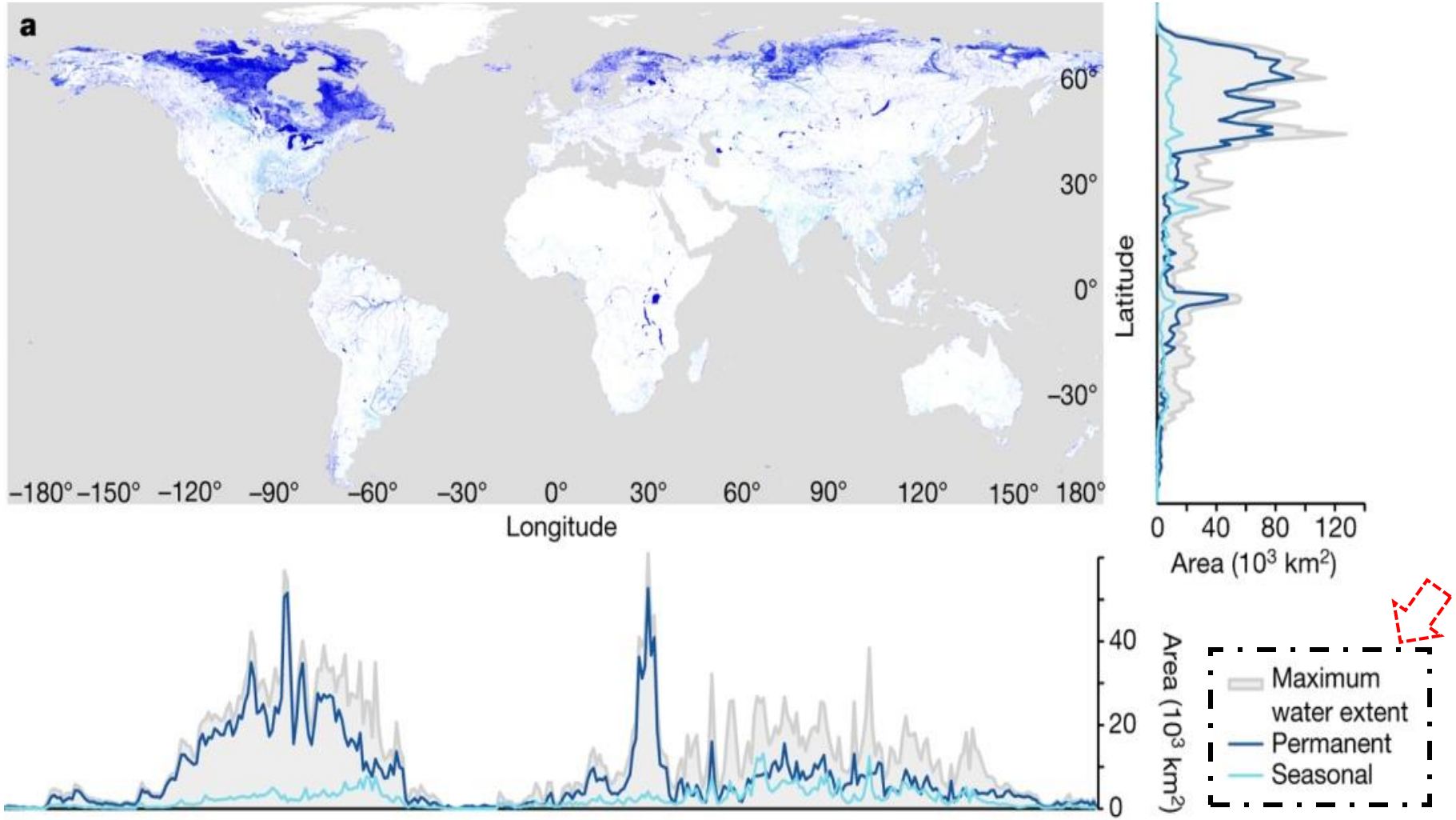
Earth's Surface Water - Known (L^2)

Where do we have surface water?

What area is covered with water (L^2)?

How L^2 is spatially distributed?

How L^2 is seasonally distributed?



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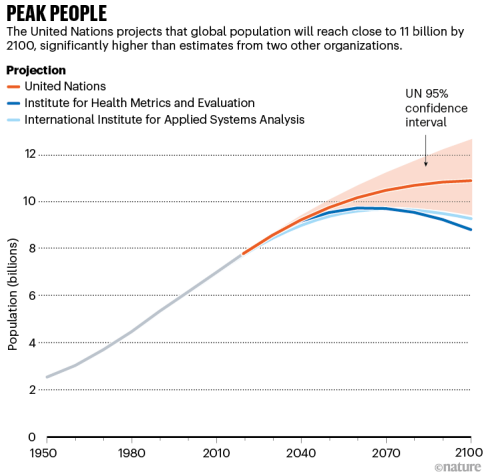


Earth's Surface Water – UnKnown (L^3)

Where do we have surface water?

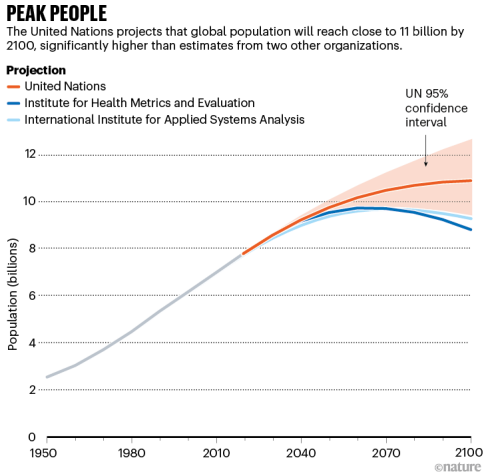
What area is covered with water (L^2)?

How L^2 is spatially distributed?

How L^2 is seasonally distributed?

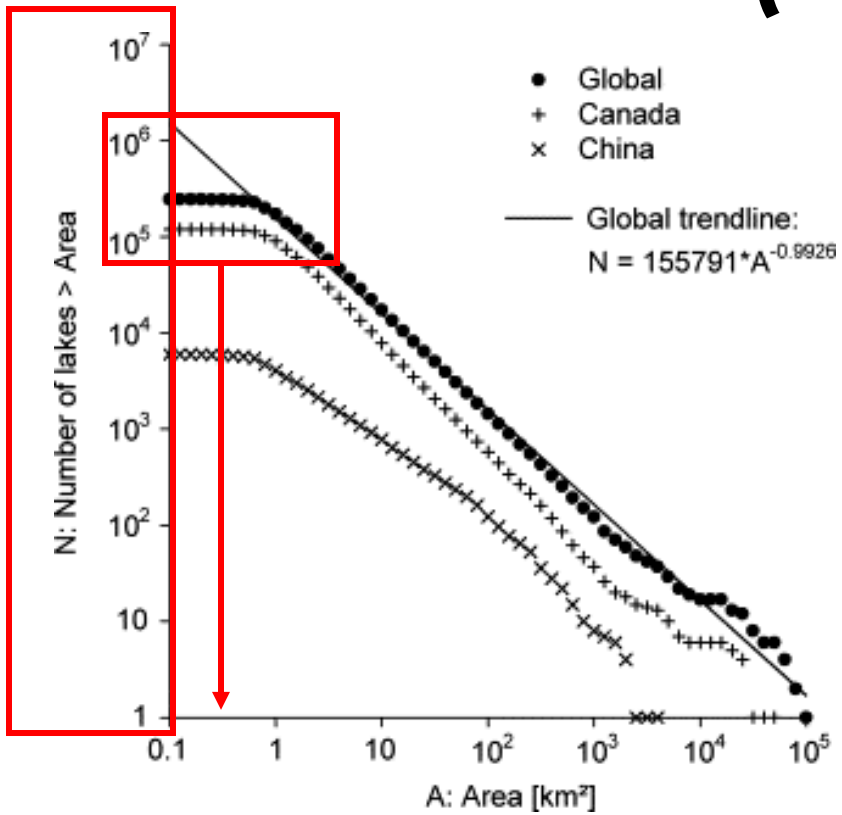
How much ($L^{\cancel{2}3}$) water do we have?

Population Stress



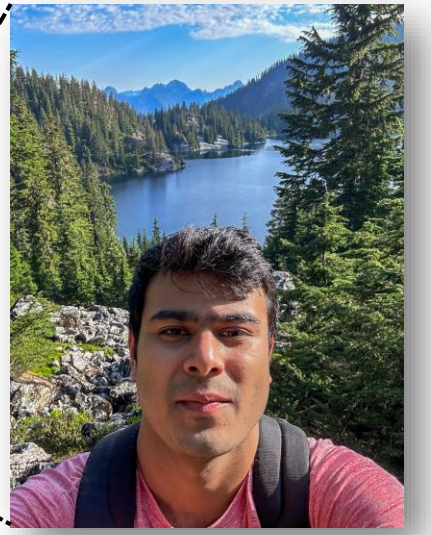
Challenges in estimating the volume of water (L^3)

Source ↔ Where L^3 is stored

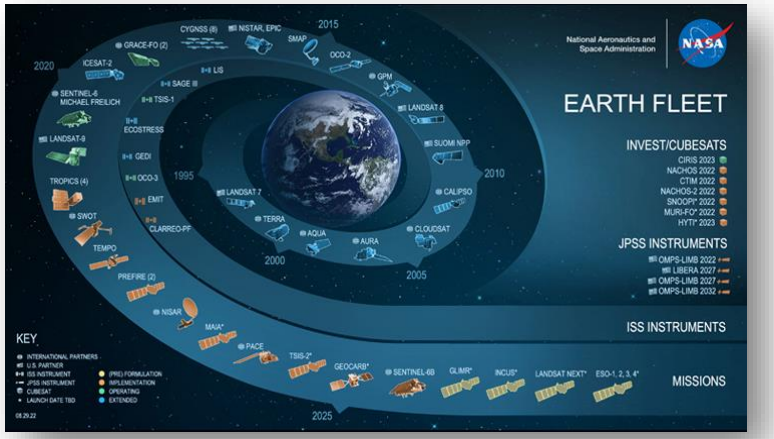


Lehner and Doll (2004), *J. of Hydrology*

- ❑ Millions of *sources* to monitor
- ❑ Most of them are small
- ❑ Some of them are remote, e.g.



Snow Lake, WA



NASA's Earth Observing System

Challenges in estimating the volume of water (L^3)

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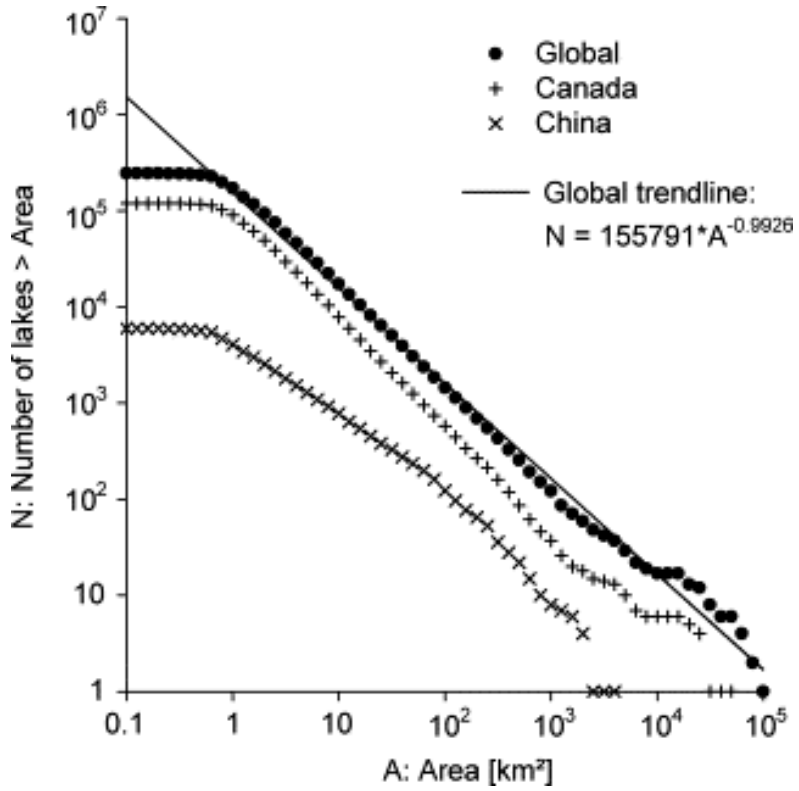

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- ❑ Millions of *sources* to monitor
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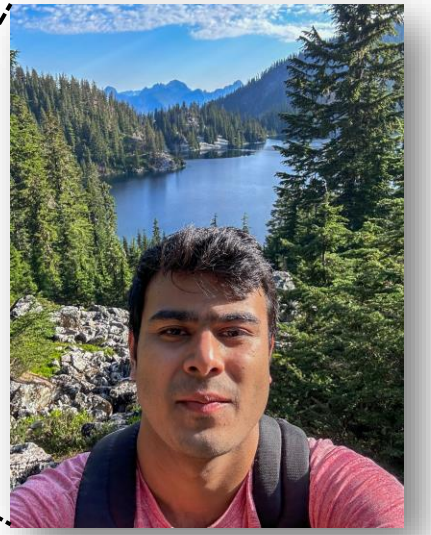
- ❑ Some of them are remote, e.g.
- ❑ *Bathymetry (will revisit)*



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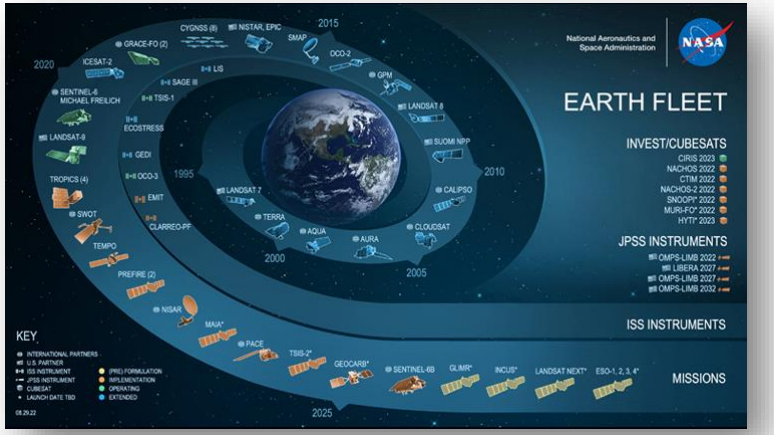


NASA's Earth Observing System

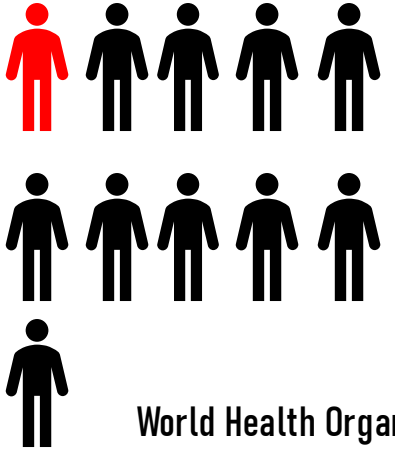
Why does L^3 matter?

Importance of Knowing Volume (L^3)

Sink ⟷ Where L^3 is used

Stored

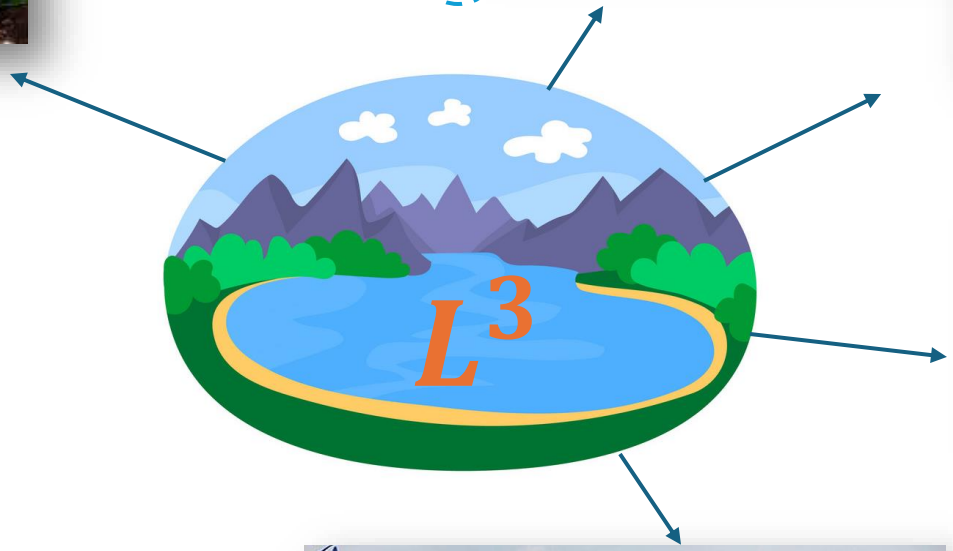
1 Irrigation



World Health Organization, 2024

Importance of Knowing Volume (L^3)

Stored with Uncertainty Estimates

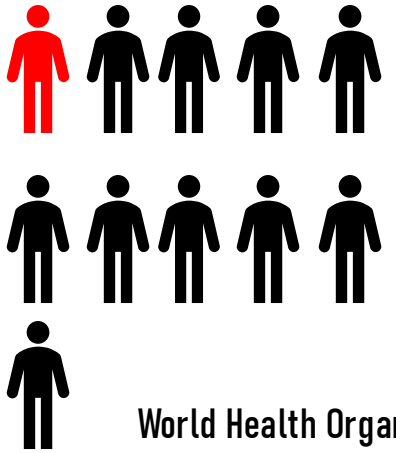


1 Irrigation

2 Aquatic Life

3 Hydropower Generation

4 Industry



World Health Organization, 2024

5 Domestic Needs

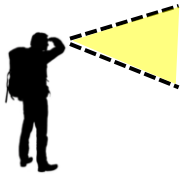
Overarching Research Question

How can satellite remote sensing be utilized to enhance surface water management?

Sources

Sinks

Roadmap



Volume

Why → Broader Impacts

Why → Motivation

How

Source

Through What → Chapter 1

Through What → Chapter 2

Sink

For What → Chapter 3

For What → Chapter 4

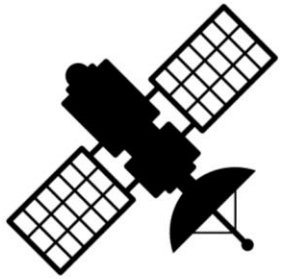
How

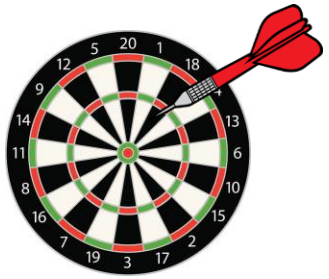
Chapter 1: How can surface water volume be estimated using state-of-the-art techniques, and how does volumetric uncertainties vary with water bodies?

Challenges in estimating the volume of water (L^3)

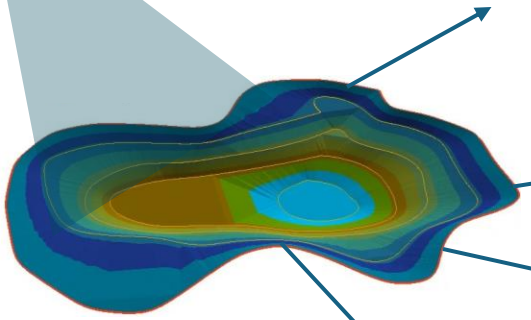
Volume (L^3) = Area (L^2) x Elevation (L)

Satellites (revisit time around a week)



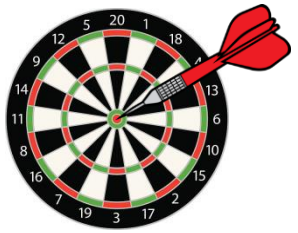


Altimeters (revisit time quite long)



Bathymetry

LiDAR



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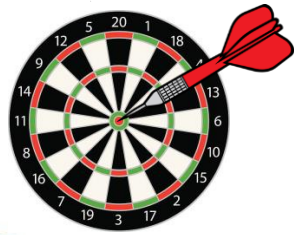

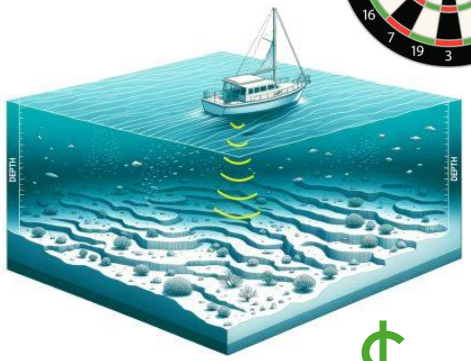

SONAR

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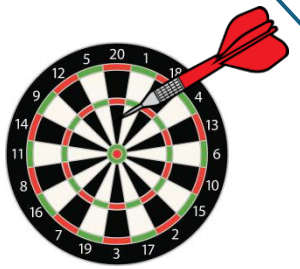
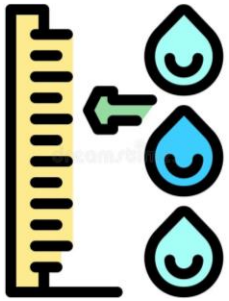


Citizen Science



Gauge

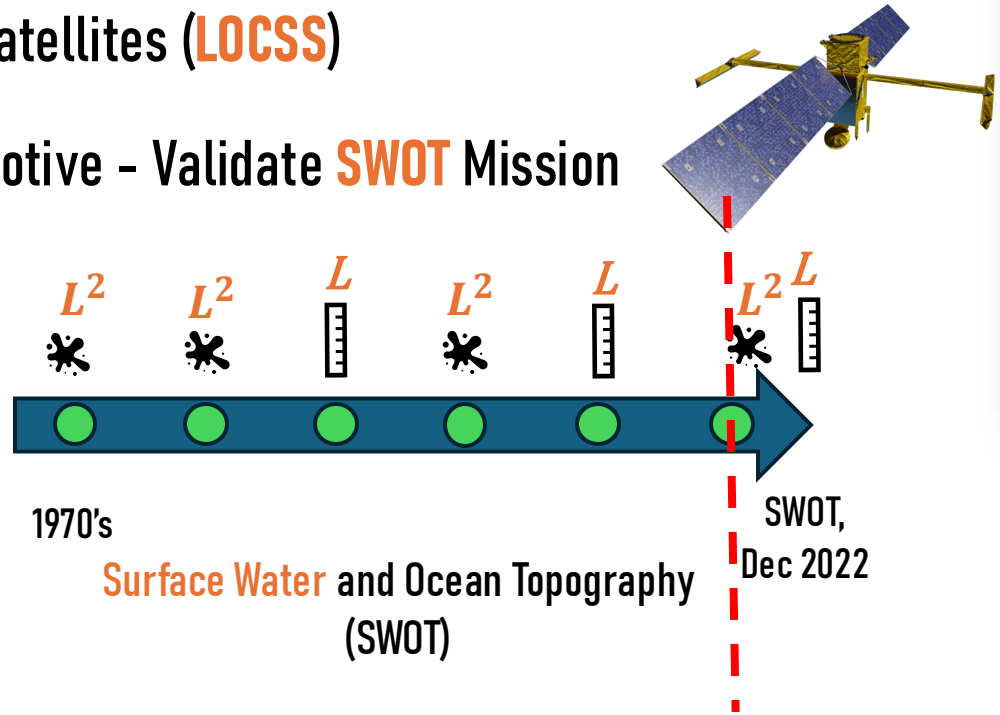
Gauges and Citizen Science

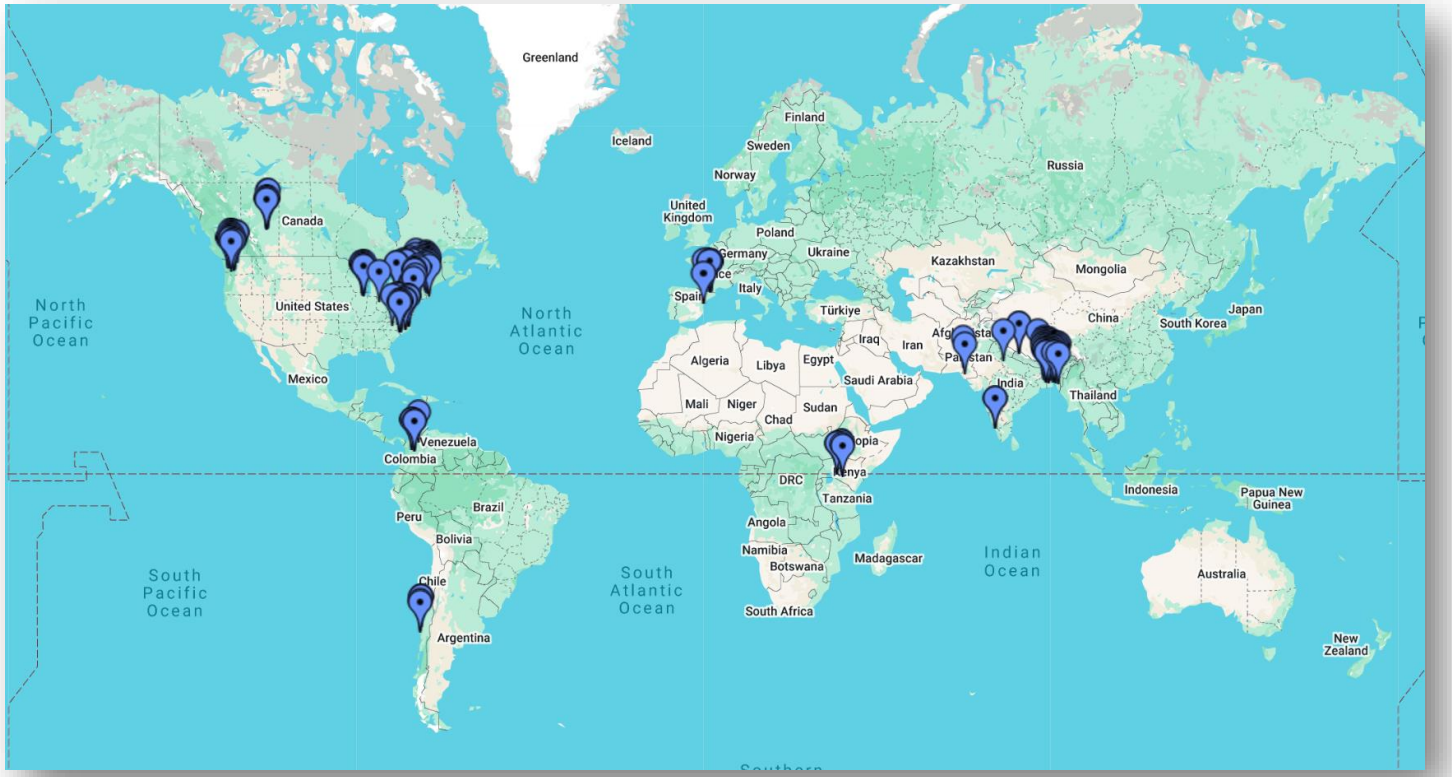
Funded by NASA

When the public volunteers to participate in scientific research by collecting or analyzing the data

Lake Observations by Citizen Scientists and Satellites (LOCSS)

Motive - Validate SWOT Mission

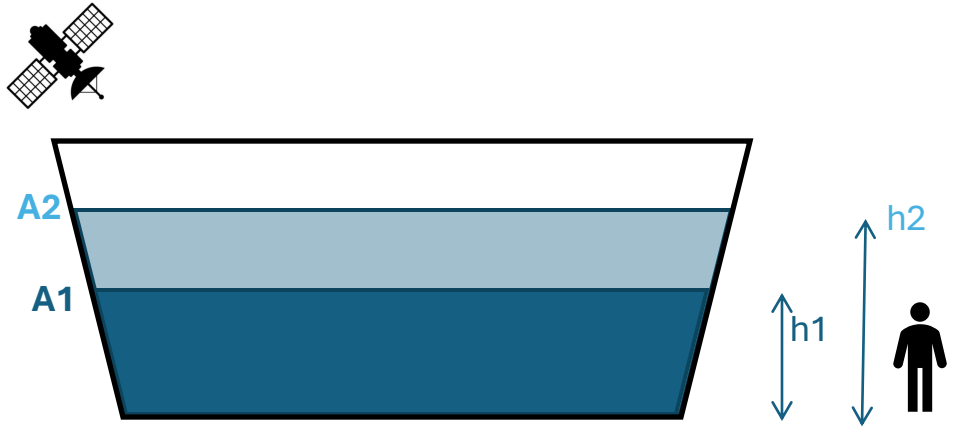




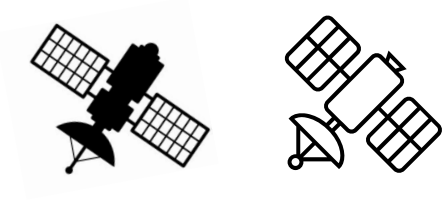
Global Presence of LOCSS

In Collaboration with: THE UNIVERSITY of NORTH CAROLINA at CHAPEL HILL, Tennessee TECH

Estimating The Storage Through Citizen Science (L^3)

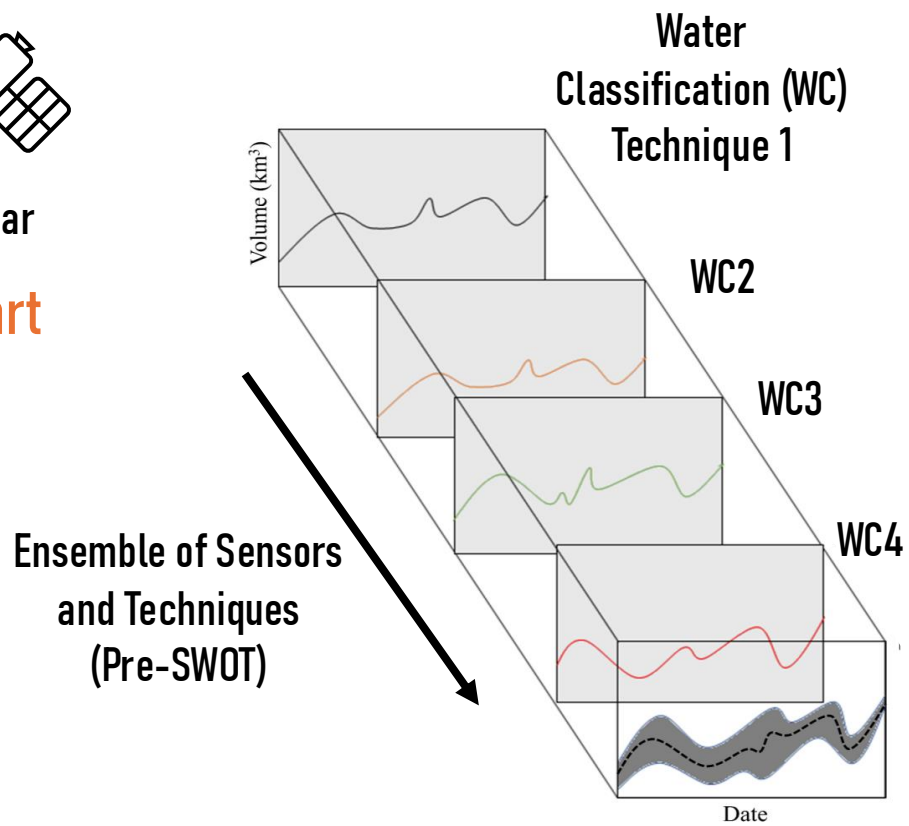


Trapezoidal Bathymetry



Optical Radar

State-of-the-art

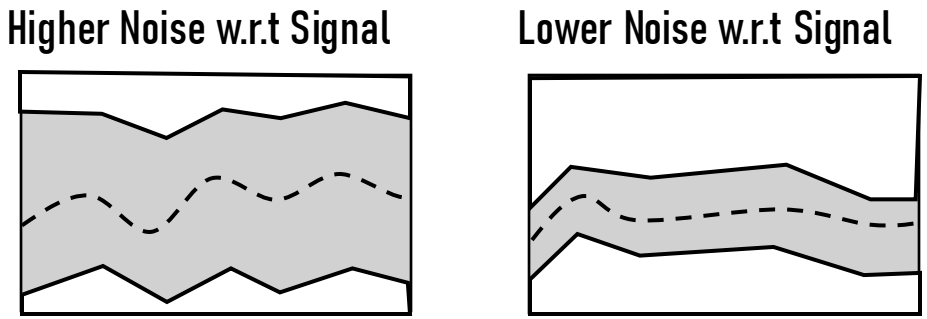


Trapezoidal Rule

$$\Delta S = A_{avg.} * \Delta h = \frac{(A_2 + A_1)}{2} * (h_2 - h_1)$$

Time-Averaged Uncertainty

Analogy of **Noise to Signal Ratio**



Uncertainties Bounds in Volume Estimates

$$Uncertainty = \sum_{0}^{n} \left[\frac{Variation\ in\ Ensemble\ Volume_t}{Mean\ Ensemble\ Volume_t} \right]$$

Uncertainty > 1: The signal's strength is weak compared to the noise

Uncertainty < 1: Signal is stronger and able to get a clear picture.

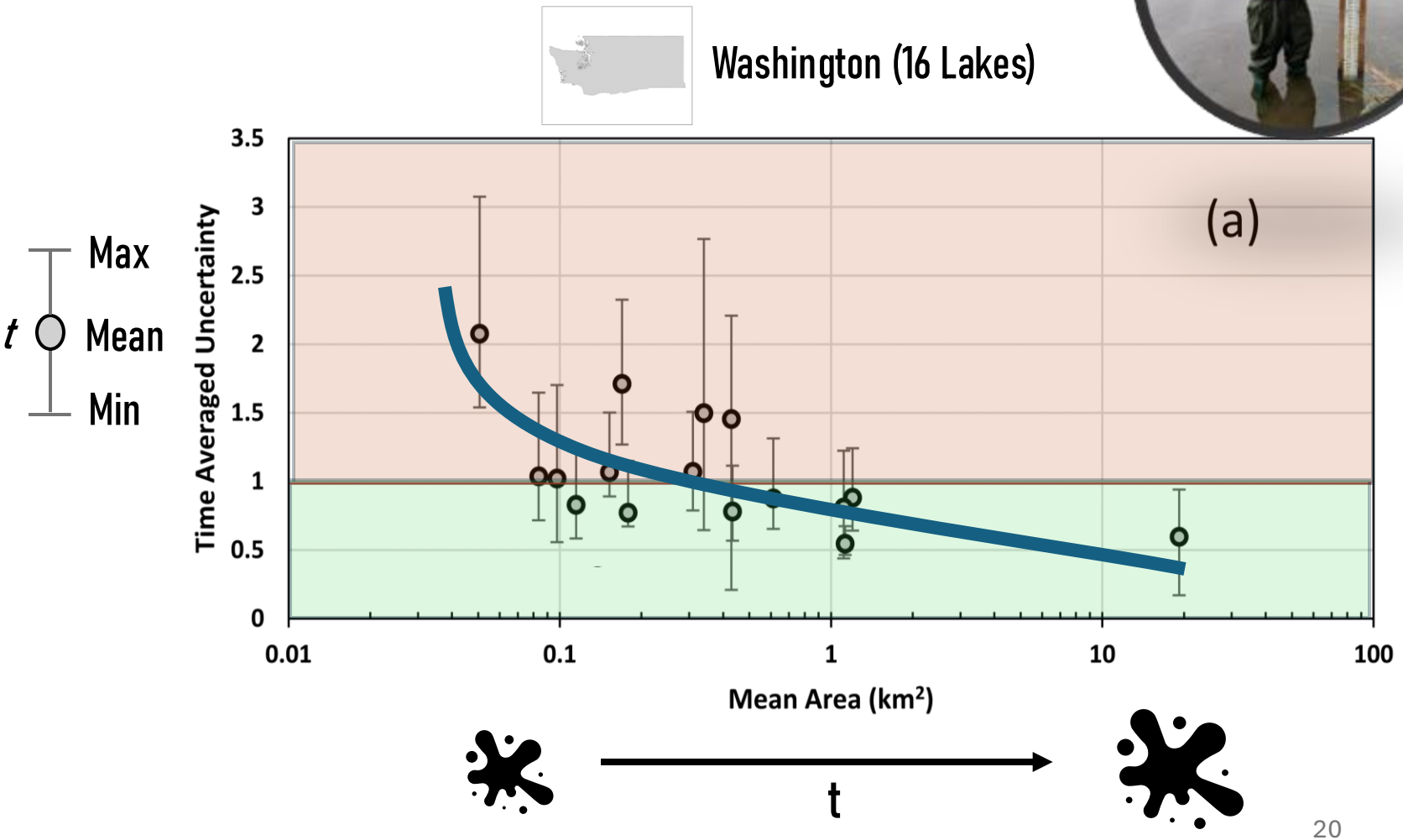
Time-Averaged Uncertainty

$$Uncertainty = \frac{Noise}{Signal} \uparrow$$

State-of-the-art techniques (Pre-SWOT) failed to estimate the change in volume due to high uncertainty

$$Uncertainty = \frac{Noise}{Signal} \downarrow$$

The volume of water stored in larger water bodies can be estimated with lower uncertainty



Key Takeaways from Chapter 1

- ✓ Smaller water bodies and their surrounding environments contribute to higher uncertainty.
- ✓ Pre-SWOT benchmarks
- ✓ Expansion of gauge network can help to validate the future missions and foster the community on water sustainability.

S. Khan et al., "Understanding Volume Estimation Uncertainty of Lakes and Wetlands Using Satellites and Citizen Science," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 16, pp. 2386-2401, 2023

Khan, S. F. Hossain, et al. (2022) The Impact of an Extra L from the SWOT Satellite Mission for Tracking Flood Volume Changes in the Developing World (November Edition)

Volume ✓
Why ✓
How ✓

Expansion of Gauges

Volume ✓
Why ✓
How ✓
Through What ?

Gauge all the *sources* (lakes and wetlands)

A few gauges and at strategic locations that can represent the region

Expansion of Gauges

Highest density of citizen science based gauges is **in Bangladesh**

What is the **optimal number** of gauges and their **locations** that can effectively represent a region to derive the volume of surface water stored?

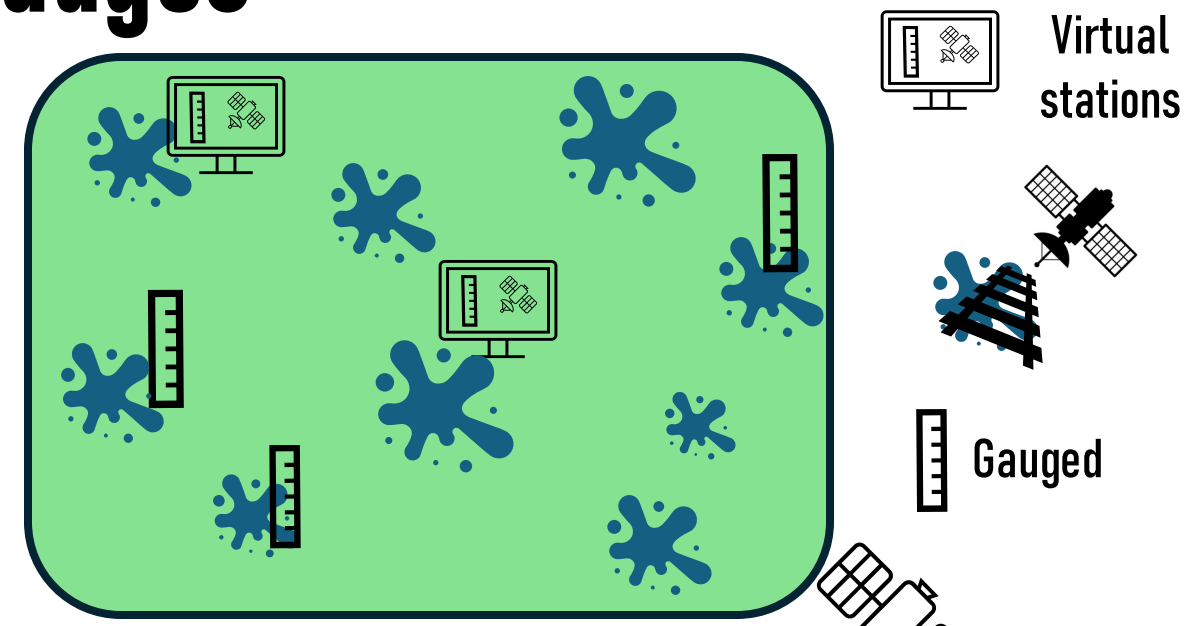
LOCSS Gauge Presence (until April 2023)

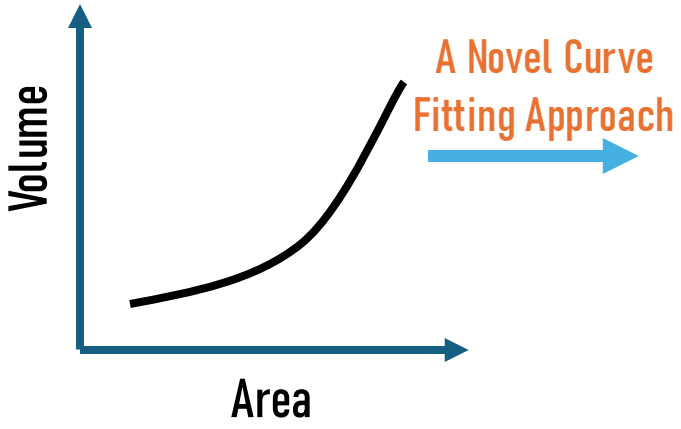
Recipe to find optimal # of gauges

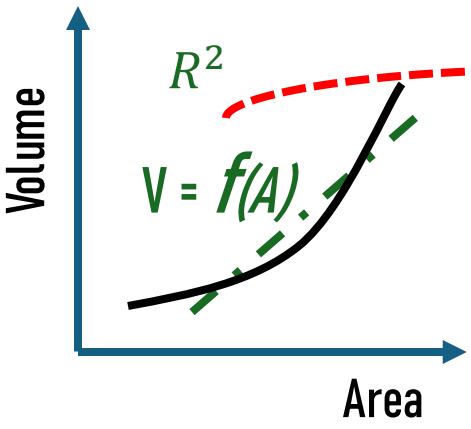
Step 1 - Estimate the benchmark volume of a region through existing density

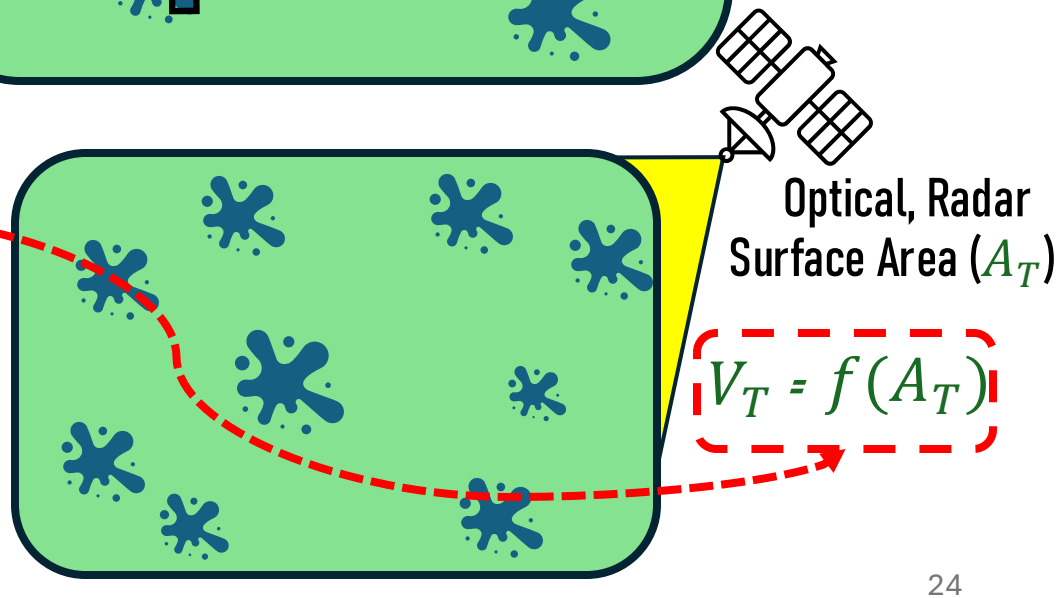
Step 2 – Degrade the gauge network at a time

Step 3 - Compare the degraded network gauge volume with the highest gauge density benchmark volume









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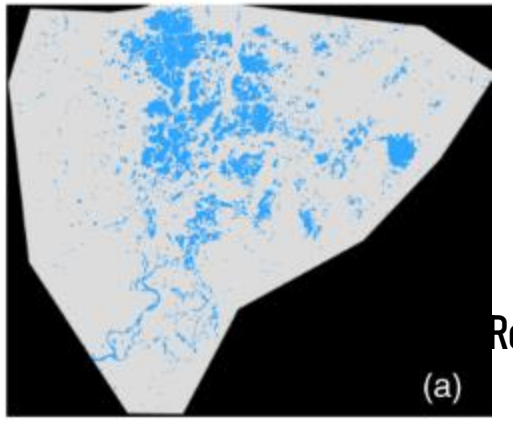
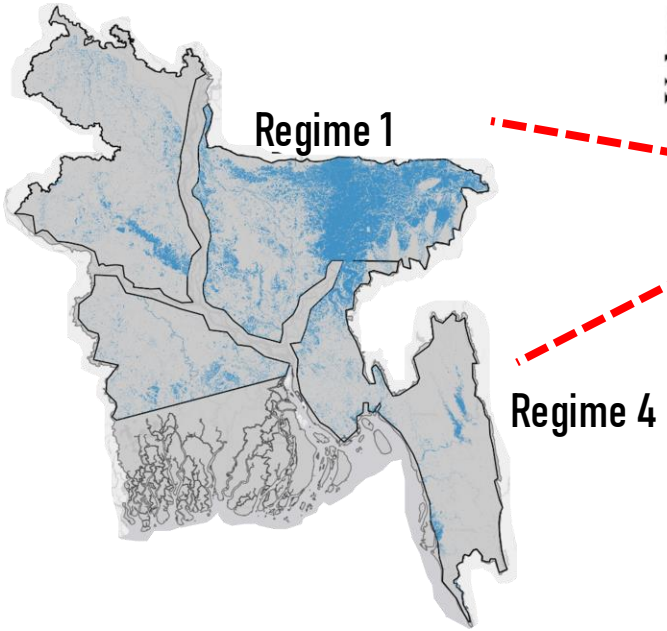
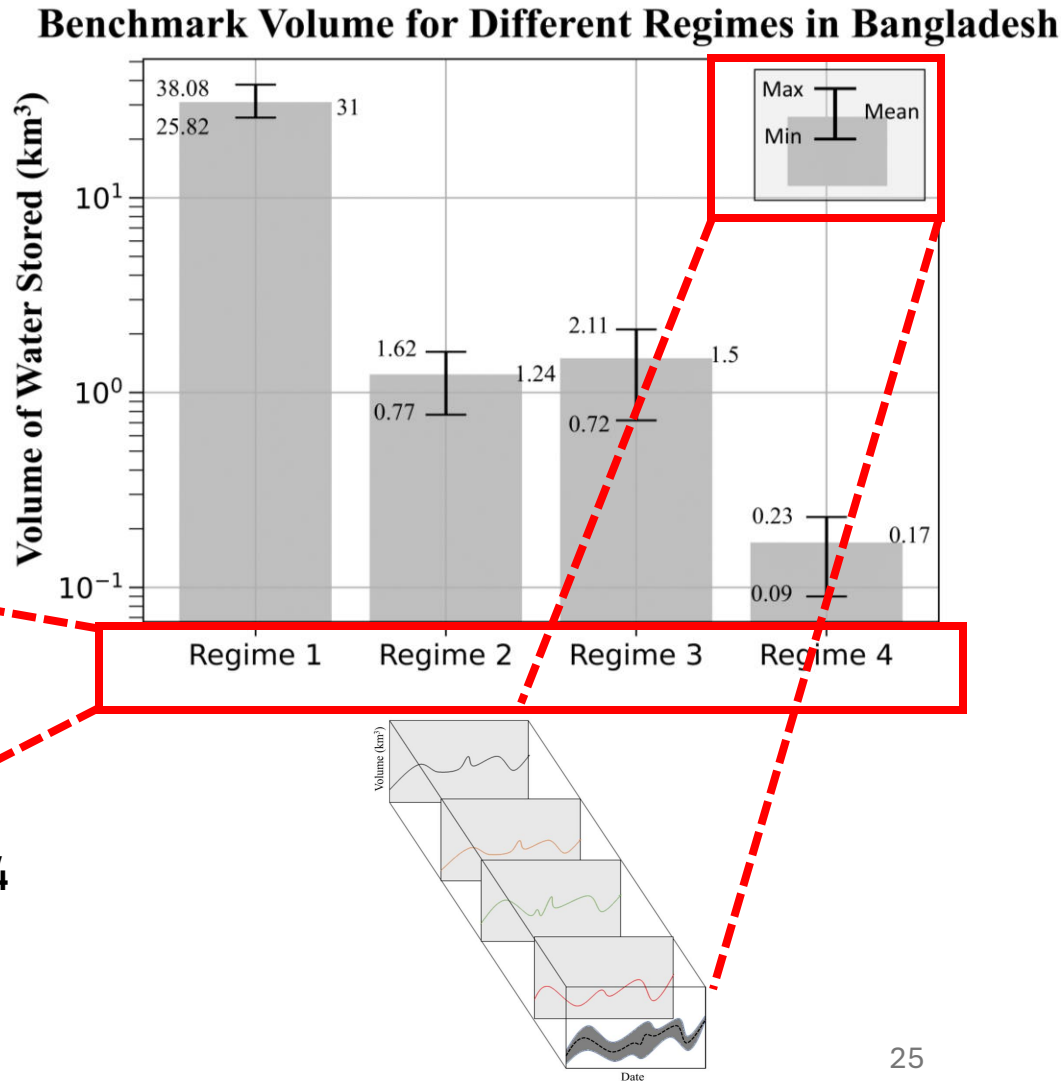
Step 1 - Estimate the benchmark volume of a region through existing density



The volume (seasonal) of surface water stored = $30.8 \pm 0 \cdot 2$ km^3 [Regime 1]

Ahmad et al. (2020)



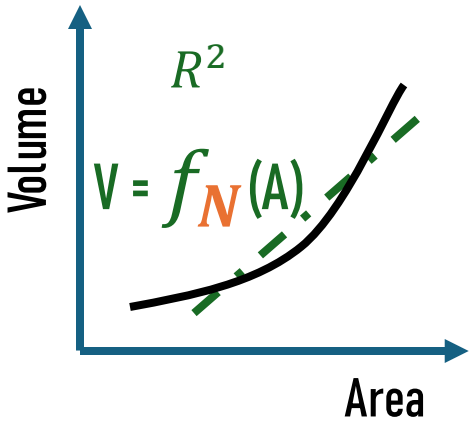


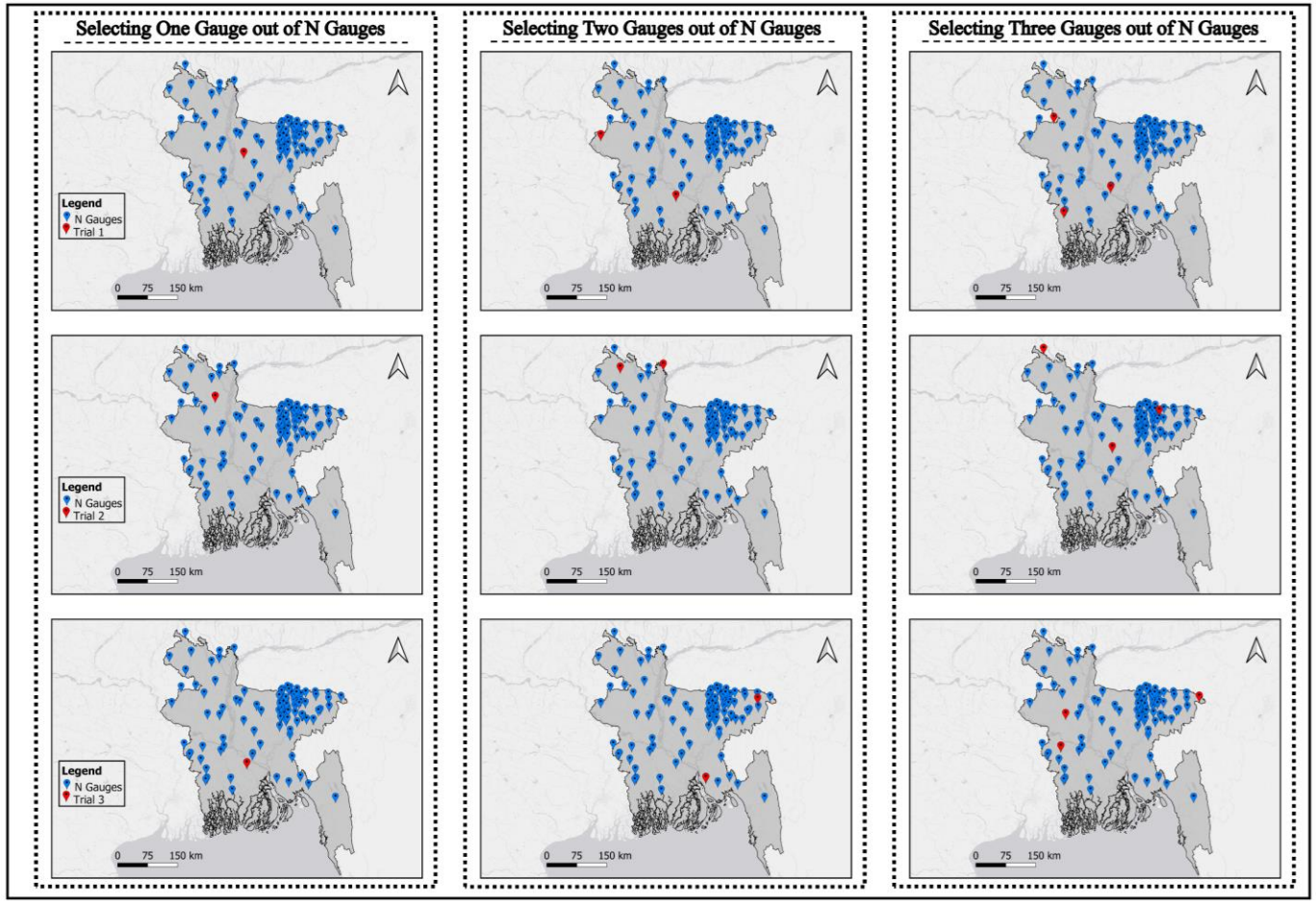
Recipe to find optimal # of gauges

Step 2 - Degrade the gauge network at a time

Monte-Carlo Simulations

$^{N}C_1 + {}^{N}C_2 + {}^{N}C_3 \ldots\ldots\ldots\ldots {}^{N}C_N$; ~1 Billion Simulations





Recipe to find optimal # of gauges

Step 3 - Compare the degraded network gauge volume with the highest gauge density benchmark volume

$$\text{Percentage Error} = \frac{Benchmark\ Volume - Step\ Volume}{Benchmark\ Volume} \times 100$$

Range of solutions

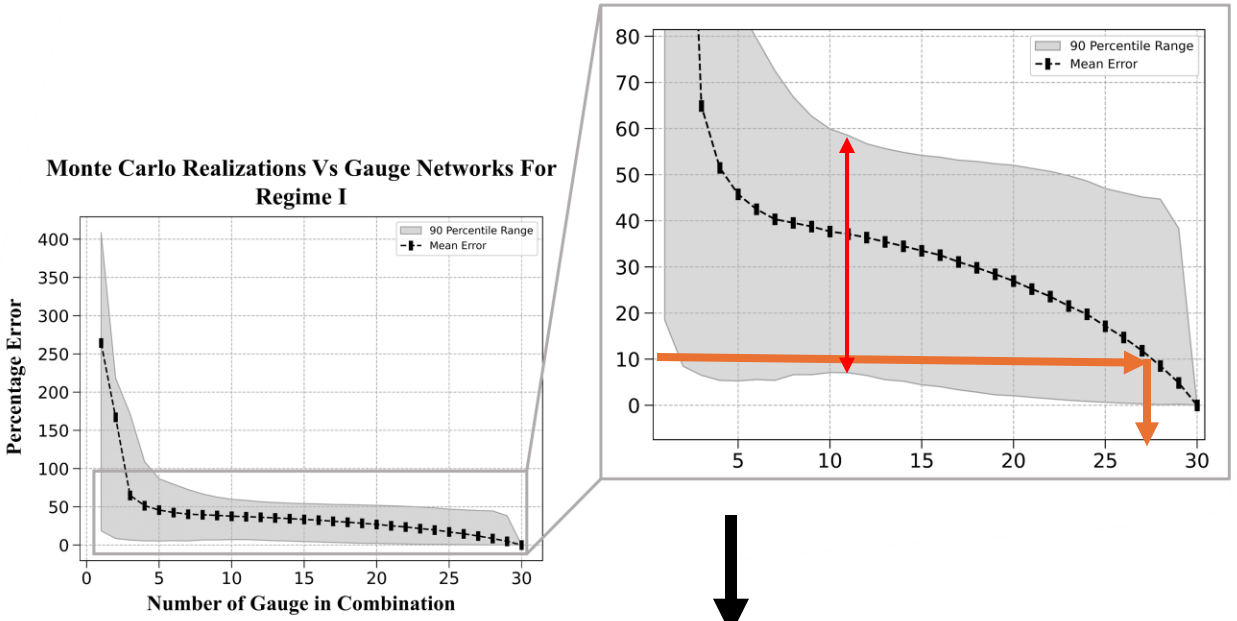
Accuracy ∝ $

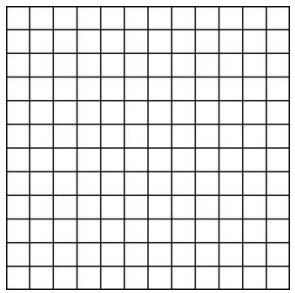
(Cost-Benefit-Analysis)

Optimal # ✓

Optimal Locations ?

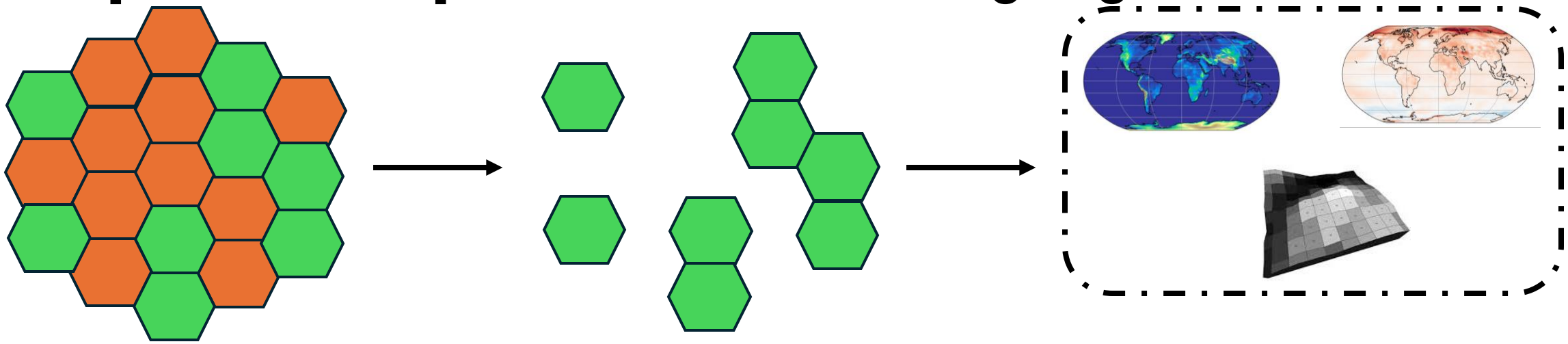
Monte Carlo Realizations





1 gauge in 34 km grid

Recipe to find optimal locations of gauges

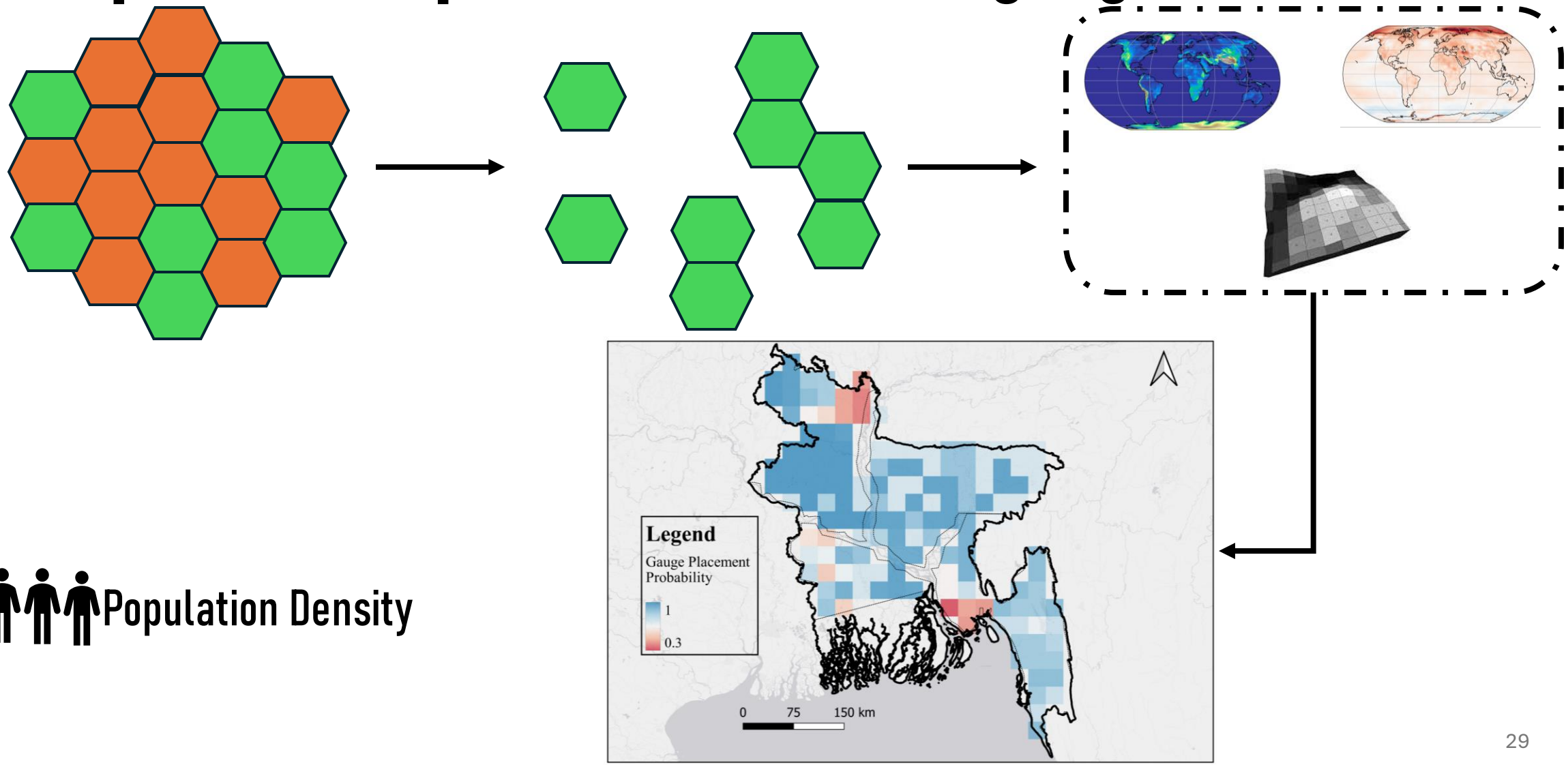


Total # simulations

$_NC_1 + {}_NC_2 + {}_NC_3 \ldots\ldots\ldots\ldots {}_NC_N$

high-performing combinations of gauges (90% accuracy) toward benchmark volume

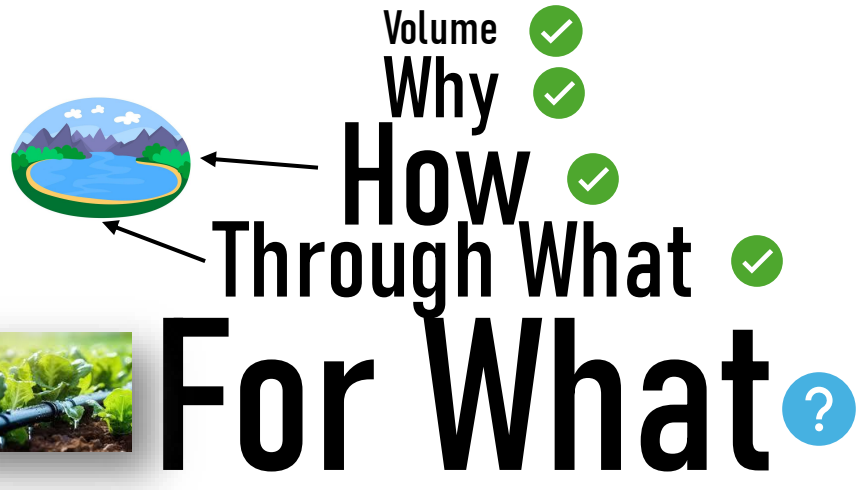
Recipe to find optimal locations of gauges

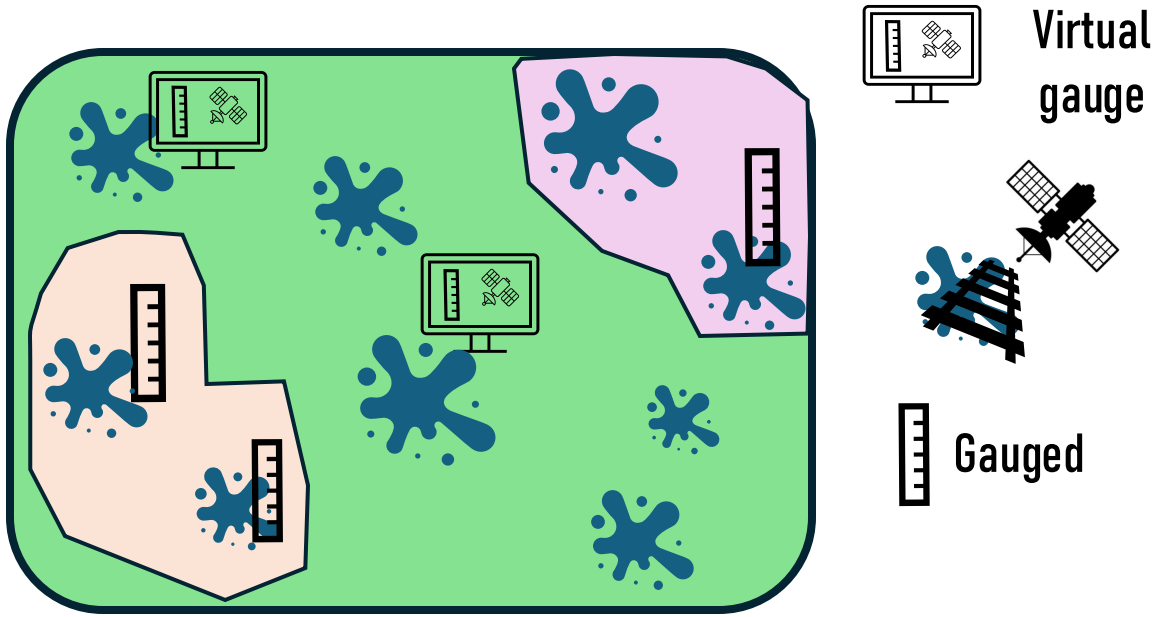


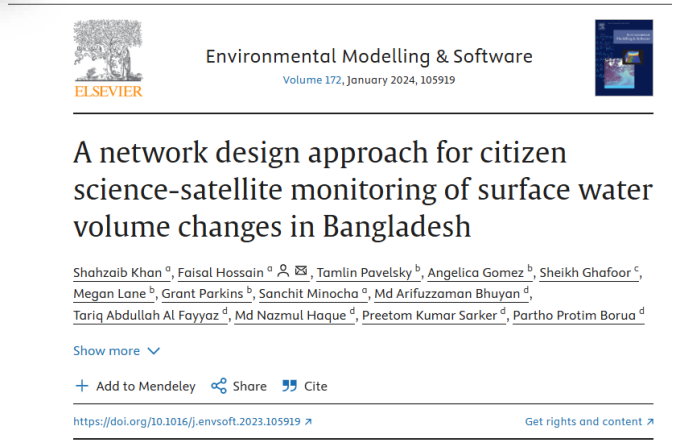
Population Density

Key Takeaways from Chapter 2

A methodology to determine the optimal number and strategic placement of gauges for estimating the volume of surface water stored, leveraging citizen science and satellite data.







S. Khan, F. Hossain, et (2024). A network design approach for citizen science-satellite monitoring of surface water volume changes in Bangladesh, *Environmental Modelling & Software*, Volume 172, 2024, 105919

Focusing on Sinks

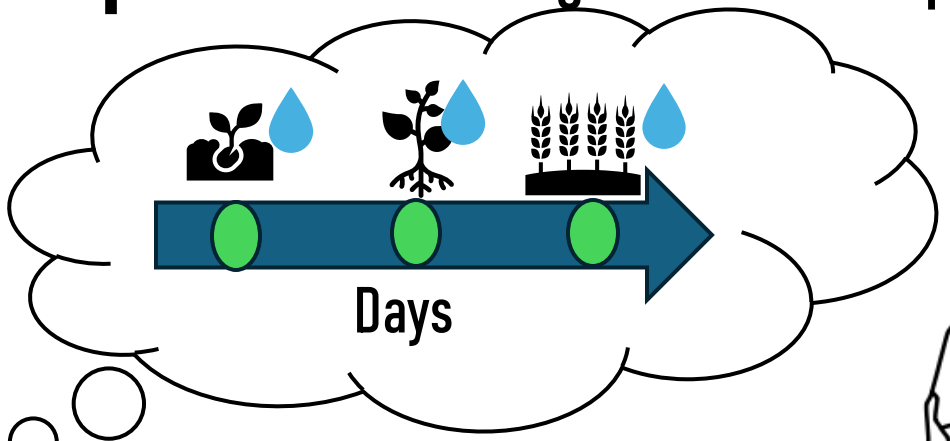
Source

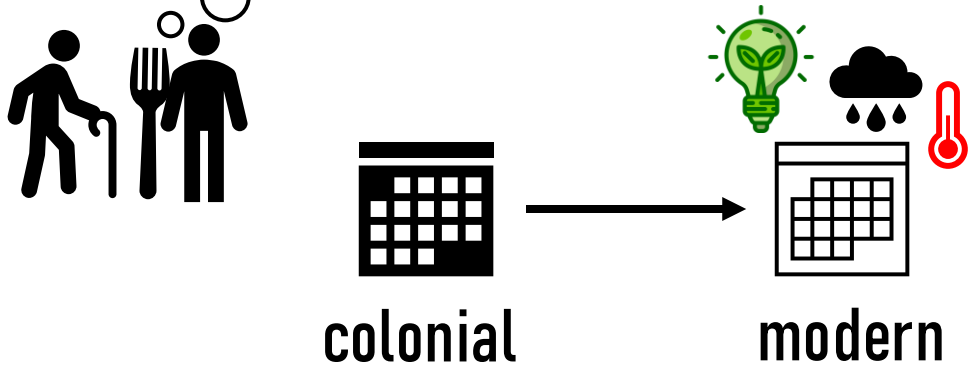
Less Contaminated

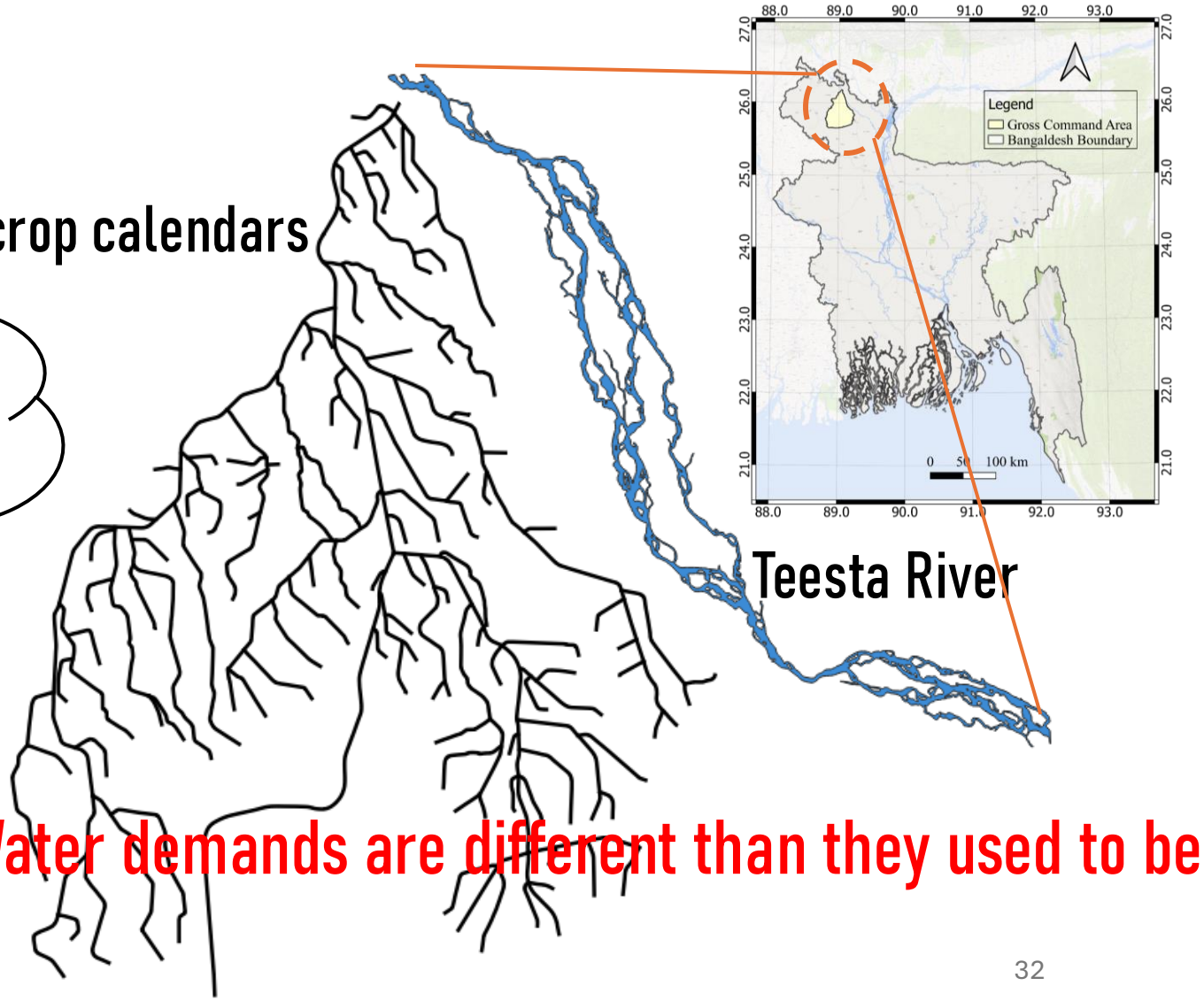
Current Irrigation Practices in TBP

TBP: Teesta Barrage Project, Bangladesh

Traditional practices – Usage of static crop calendars







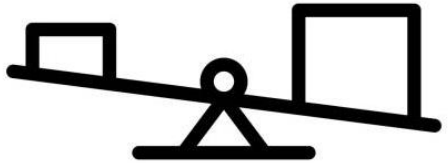
Water demands are different than they used to be

Current Irrigation Practices via Satellites

Farmers Oriented

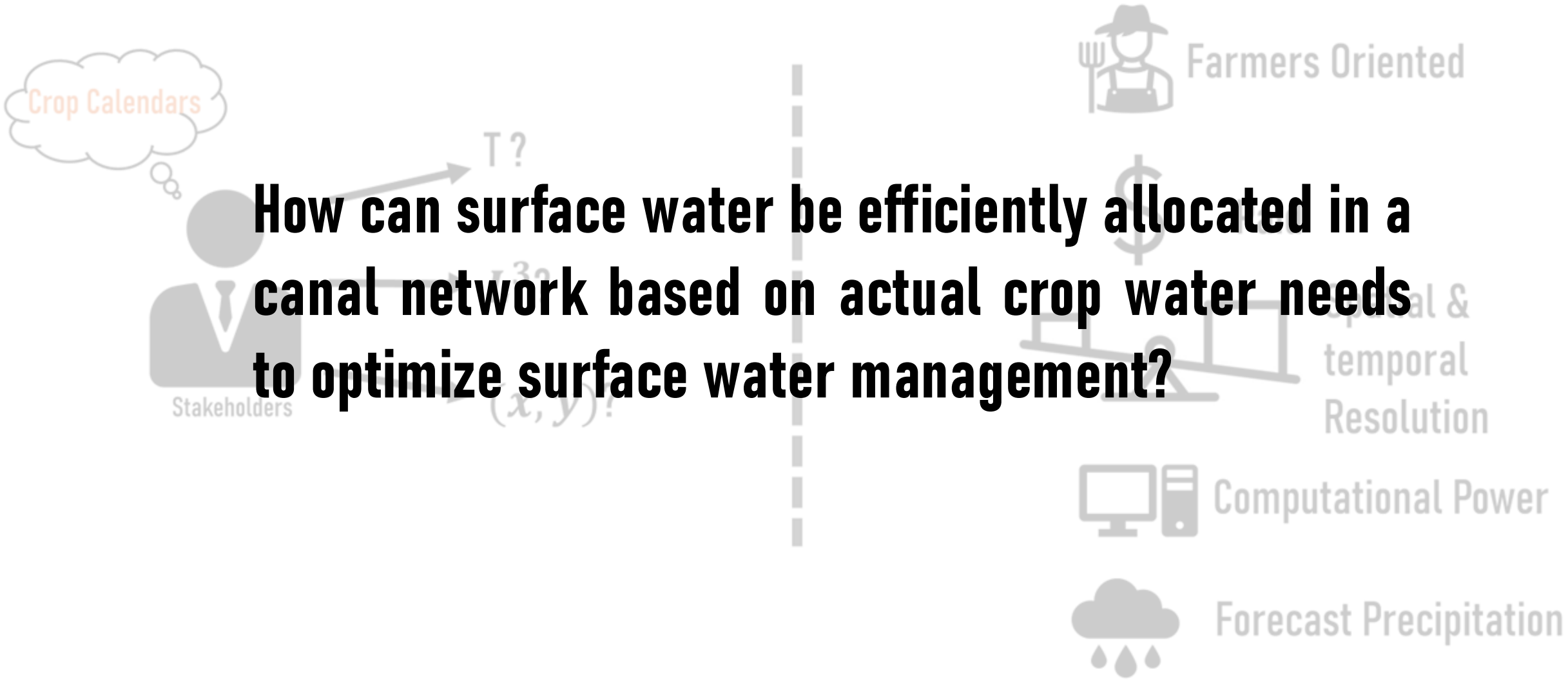
Paid
(Recurring Subscription Fee)

- Purchase sensors
- Storage on Cloud
- Generating advisories



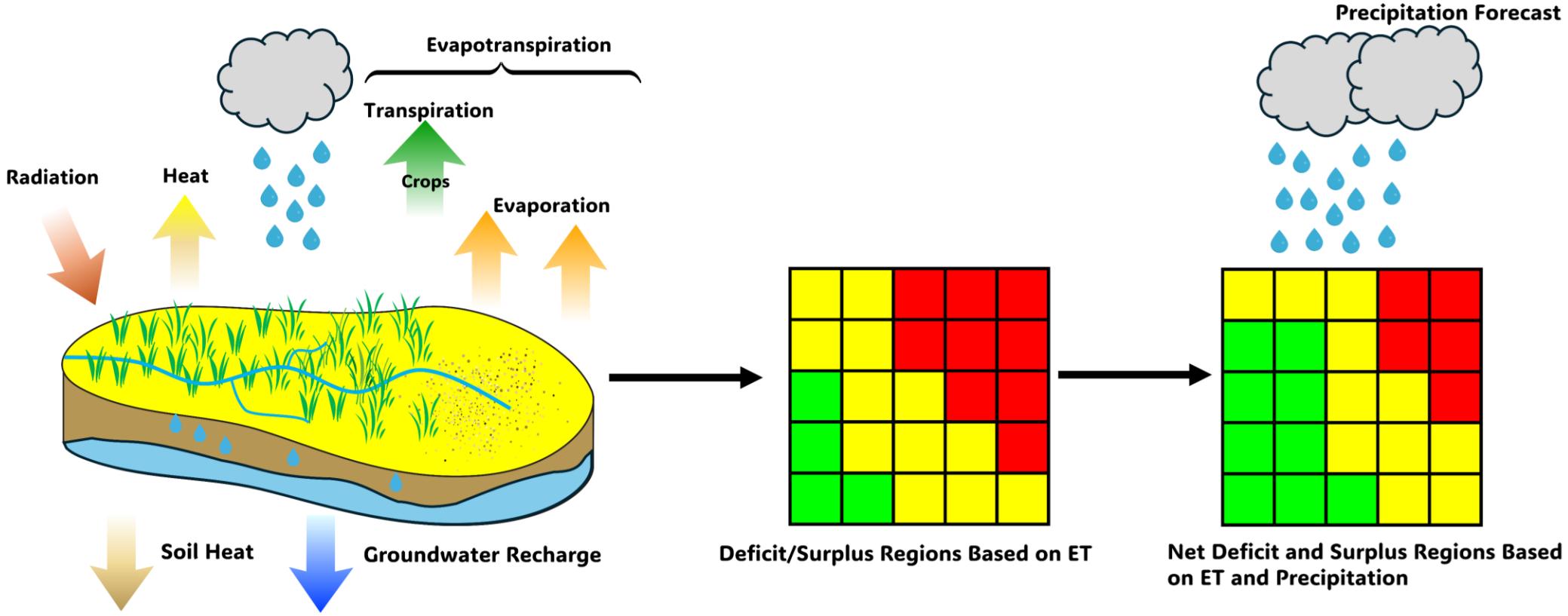
Spatial & temporal Resolution

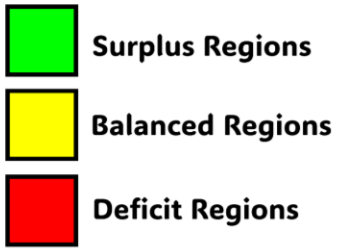
Computational Power



How can surface water be efficiently allocated in a canal network based on actual crop water needs to optimize surface water management?

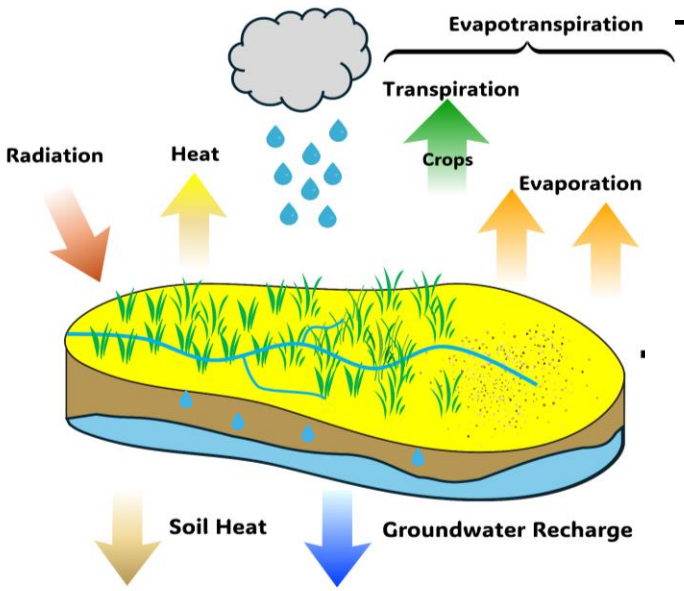
A Framework to Optimize Current Irrigation (sDRIPS-TBP)





s.D.R.I.P.S – Satellite Data Rendered Irrigation using Penman-Monteith and SEBAL

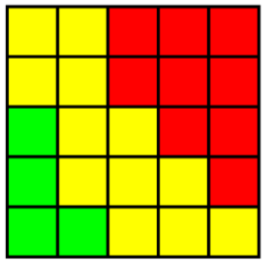
sDRIPS-TBP Detailed



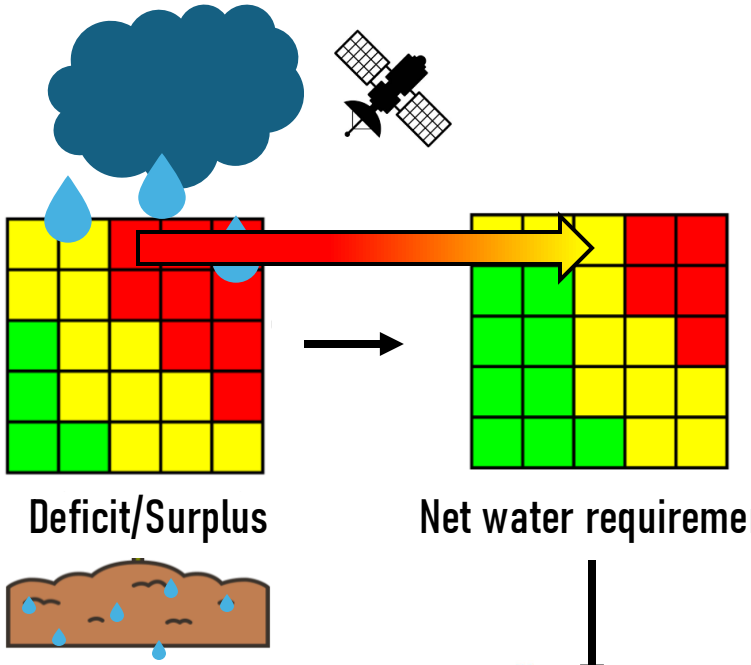
Actual ET

Potential ET

Actual-Potential



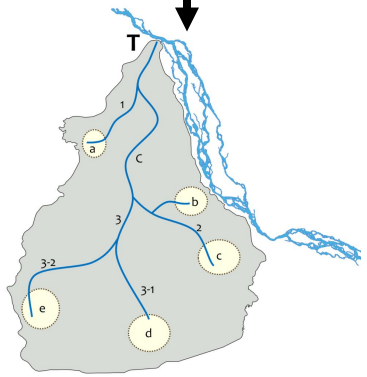
Deficit/Sufficient



Deficit/Surplus

Percolation

Net water requirement



Water Allotment

Surplus Regions

Balanced Regions

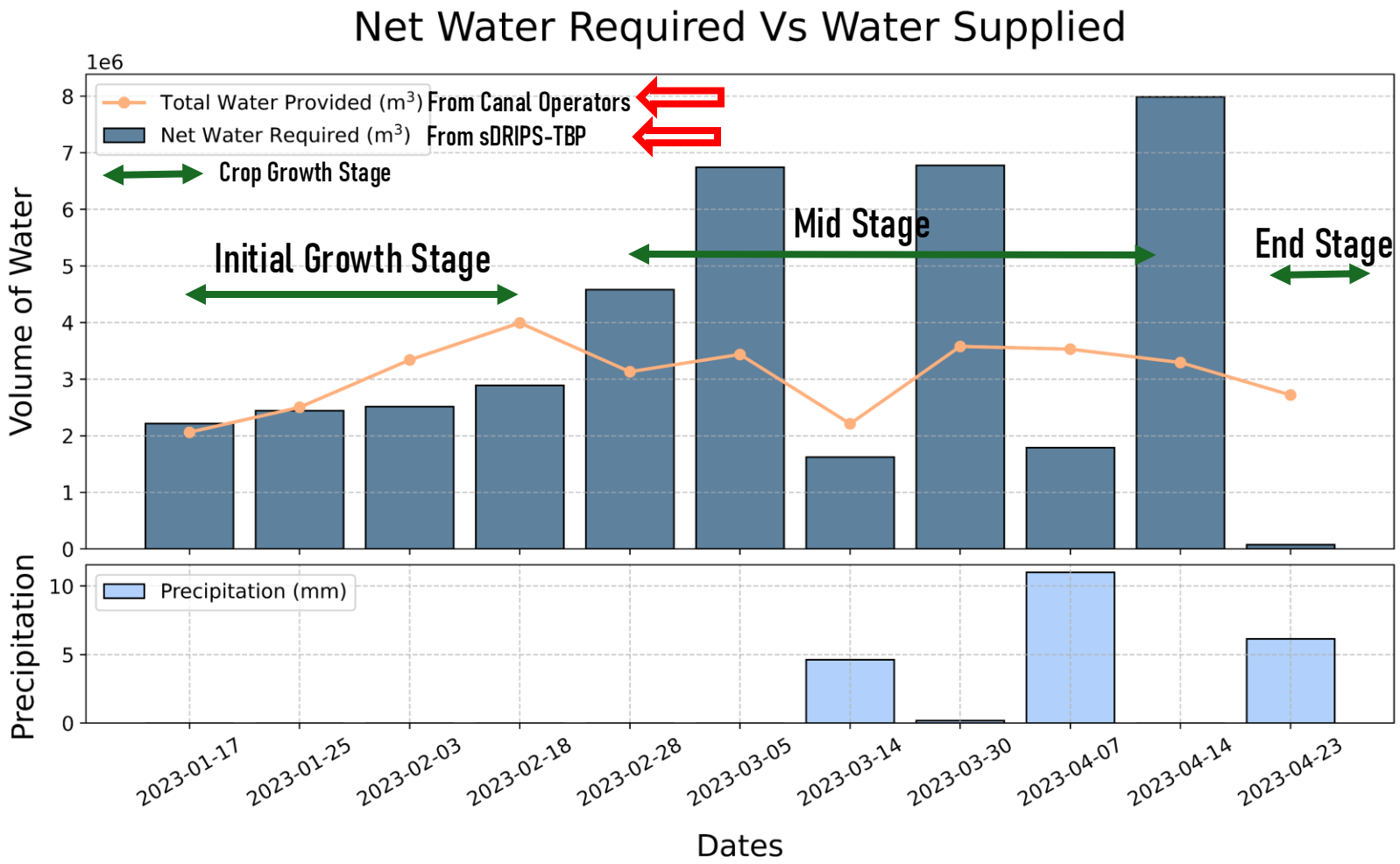
Deficit Regions

Actual ET	Estimated using Surface Energy Balance Algorithm (SEBAL) **Proxy of actual water consumed by the plants**
Potential ET	Estimated using Penman – Monteith Equation **Proxy of water needed by the plants**

Comparing Framework Estimates with In-situ Data

Comparing the sD.R.I.P.S estimates with in-situ data

Rice is the most water-intensive crop

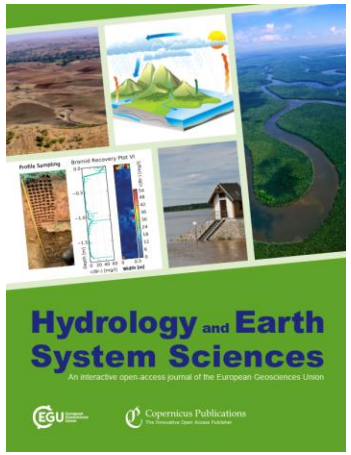


Assumption:

Rice is grown all over the region, due to a lack of cropping data

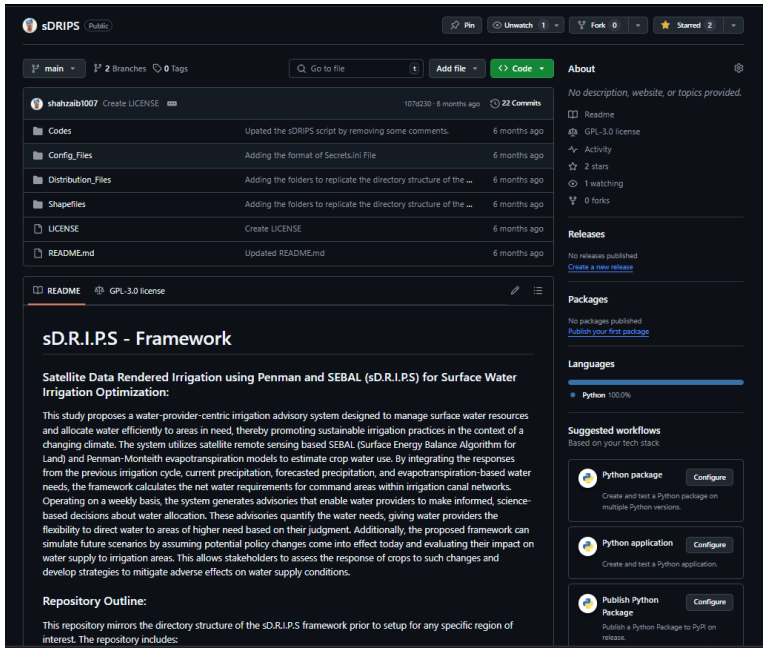
Key Takeaways from Chapter 3

A framework to allocate water in canal network based on the actual crop water need and is under consideration by stakeholders to get satellite based advisories



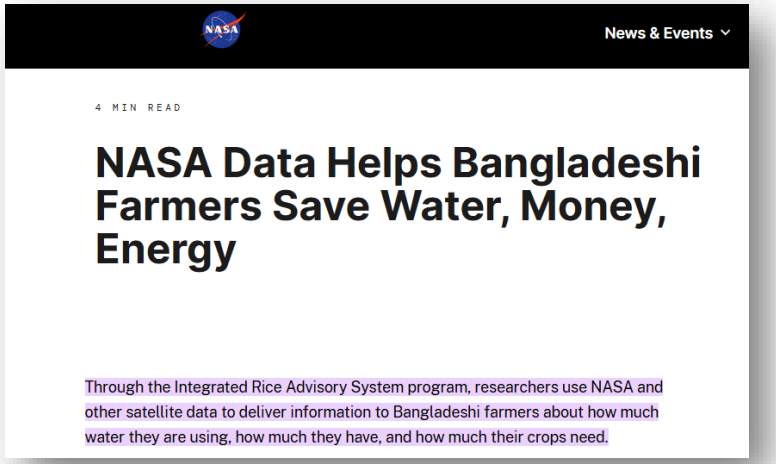
HESS, In Review

Volume ✓
Why ✓
How ✓
Through What ✓
For What ✓ ?



Github Repo

A Scalable sDRIPS For Everyone



Requirements and Differences

BRING IT HOME!

	TBP, BD	University of Washington, USA	Crown Farms, South Africa
Target User	Canal Operator	Landscape Workers	Farmers
COI	Rice	Grass	Multi-Crop
Environment ?	Homogenous	Heterogenous	Homogenous

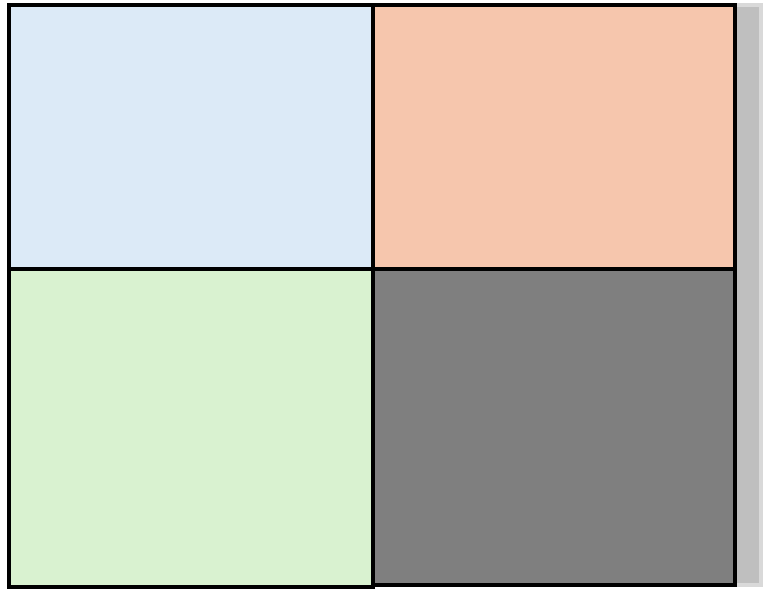
Requirements and Differences

Vast Fields in Bangladesh

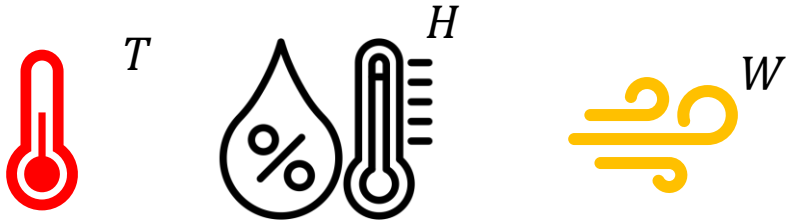
UW Landscape

Challenges with Spatial Resolution in Heterogenous Environment

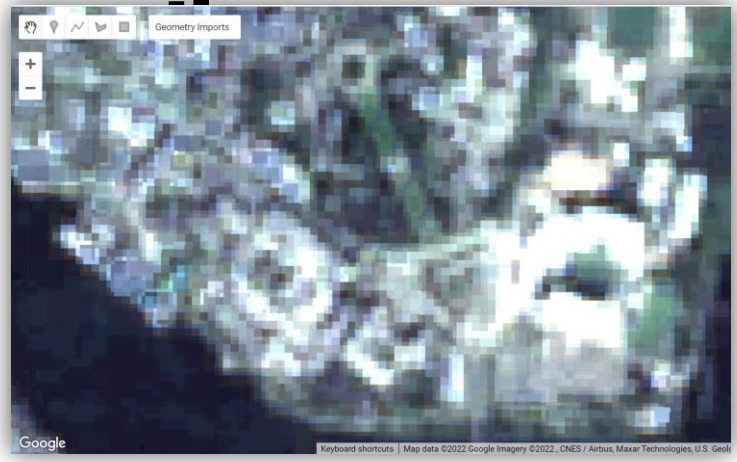
Meteorological variables from global models



At **25 km** resolution



Reference: **30 m** resolution @ Rainier Vista



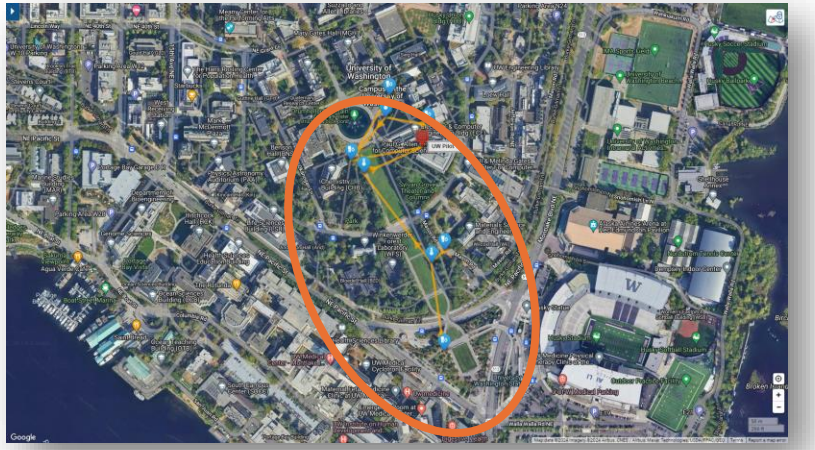
Noise/Signal Ratio

Signal over landscape is contaminated by Noise due to complex landcover

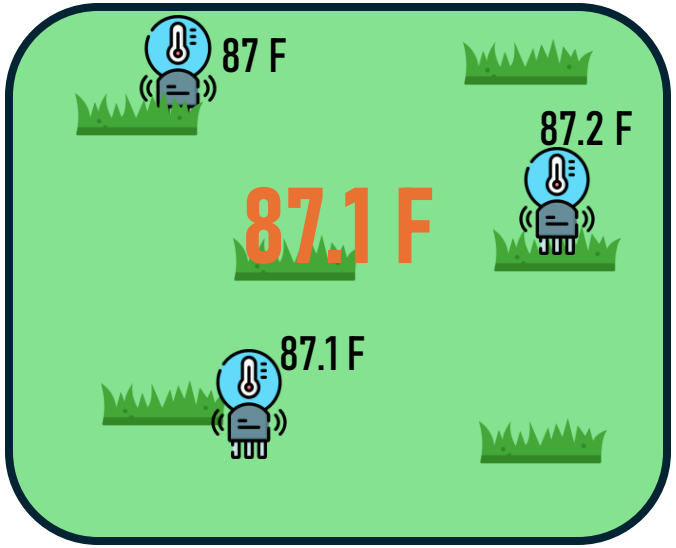
sDRIPS-Sense

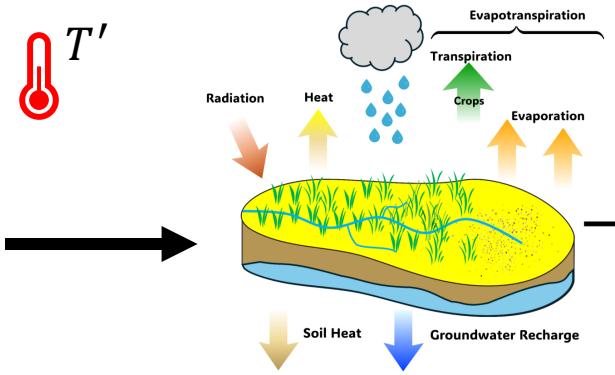
Rainier Vista

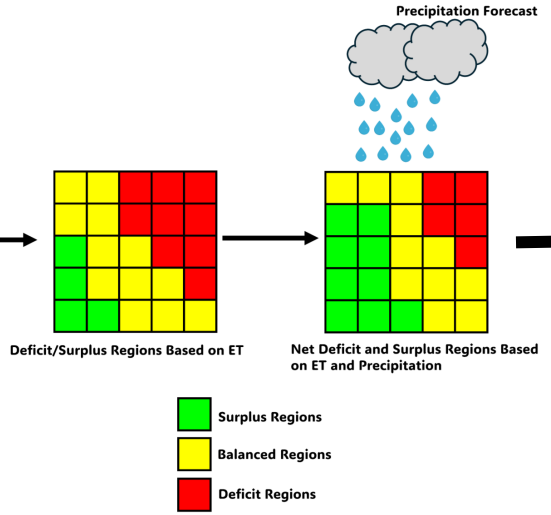
HoboLink Sensor
~$200

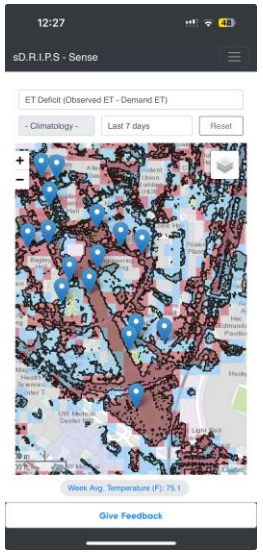


Sensors installed mainly at Rainier Vista





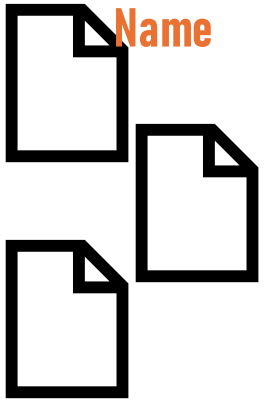




sDRIPS Mobile App, Co-Developed with Capstone Students

Single Digital Umbrella

sDRIPS – Region Name



Fragmented Versions

Mix it well

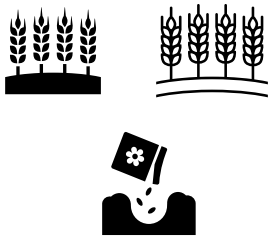
Ready to bake

CHOOSE YOUR FLAVOR

Farmers

Stakeholders

Sensors



Lowering the Barrier to Entry

sDRIPS

True/False Conditions

Farmers | Stakeholders | Sensors | Weather Stations

Multi-Crop Analysis

Spatio-Temporal Resolution

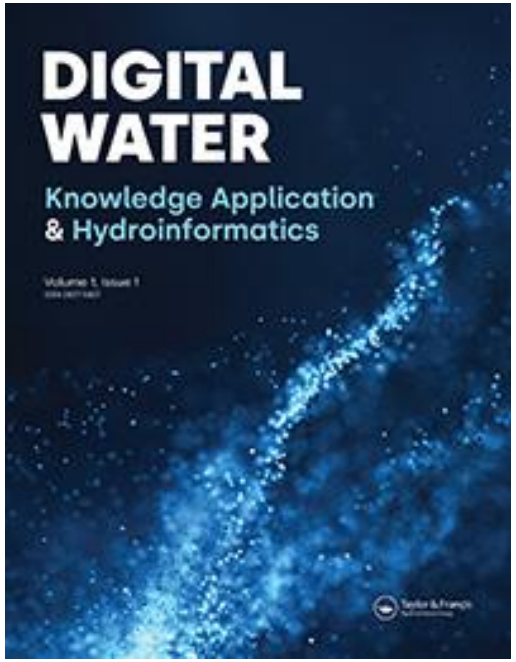
Farm Scale (30m)

7

Weekly Advisories

Step-by-Step Tutorials

Read the Docs

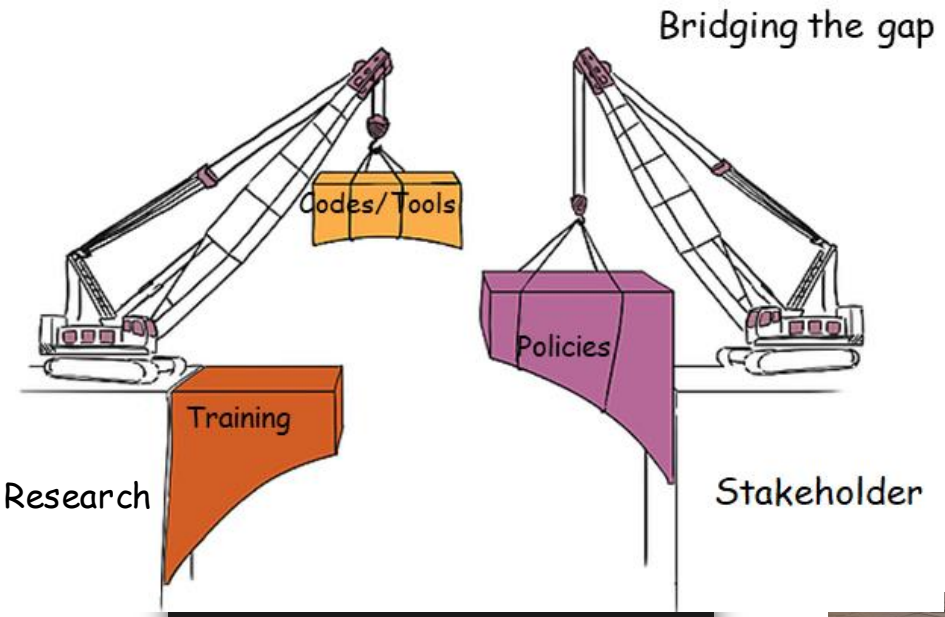


Volume ✓
Why ✓
How ✓
Through What ✓
For What ✓ ✓

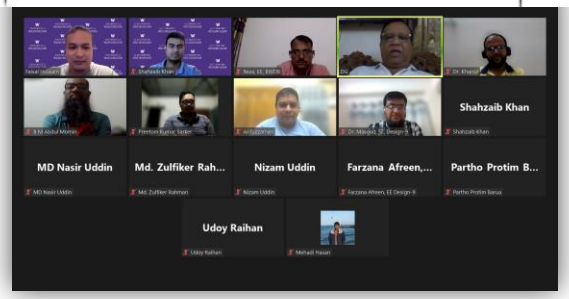
Publications

1. **S. Khan** and F. Hossain (2025). sDRIPS: A Cloud-Based, Open-Source Python Package for Satellite-Informed Surface Water Irrigation Optimization, *Digital Water,* (In Review)
2. **S. Khan**, F. Hossain, M. Ahamed (2025). Satellite Data Rendered Irrigation using Penman-Monteith and SEBAL (sD.R.I.P.S) for Surface Water Irrigation Optimization, *Hydrology and Earth System Sciences,* (In Review)
3. **S. Khan**, Z. N. Hossain, S. Suresh, and F. Hossain (2025). The Untapped Hydropower Potential of World's Cities, *Next Energy* (In Review).
4. **S. Khan**, F. Hossain, et al. (2024). A Network Design Approach for Citizen Science-Satellite Monitoring of Surface Water Volume Changes in Bangladesh, *Environmental Modelling and Softwar*e.
5. **S. Khan**, F. Hossain, et al. (2022) Understanding Volume Estimation Uncertainty of Lakes and Wetlands Using Satellites and Citizen Science, *IEEE JSTARS*.
6. **S. Khan**, N. Kamboj, U. Bhatia (2020) Lifeline Infrastructures and Hydro-climate Extremes: A Future Outlook, Climate Change and Extreme Events, *Elsevier*.
7. M. Gómez, S. Biancamaria, T. Pavelsky, K. Nielsen, G. Parkins, M. Lane, **S. Khan**, F. Hossain, R. Bhattarai, S. Ghafoor, J.F. Crétaux, C. Yanez, N. Picot (2024). Evaluation using In-Situ Observations from National Governments and Citizen Scientists Suggests Nadir Altimeters can Accurately Measure Water Levels Changes Regardless of Lake Area. *GIScience and Remote Sensing.*
8. Darkwah, G, F. Hossain, V. Tchervenski, G. Holtgrieve, C. Seaton, D. Graves, S. Minocha, P. Das, **S. Khan**, S. Suresh (2024) Reconstruction of the Hydro-Thermal History of Regulated River Networks Using Satellite Remote Sensing and Data-driven Techniques, *Earth's Future*, vol 12(10)
9. Minocha, S., F. Hossain, P. Das, S. Suresh, **S. Khan**, G. Darkwah, K. Andreadis, H. Lee, G. Holt, S. Galelli (2023). Reservoir Assessment Tool: A scalable and easy-to-apply python based software architecture to empower the global water community, *Geoscientific Model Development*
10. P. Das, F. Hossain, **S. Khan**, N. K. Biswas, H. Lee, T. Piman, C. Meechaiya, U. Ghimire, K. Hosen (2022) Reservoir Assessment Tool 2.0: Stakeholder driven Improvements to Satellite Remote Sensing based Reservoir Monitoring, *Environmental Modeling and Software*.
11. S. Suresh, F. Hossain, S. Minocha, P. Das, **S. Khan**, H. Lee, K. Andreadis and Perry Oddo (2023). Satellite-based Tracking of Reservoir Operations for Flood Management during the 2018 Extreme Weather Event in Kerala, India, *Remote Sensing of Environment,* vol. 307

Broader Impacts



Stakeholder	Country	Stakeholder	Country
Bangladesh Water Development Board	Bangladesh	Crown Farms	South Africa
Department of Agricultural Extension	Bangladesh	Pakistan Council of Research in Water Resources	Pakistan
University of Washington Landscape Workers	USA	Department of hydrology and meteorology	Nepal



Meeting with water managers in Bangladesh, 17th Sept 2022

SWOT Training, 19th-20th Dec 2023

Department of Agricultural Extension, 18th Dec 2023

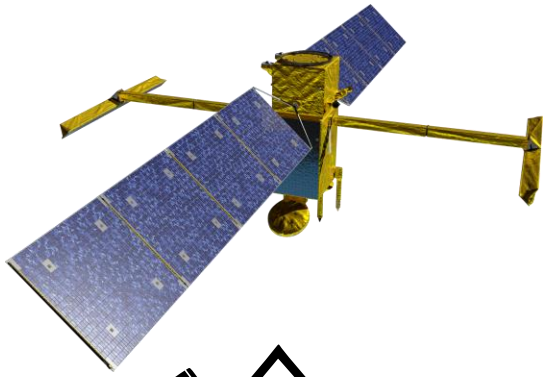
UW Landscape Workers, 12th Jun 2024

What's Next

Current

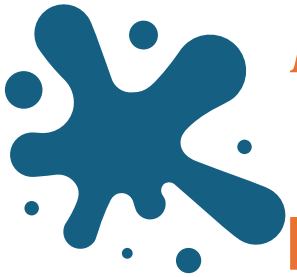
2-4 Years

5-10 Years



SWOT Guided Fusion

Small & Large



L^3

Frequent & Accurate

Narrow & Wide

L^3/T

Crop Atlas

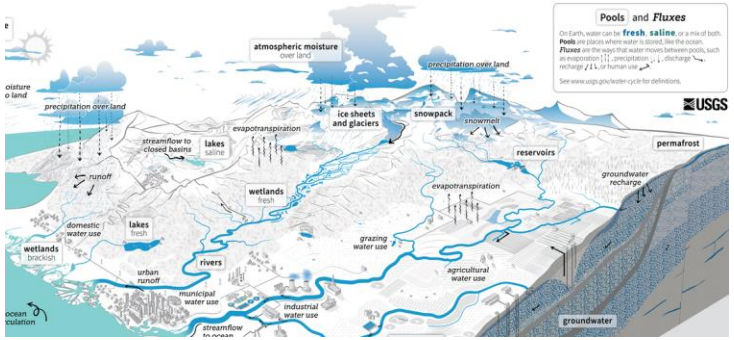
SWOT Guided Fusion

+

Future GRACE Mission (Groundwater)

+

GPM (Precipitation)



Better Representation

sDRIPS

Doctoral Committee

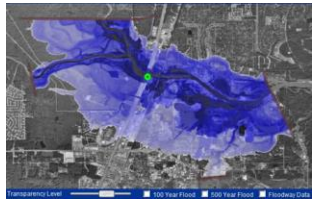
Faisal Hossain

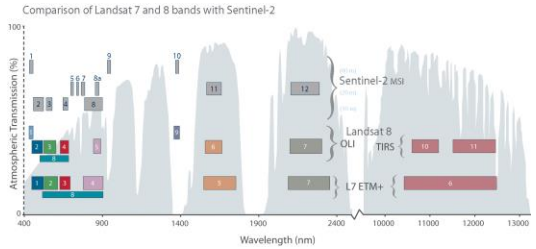
Erkan Istanbulluoglu

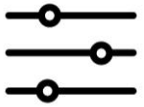
Nicoleta Cristea

Follow Up Slides

Water Classification Techniques

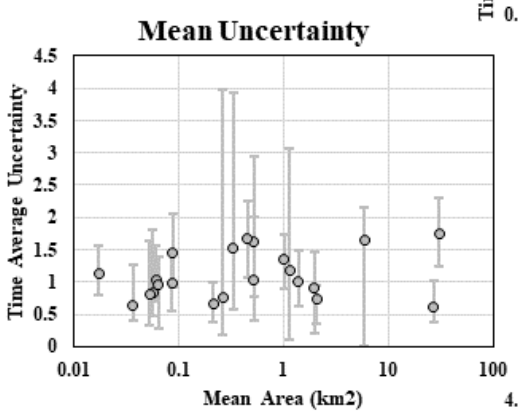


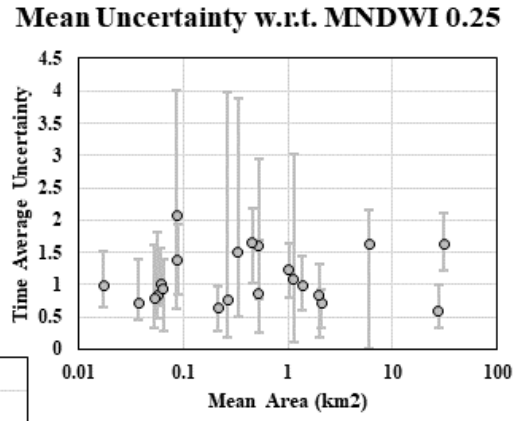


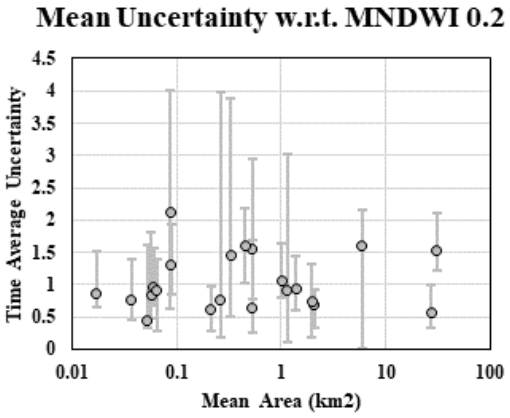


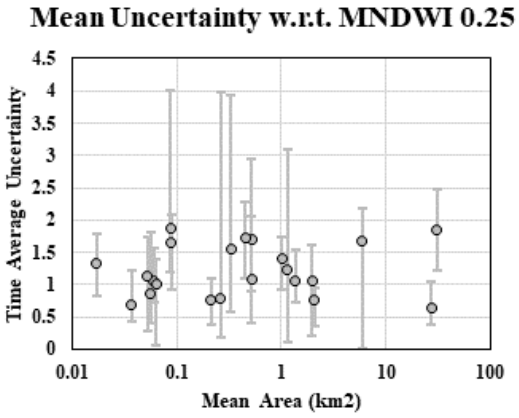
Method #	Sensor	Water Classification Technique	Bands	Threshold
1	**Landsat 8**	*Dynamic Surface Water Extent (DSWE)*	*Multiple*	*N/A*
2		*Modified Normalized Difference Water Index (MNDWI)*	*Green band (Band 3),short-wave infrared (Band 6)*	*0.3*
3	**Sentinel 1**	*Backscattering threshold*	--	*< -13 db*
4	**Sentinel 2**	*Dynamic Surface Water Extent (DSWE)*	*Multiple*	*N/A*

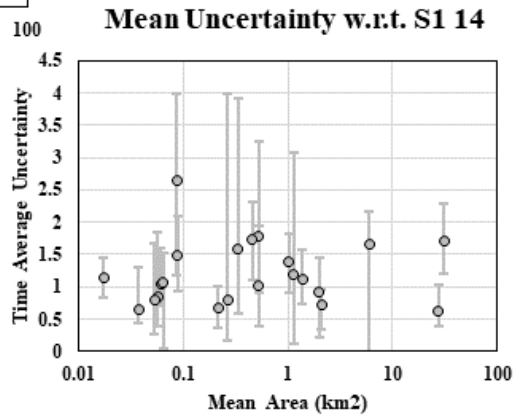
Water Classification Techniques – Uncertainty Estimates

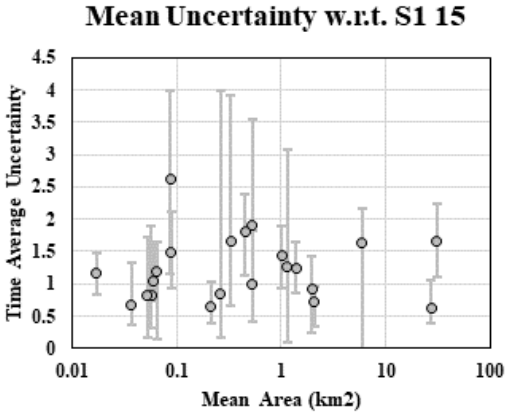


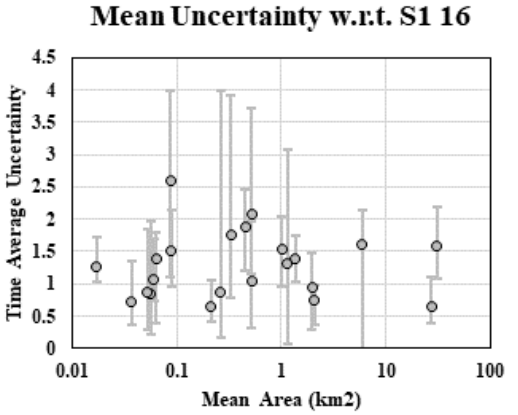




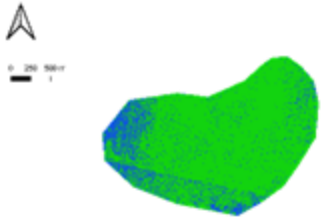
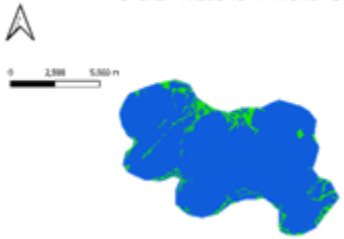






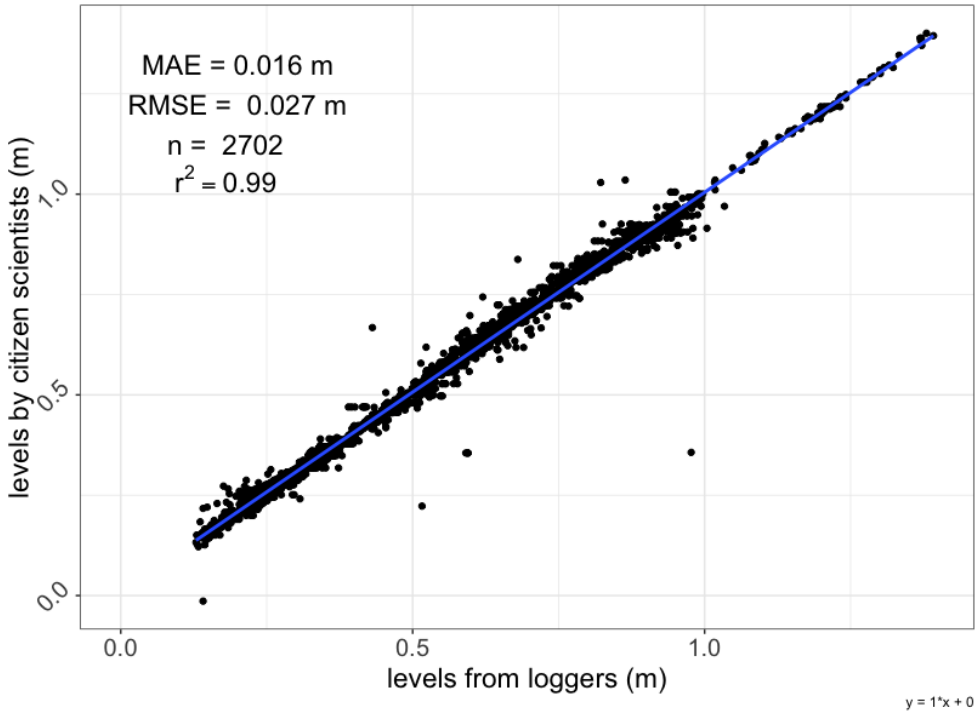


Water Classification Techniques – Uncertainty Estimates

Lake Name and Extent (Blue: water; Green: non-water)	Benchmark Volume Change (million m³) based on 3 m Planet Data	Ensemble Mean Volume Change (million m³)	Ensemble Range of Volume Change (million m³)
Dekhar Wetland in month of July	5.856608	4.497891	6.279993-3.172306
Dekhar Wetland in month of November 	0.113676	0.197754	0.235305-0.154453
Korchar Wetland in month of July 	265.543071	272.620922	334.539032-215.684203

Lake Name and Extent (Blue: water; Green: non-water)	Benchmark Volume Change (million m³) based on 3 m Planet Data	Ensemble Mean Volume Change (million m³)	Ensemble Range of Volume Change (million m³)
	11.221755	9.247892	13.259703-4.489667

How Reliable is Citizen Science Data



Highly Accurate!

- **2702** corresponding lake level measurements.
- **R2** value of **>0.99**
- Mean absolute error (**MAE**) = **1.6 cm.**
- Root mean squared error (**RMSE**) = **2.7 cm.**
- The measurement error of the pressure transducers is **0.8 cm.**

Little, S., Pavelsky, T. M., Hossain, F., Ghafoor, S., Parkins, G. M., Yelton, S. K., Rodgers, M., et al. (2021). Monitoring Variations in Lake Water Storage with Satellite Imagery and Citizen Science. *Water*, *13*(7), 949. MDPI AG. Retrieved from http://dx.doi.org/10.3390/w13070949

Standard Deviation in WSE Observations

Water Body Name	Standard deviation in height (meter)
Korchar (Bangladesh)	1.702
Cassidy Lake (Washington)	0.192
Timber Lake (Illinois)	0.044
Lac Majeur (France)	0.192
Pookode Lake (India)	0.144
Phillips Pond (New Hampshire)	0.100
White Lake (North Carolina)	0.044
Tanguar (Bangladesh)	1.367

Volume Estimations Compared to Other Data

- **No in-situ data** (Elevation/Volume Stored) was found.
- Hence the results were compared with **Ahmad et.al.** for wetlands in Bangladesh, **Sarina et.al** for lakes in USA

USGS 14231670 WALUPT LAKE NEAR PACKWOOD, WA

Available data for this site SUMMARY OF ALL AVAILABLE DATA GO

Stream Site

DESCRIPTION:

Latitude 46°25'15", Longitude 121°28'17" NAD27
Lewis County, Washington, Hydrologic Unit 17080004
Drainage area: 13.70 square miles

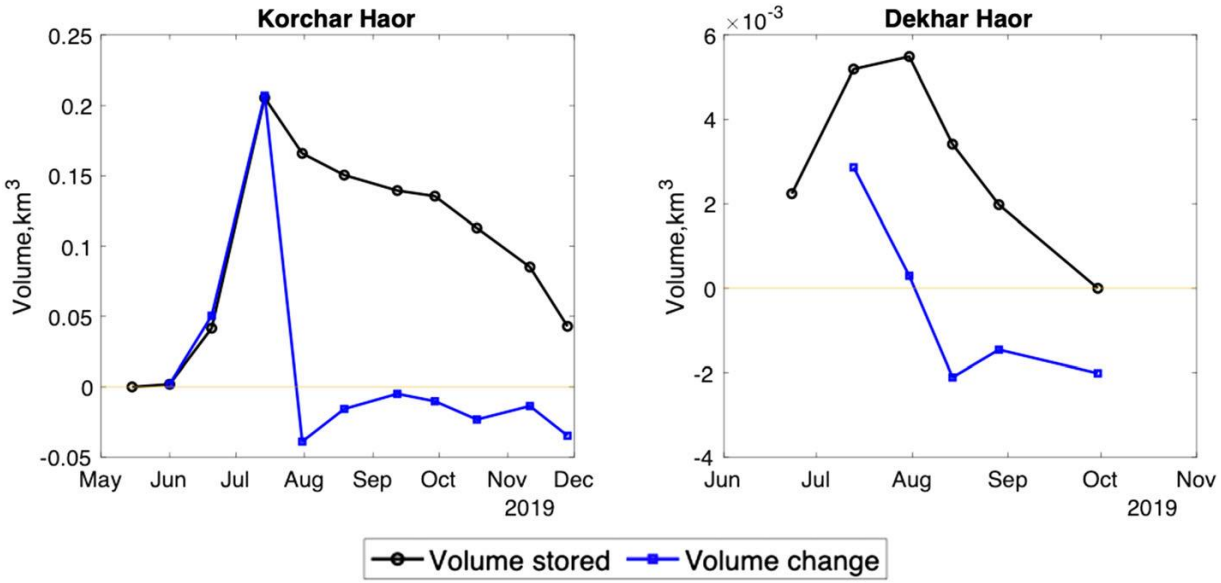
AVAILABLE DATA:

Data Type	Begin Date	End Date	Count
Field/Lab water-quality samples	1971-07-08	1971-10-05	5
Revisions	Unavailable (site:0) (timeseries:0)		

OPERATION:

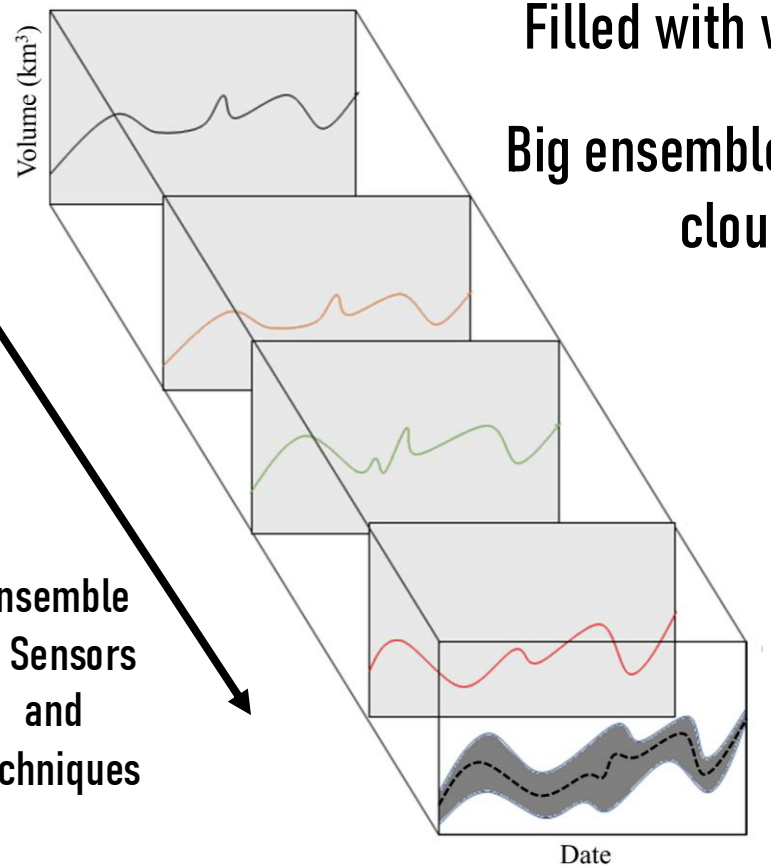
Record for this site is maintained by the USGS Washington Water Science Center
Email questions about this site to Washington Water Science Center Water-Data Inquiries

E.g. USGS data from Walupt Lake, WA



Ahmad, S. K., Hossain, F., Pavelsky, T., Parkins, G. M., Yelton, S., Rodgers, M., et al. (2020). Understanding volumetric water storage in monsoonal wetlands of northeastern Bangladesh. *Water Resources Research*, 56, e2020WR027989. https://doi.org/10.1029/2020WR027989

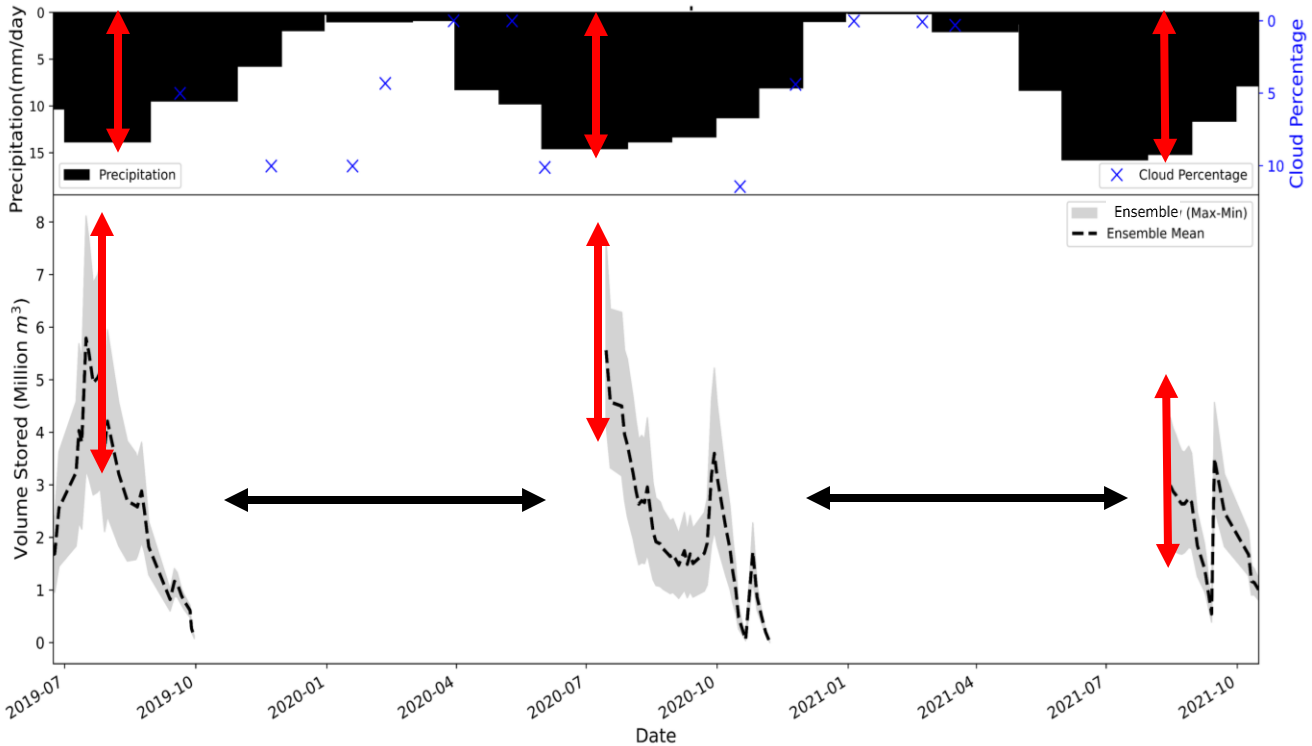
Ensemble of Storage Change



Ensemble of Sensors and Techniques

Filled with water Jul-Oct

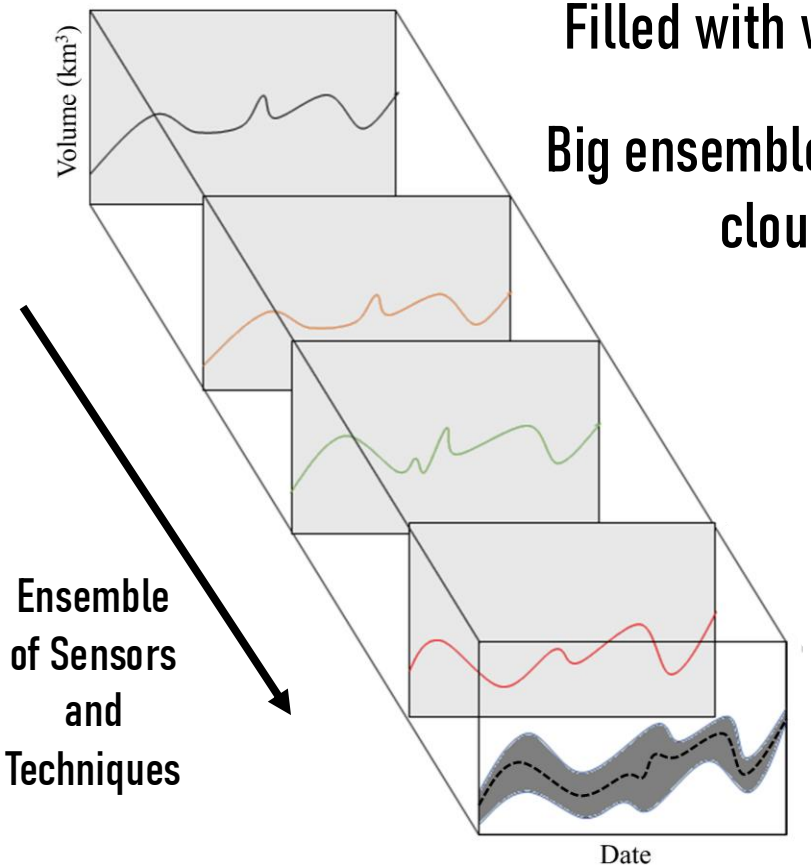
Big ensemble spread during cloud cover



A wetland in Bangladesh

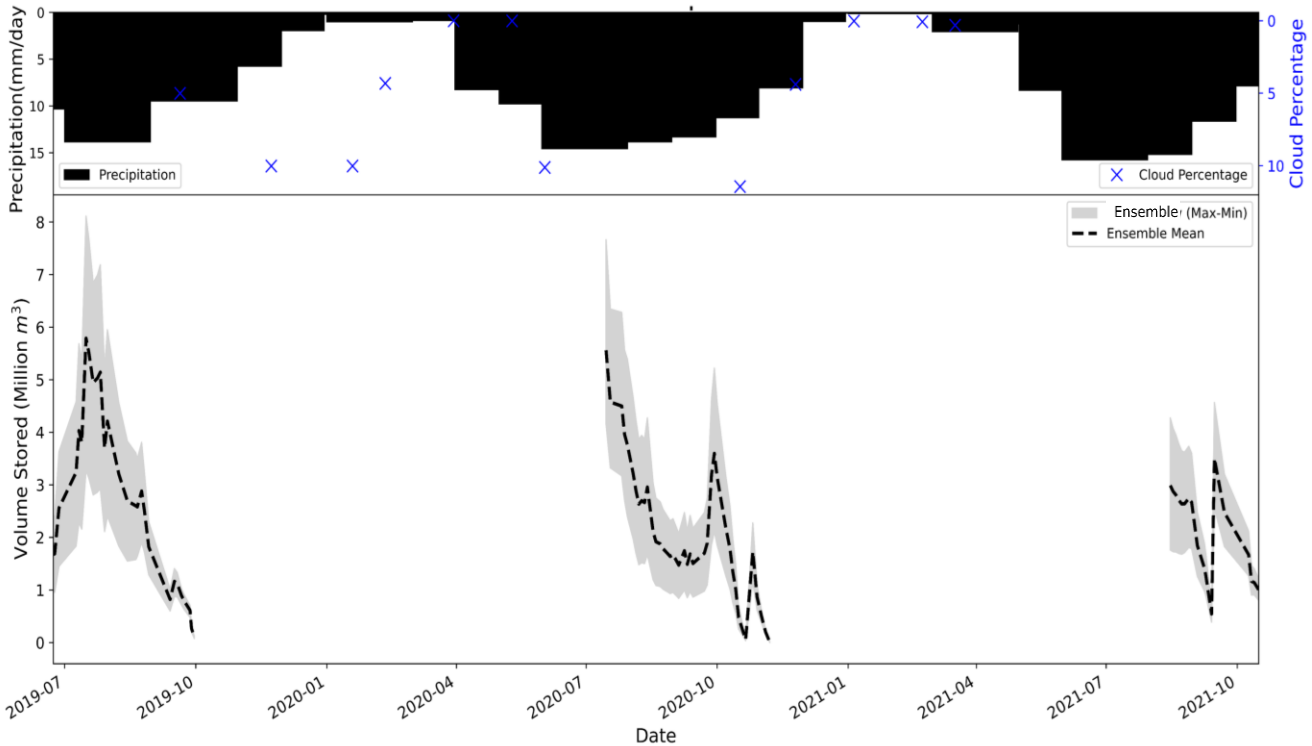
Helped to understand the dynamics of wetlands and quantify the storage

Ensemble of Storage Change



Filled with water Jul-Oct

Big ensemble spread during cloud cover



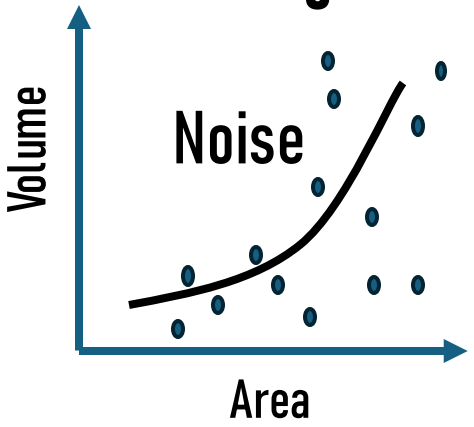
A wetland in Bangladesh

Helped to understand the dynamics of wetlands and quantify the storage

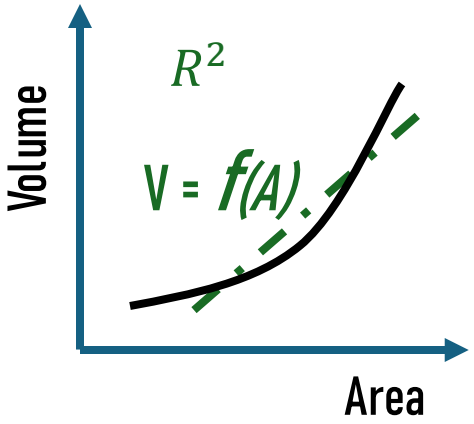
Cookbook to find optimal # of gauges

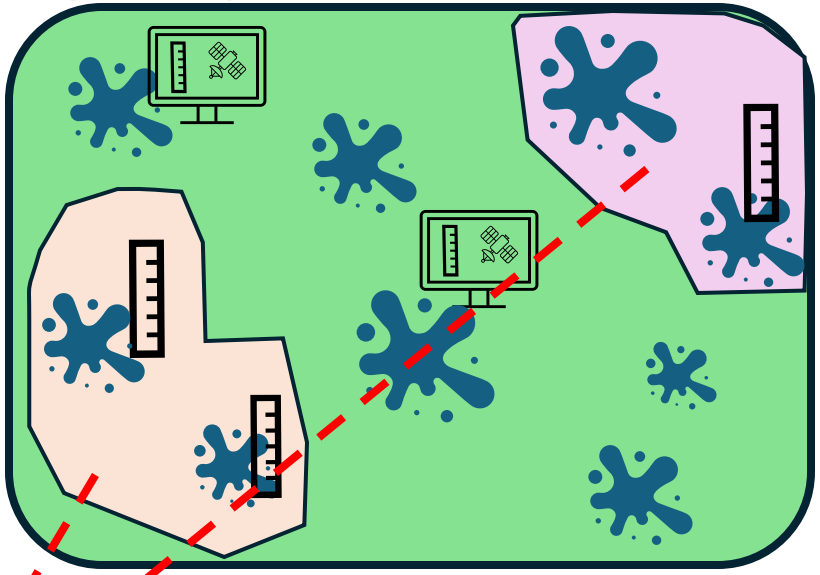
Estimating benchmark volume of a region

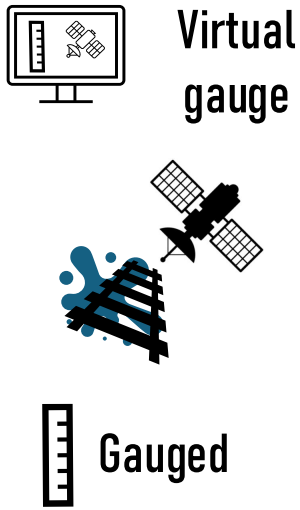
- Challenges



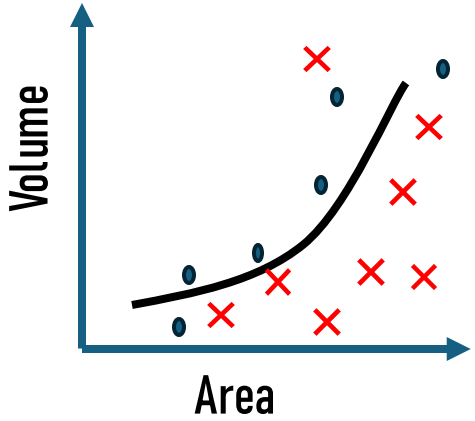
Hybrid of the two approaches







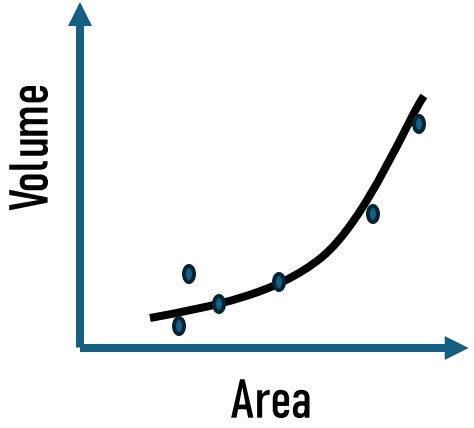
A Robust approach



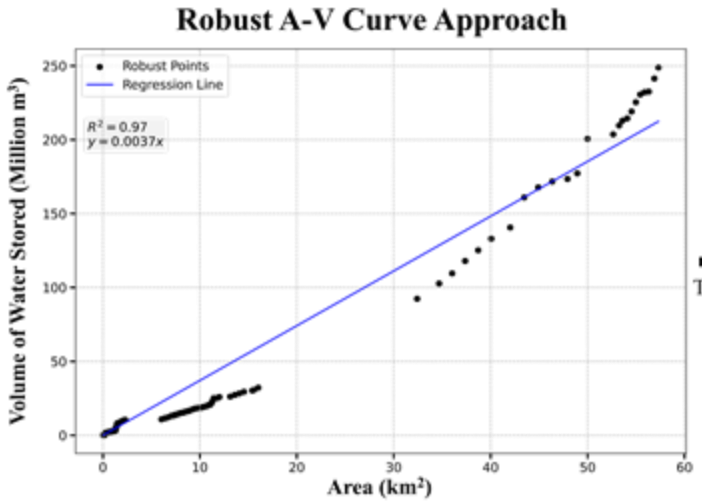
Hydrologic Parameter Derived Approach

Lakes with distinct hydrophysical regimes may introduce noise into combined volume-area curve

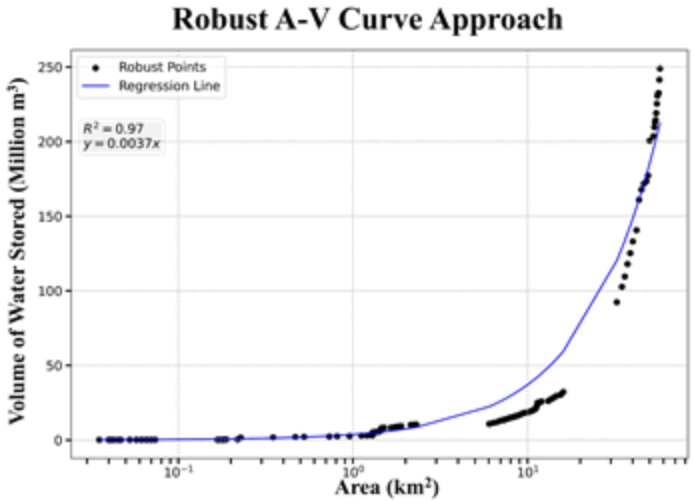
V = f(Area, Precipitation, Temperature, Terrain)

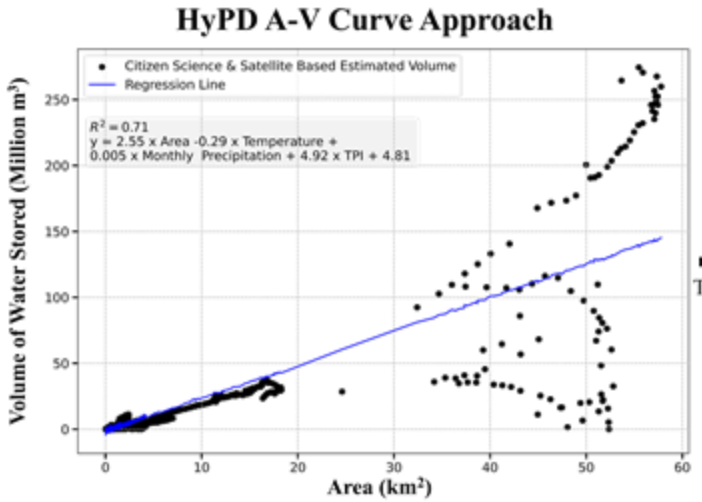


Robust Curve and HyPD Curve



Log Transform





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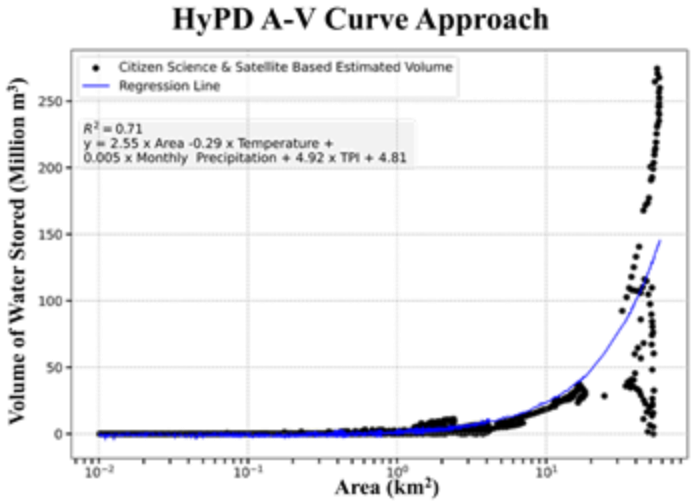
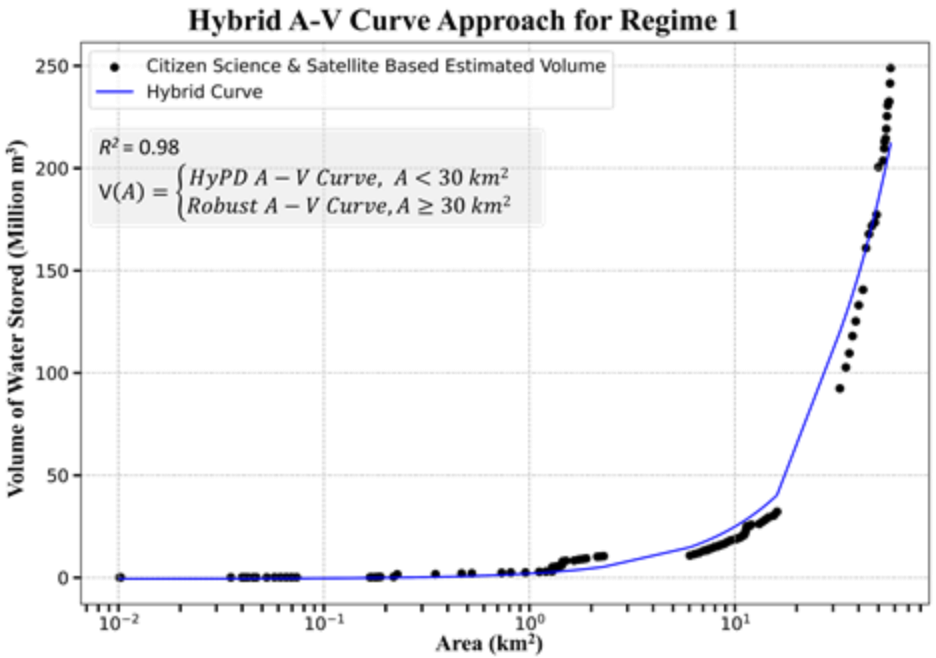
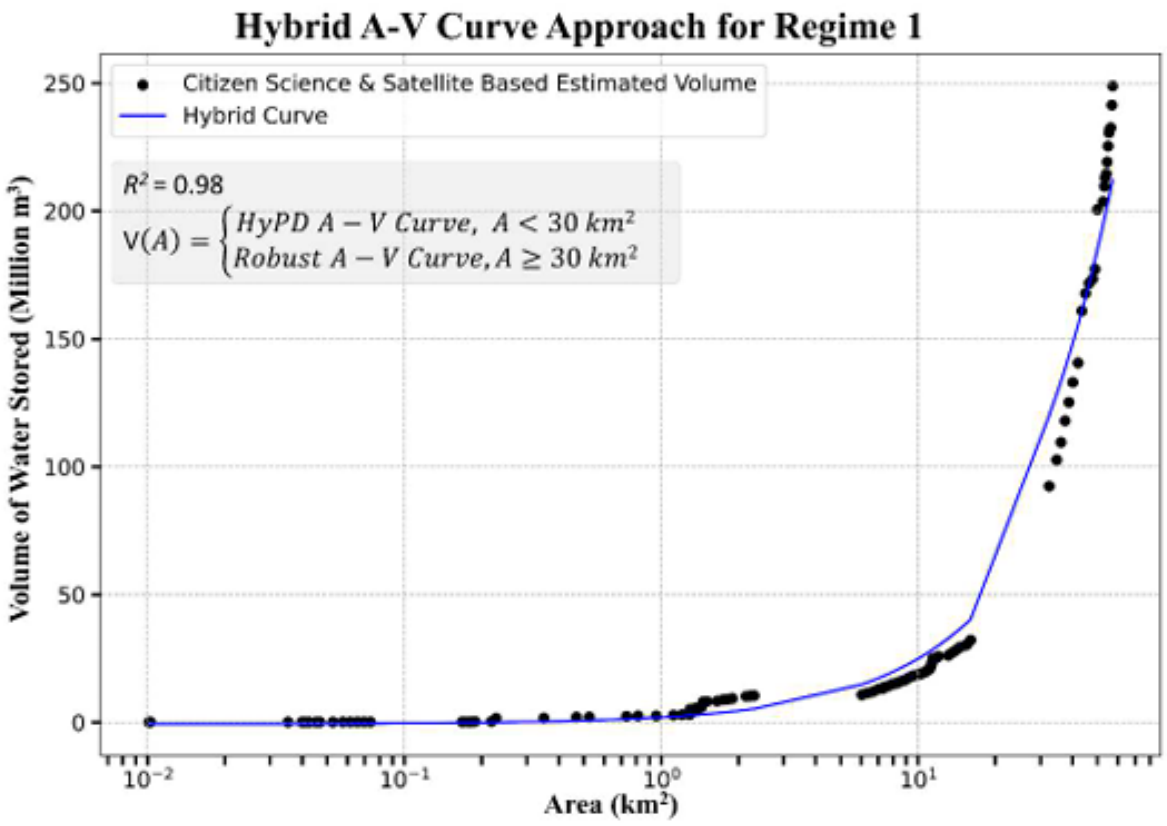
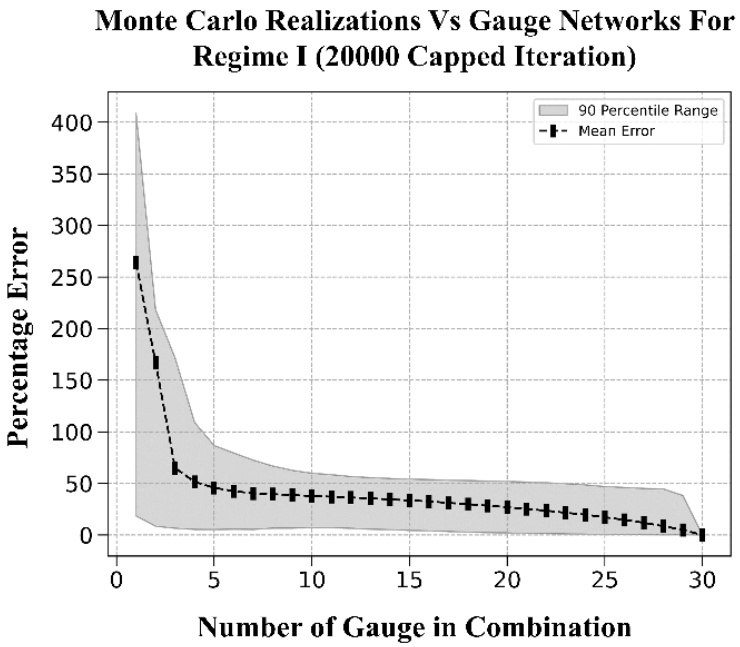


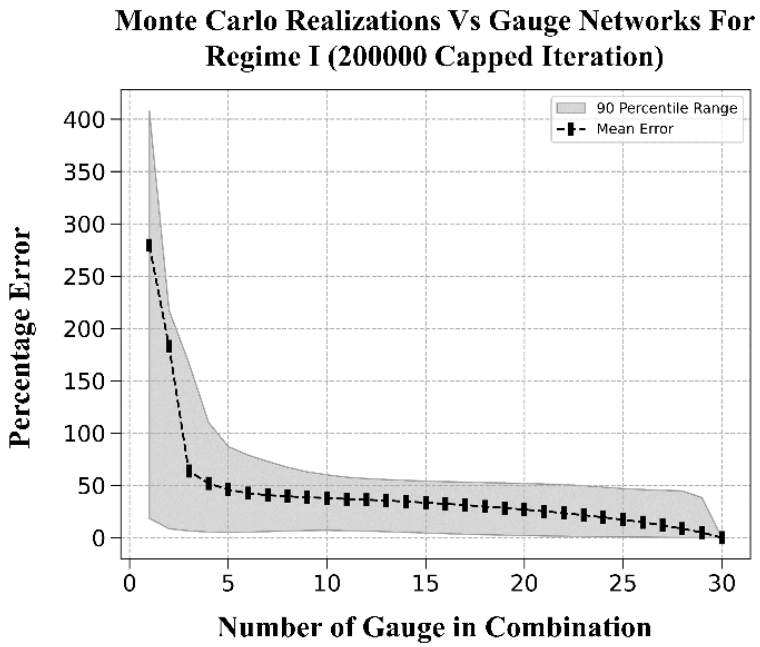


Hybrid Curve

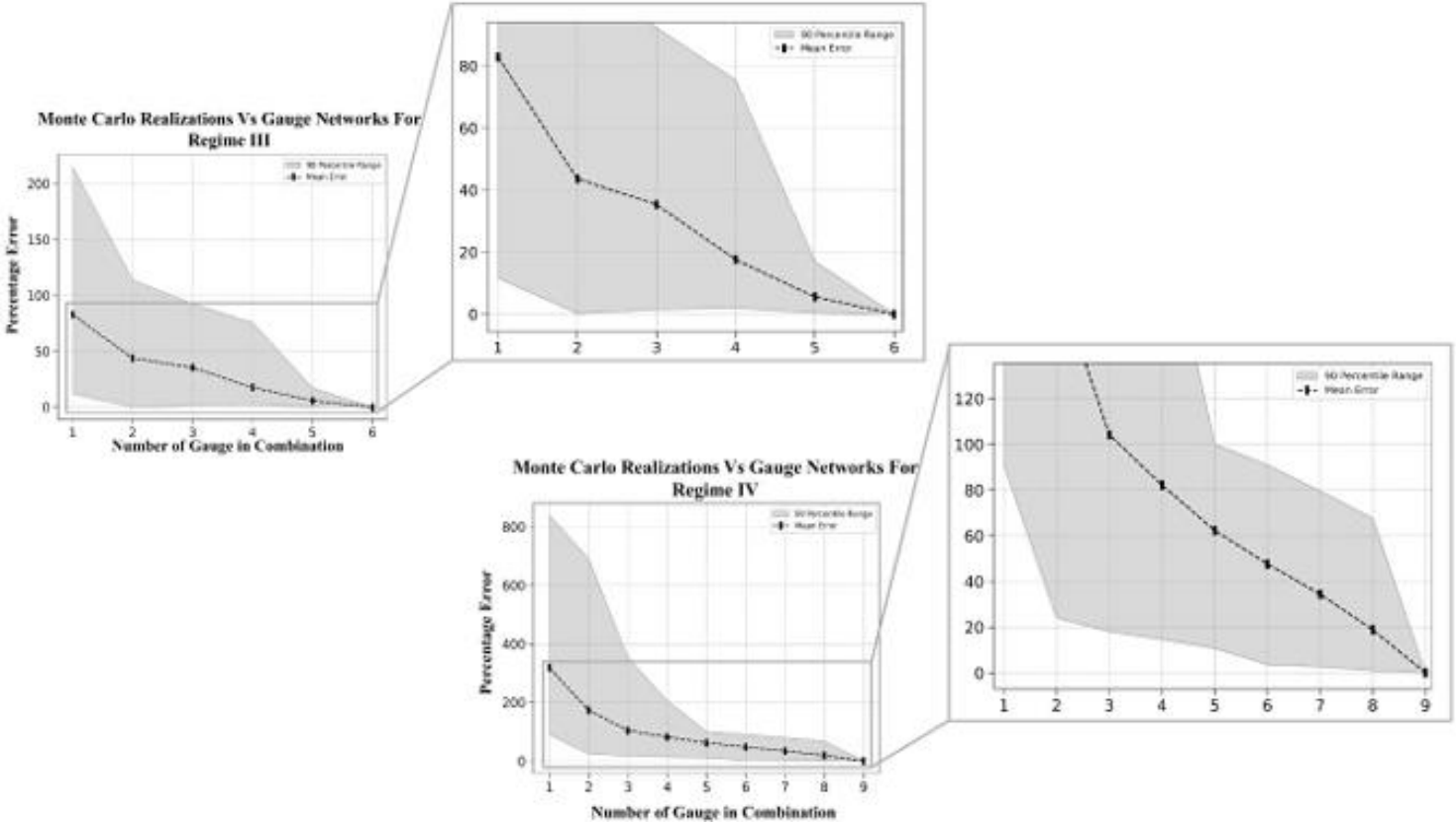


Capping Large Number of Monte – Carlo Simulations

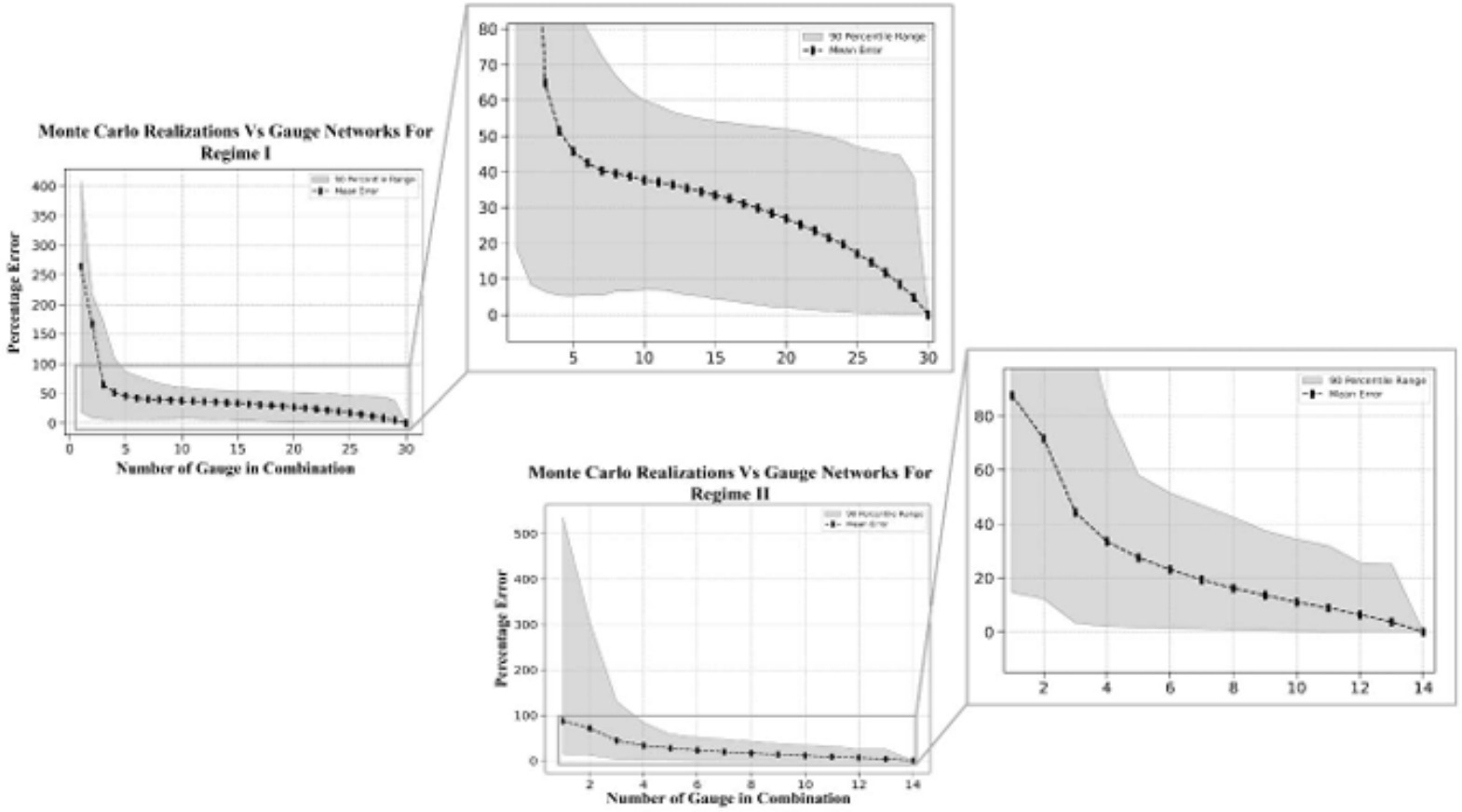




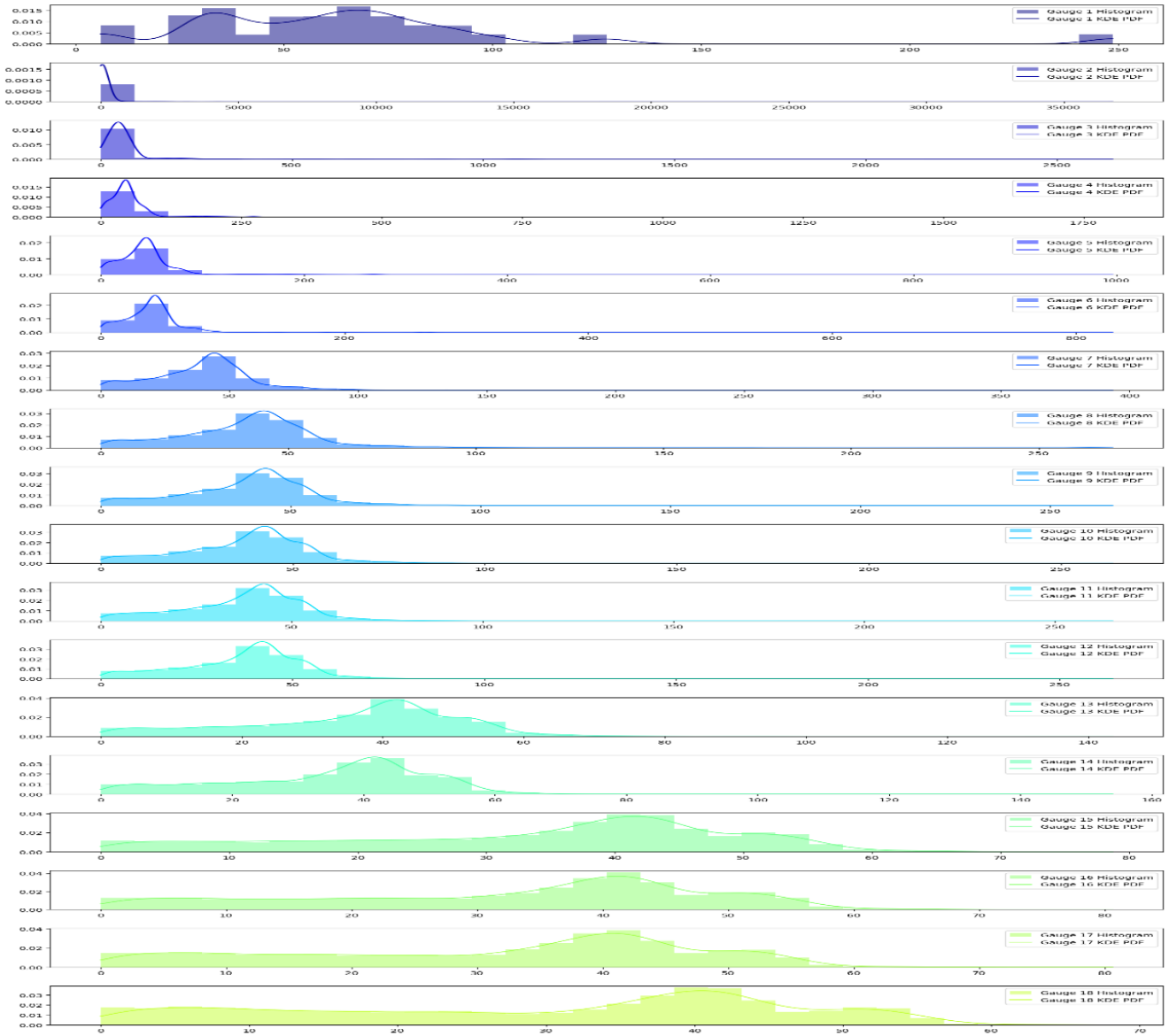
Percentage Error



Percentage Error



PDF


Gauge 1 Histogram
Gauge 1 KDE PDF
Gauge 2 Histogram
Gauge 2 KDE PDF
Gauge 3 Histogram
Gauge 3 KDE PDF
Gauge 4 Histogram
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Gauge 5 KDE PDF
Gauge 6 Histogram
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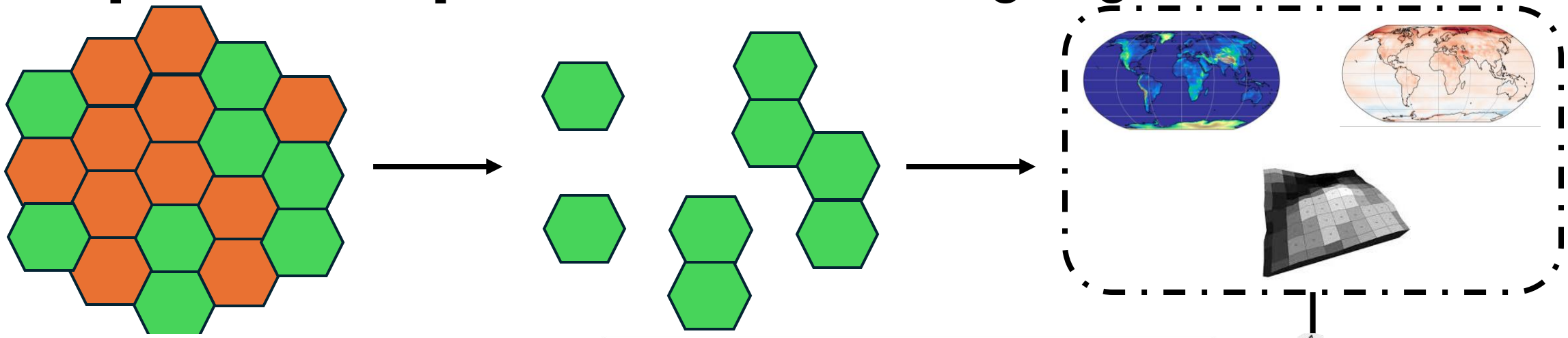
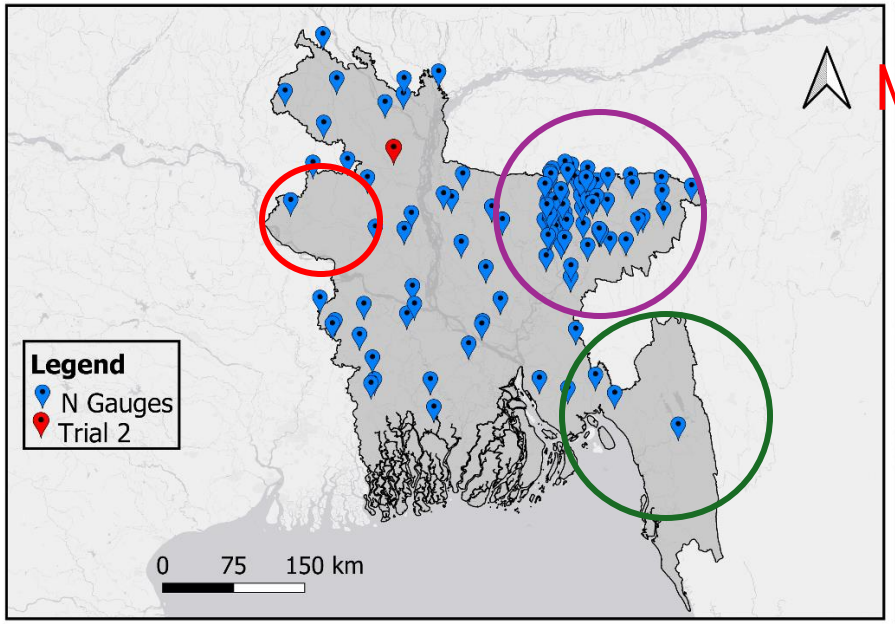
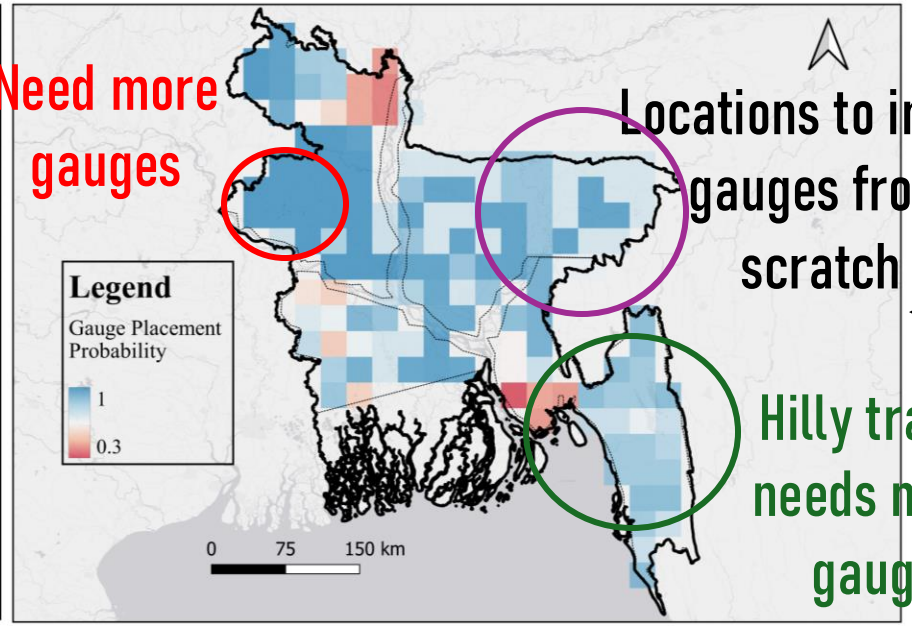
Recipe to find optimal locations of gauges

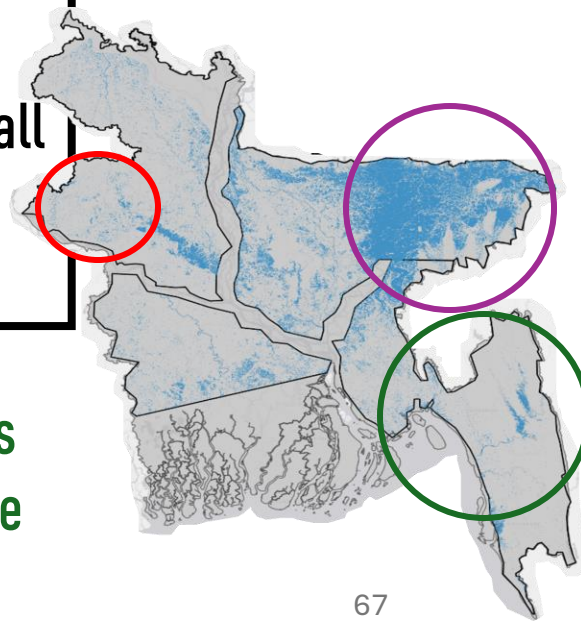






Locations to install gauges from scratch

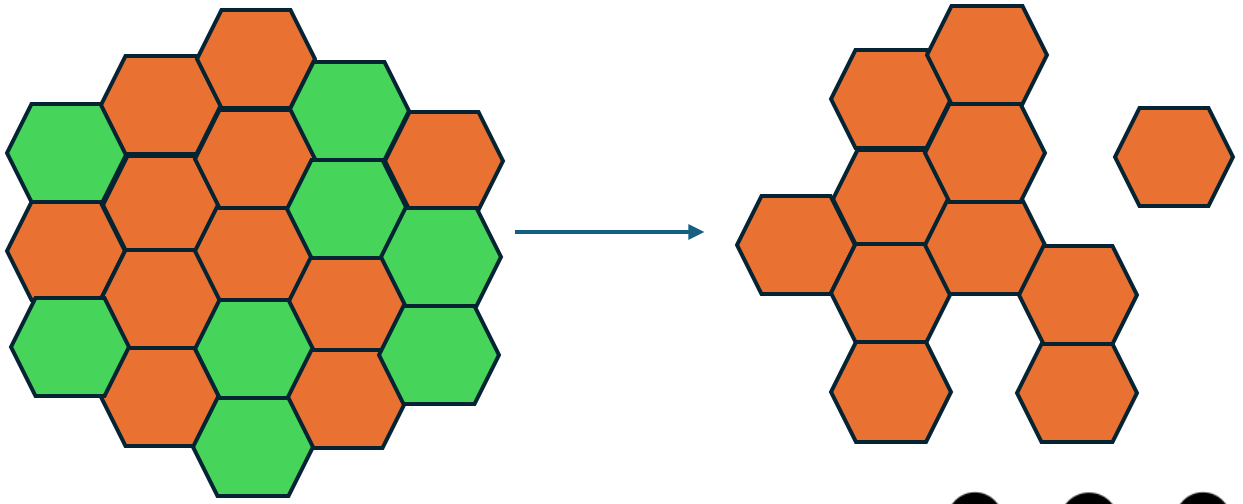
Hilly tracts needs more gauge



Cookbook to find optimal locations of gauges

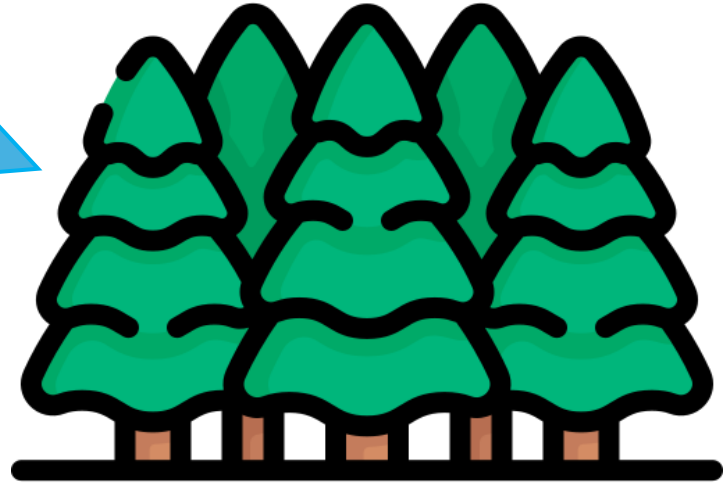
Total # simulations

$^{N}C_1 + {}^{N}C_2 + {}^{N}C_3 \ldots\ldots\ldots\ldots {}^{N}C_N$



Frequency of occurrence in low-performance combinations is also observed

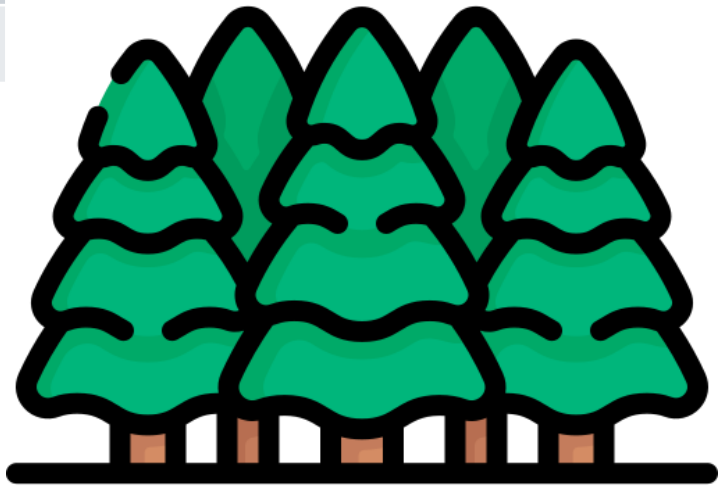
Hydrophysical regimes characteristics – Precipitation, Temperature, and Terrain for both high and low-performance combinations are normalized



Random Forest

Cookbook to find optimal locations of gauges

Regimes	Model Accuracy	F1 Score
Regime I	1	1
Regime II	0.75	0.86
Regime III	0.5	0.67
Regime IV	1	1

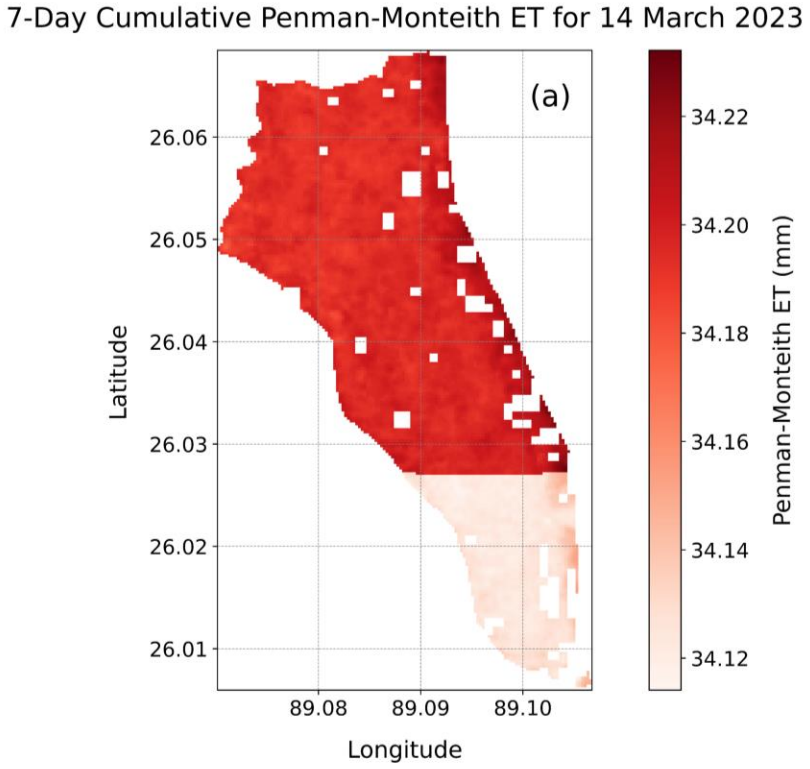


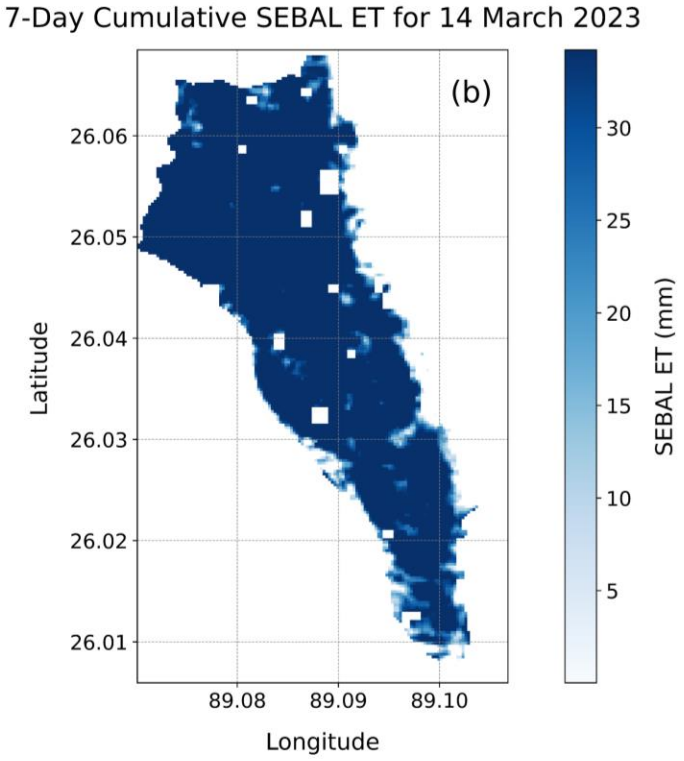
Random Forest

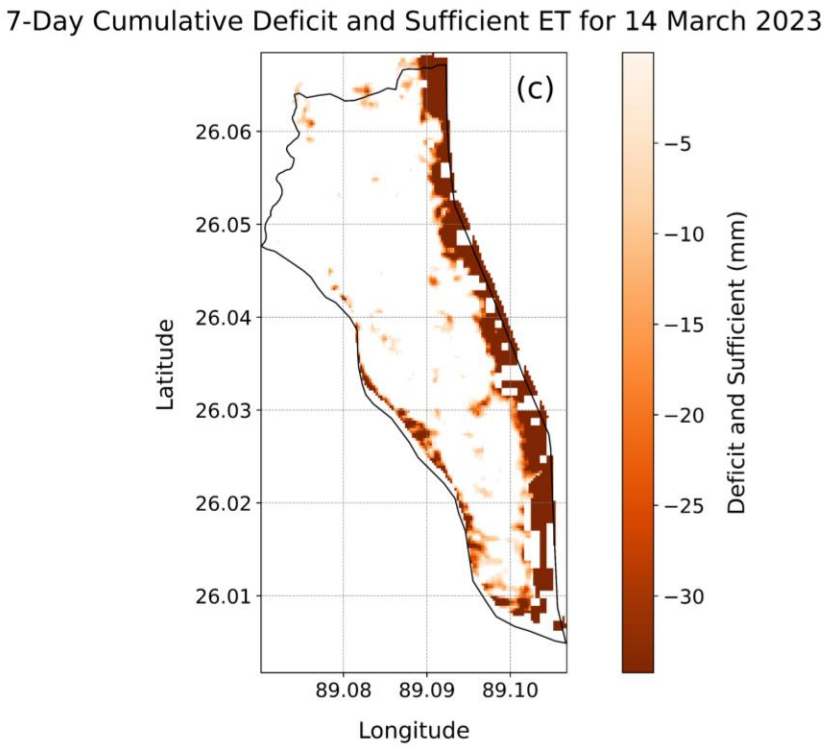
Dataset Used in the Study

Dataset	Dataset ID on GEE	Band Name	Description	Spatial Resolution	Temporal Resolution
Global Forecasting System (GFS)	NOAA/GFS0P25	temperature_2m_above_ground	Air Temperature	25 km	6 hours
		u_component_of_wind_10m_above_ground	Wind Speed (u component)		
		u_component_of_wind_10m_above_ground	Wind Speed (v component)		
		specific_humidity_2m_above_ground	Specific Humidity		
		----	Pressure (Estimated using Hypsometric Equation)		
	GEE and NOAA	total_precipitation_surface	168-hour Precipitation		
Landsat 8 and Landsat 9 satellite series	LANDSAT/LC08/C02/T1_TOA and LANDSAT/LC09/C02/T1_TOA	B2	Blue	30 m	16 days individual, 8 days combined
		B4	Red		
		B5	NIR		
		B6	Shortwave IR		
Sentinel 1 satellite	COPERNICUS/S1_GRD	VV	Single co-polarization, vertical transmit/vertical receive	10 m	10 days
Shuttle Radar Terrain Mapping (SRTM)	USGS/SRTMGL1_003	---	Digital Elevation Map	30 m	---
Global Land Cover Classification (GLCC)	COPERNICUS/Landcover/100m/Proba-V-C3/Global	discrete_classification	Land Use Land Cover	100 m	---
IMERG GPM	---	---	Precipitation	10 km	Around 4 hours

Deficit and Sufficient Regions (ET)

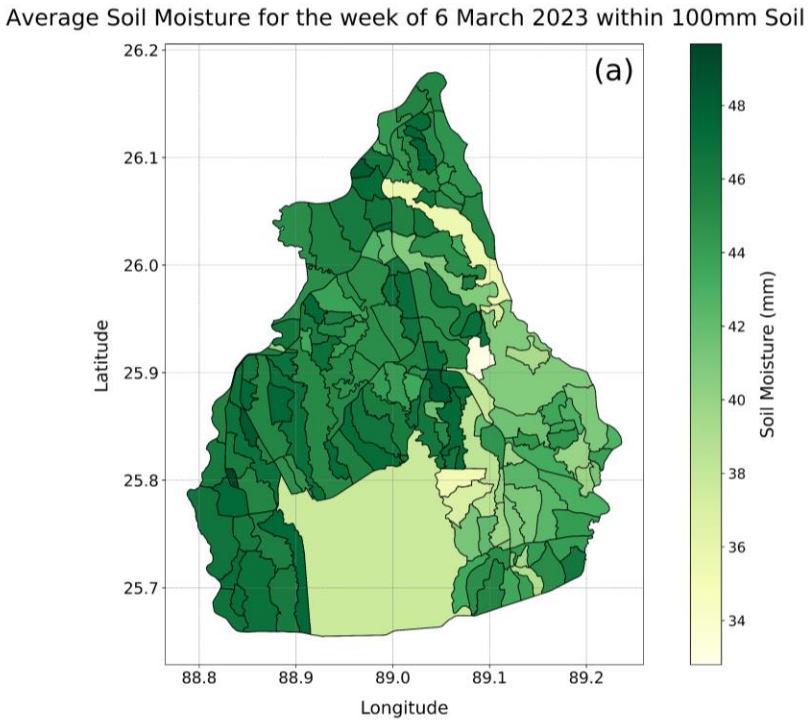


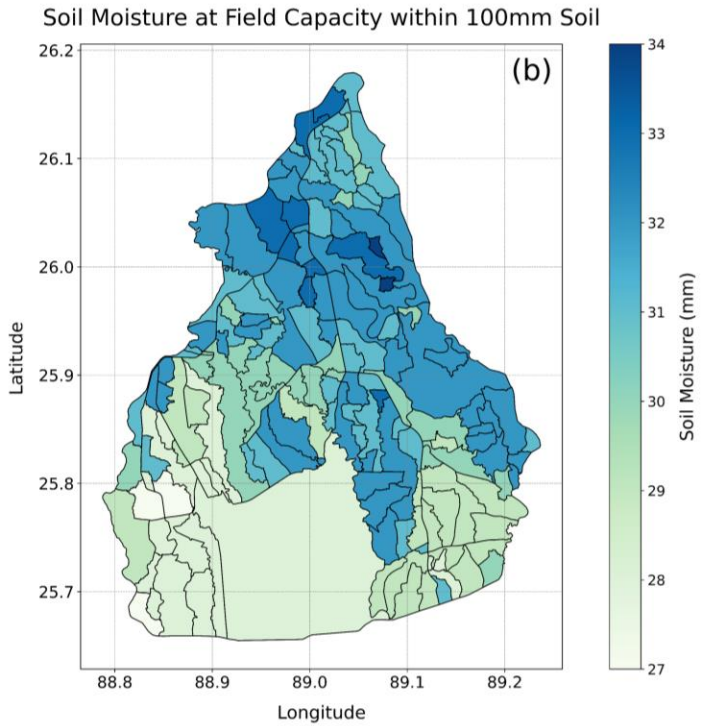


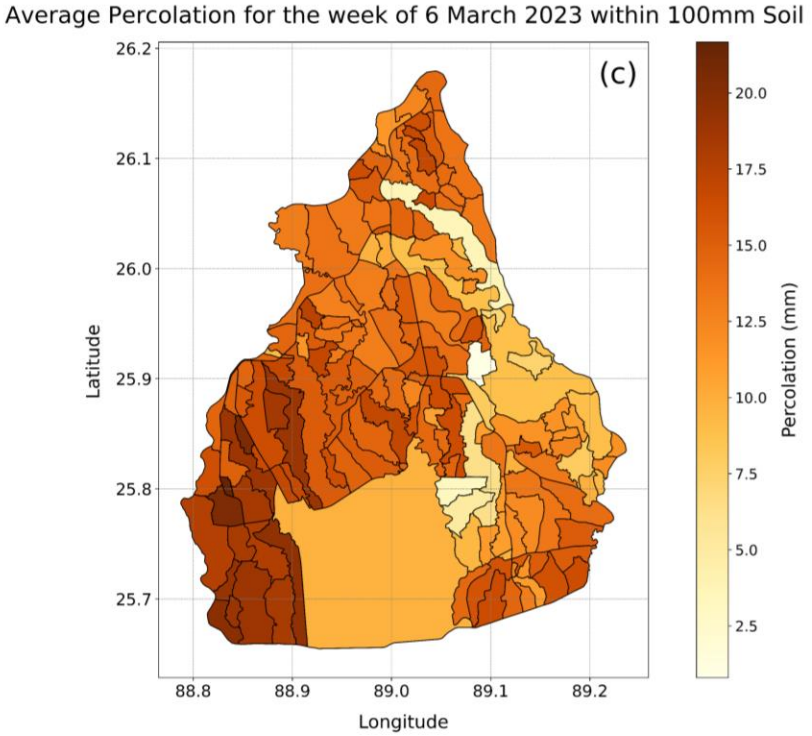


Soil Moisture and Percolation

$$Percolation = \begin{cases} Soil\ Moisture\ - Field\ Capacity\ ;\ \geq 0 \\ 0;\ else \end{cases}$$







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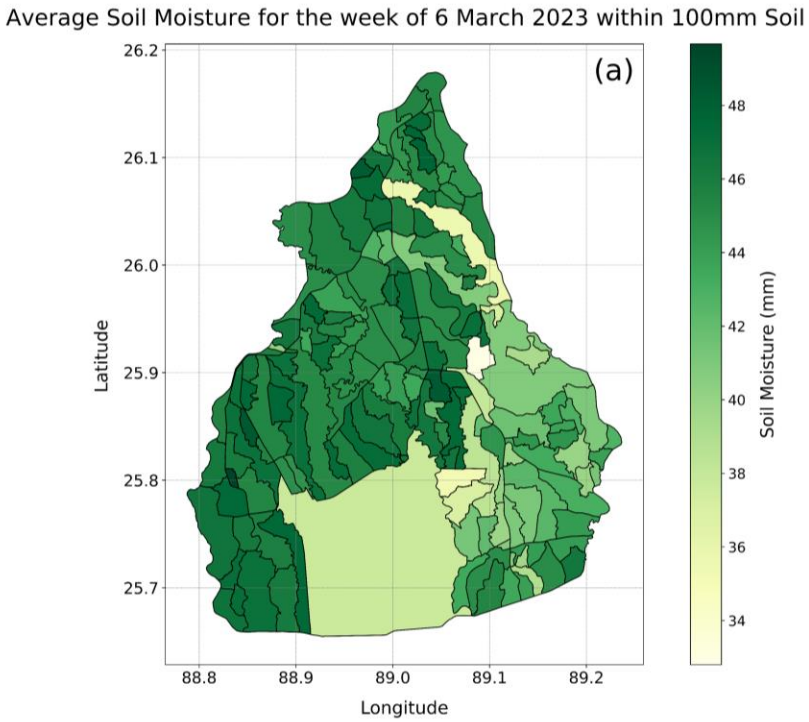
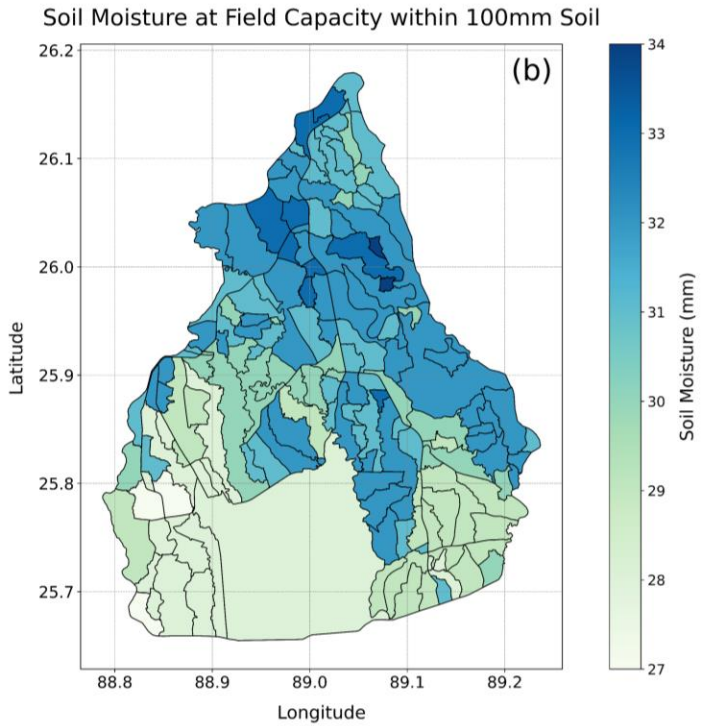
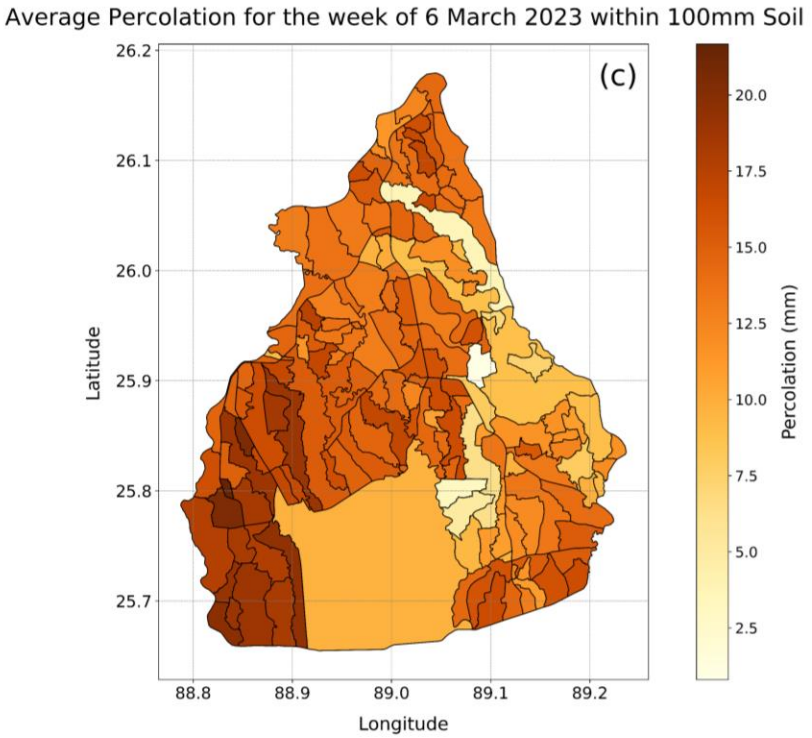






Command Area Irrigation Status

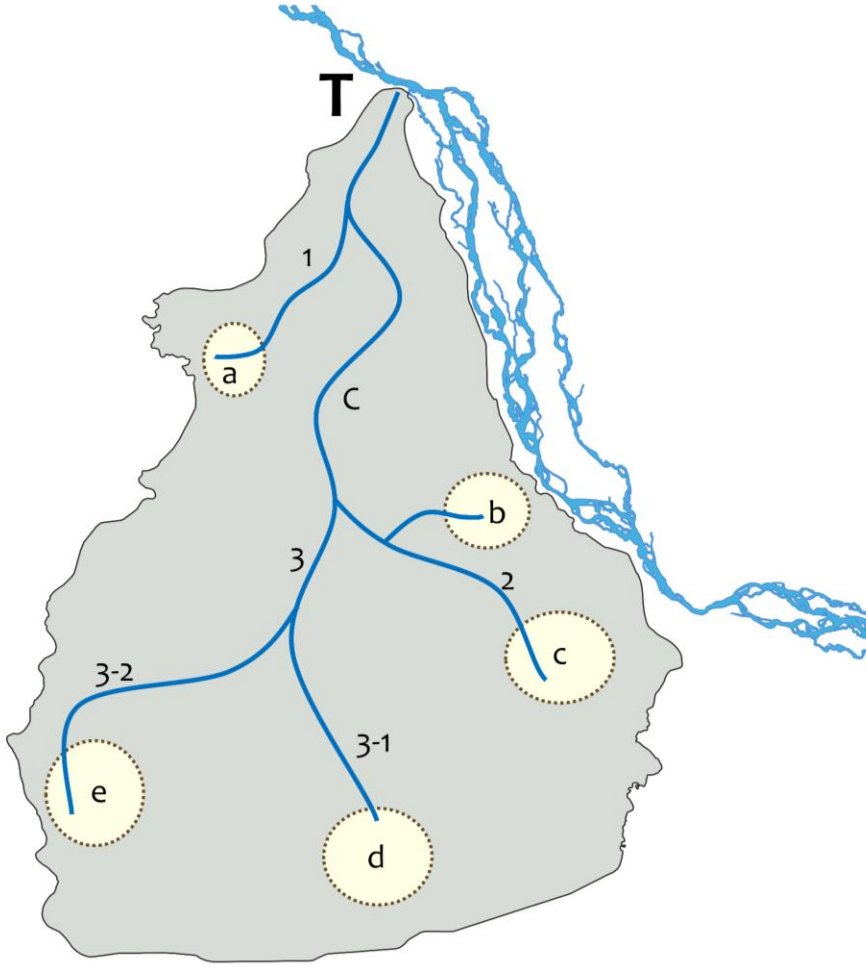
Water at the **head canal** is **proportioned** based on **command area size.**

Water is distributed through **Distribution Factors**

$$DF_i = \frac{A_i}{\sum_{i=1}^{N} A_i}$$

$$DF_b = \frac{b}{a+b+c+d+e}$$

$$WS_b = T \times (DF_b) \qquad W_{S2C} = WS_b + WS_c$$

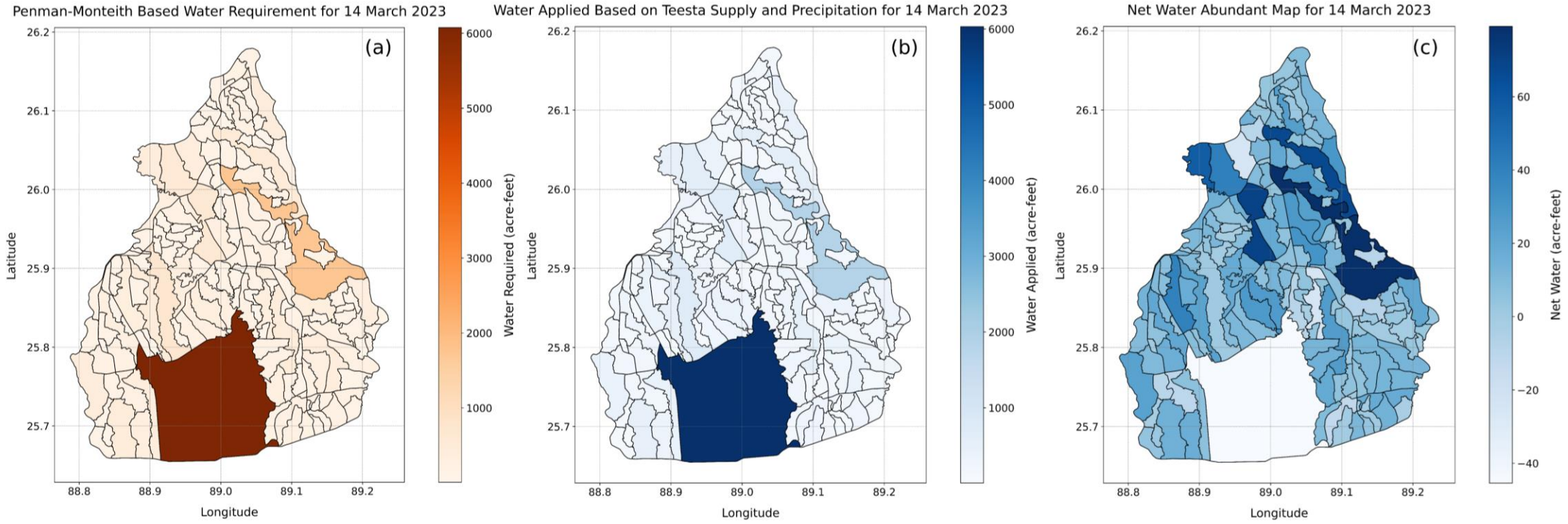


Comparative Assessment of sD.R.I.P.S Scenarios

First Scenario - Traditional Irrigation Practices (without s.D.R.I.P.S):

Water Providers' Perspective: Allocate water across command areas without considering specific water needs or precipitation.

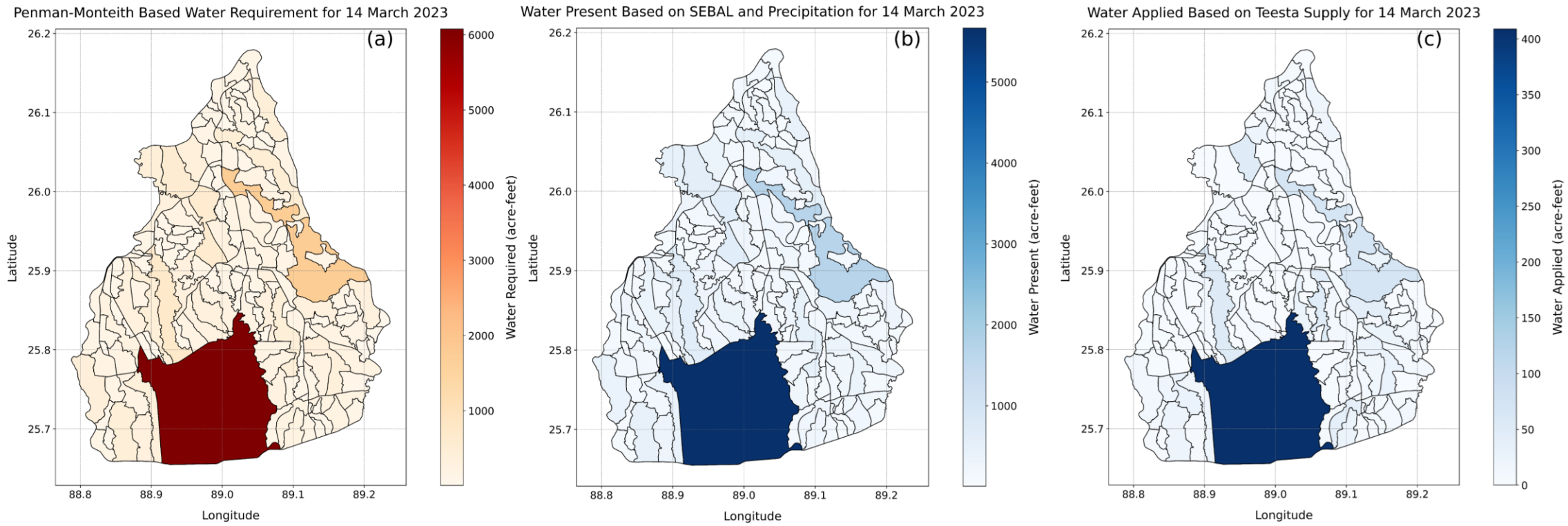
Water Consumers' Perspective: Irrigate crops based solely on allocated water, again without considering precipitation.



Comparative Assessment of sD.R.I.P.S Scenarios

Second Scenario - Adaptive Irrigation Practices (with s.D.R.I.P.S):

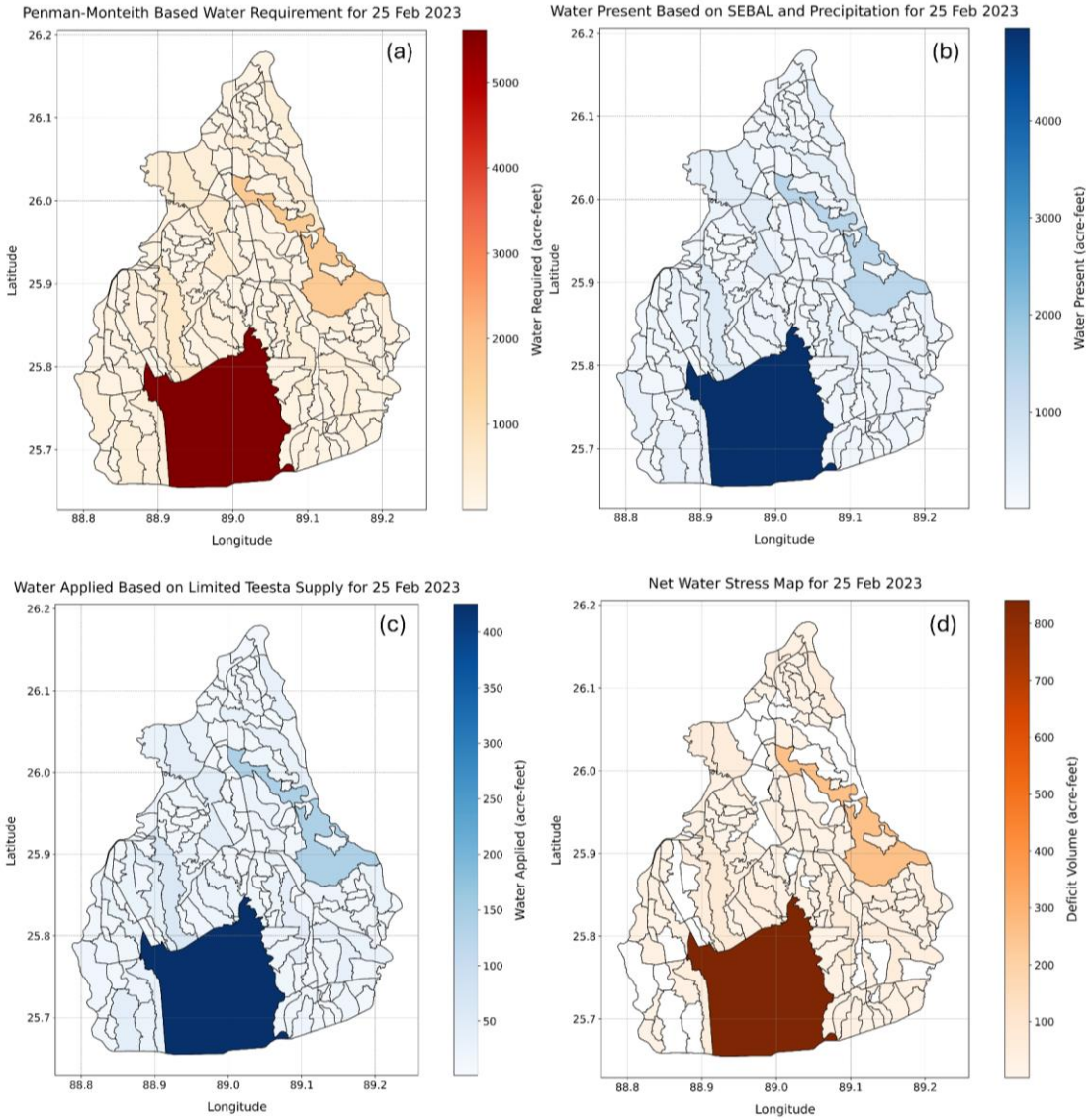
Consider the same time frame as in Scenario 1, however, here, water providers use the sD.R.I.P.S system



By comparing Scenario 1 and Scenario 2, approximately **475 acre-feet of water** (26%) could have been saved

Comparative Assessment of sD.R.I.P.S Scenarios

Second Scenario [B] - Adaptive Irrigation Practices (with s.D.R.I.P.S):



Uncertainty Propagation in sDRIPS

What is the major source of uncertainty, and how does it propagate?

- Parameters
- Variables

GLUE (Generalized Likelihood Uncertainty Estimation)

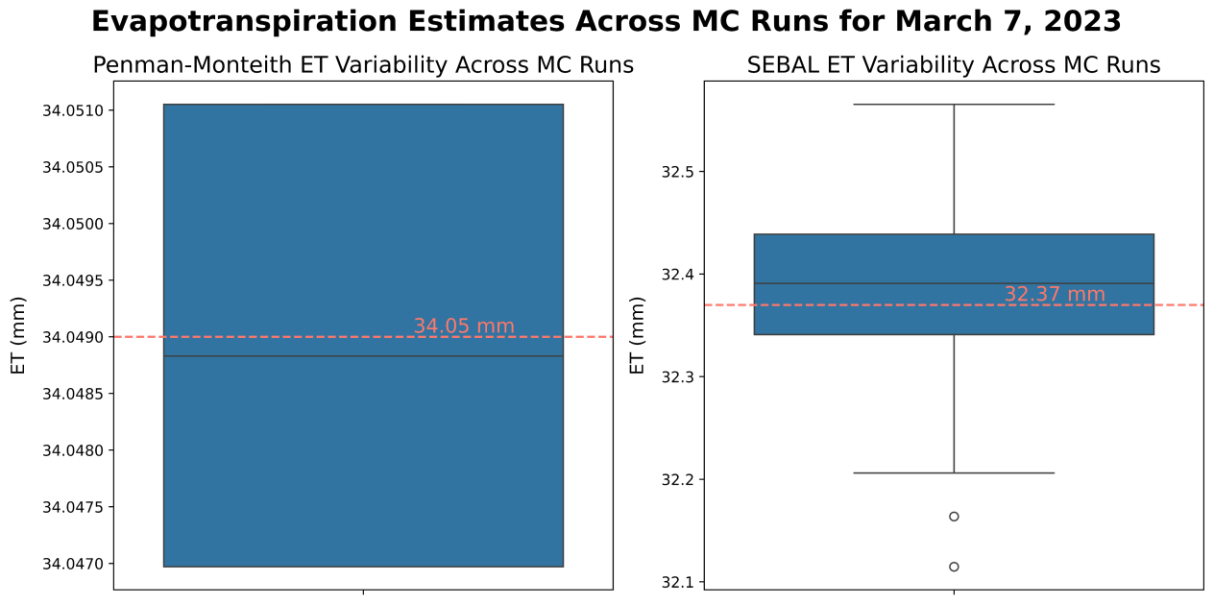
Sensitivity Analysis

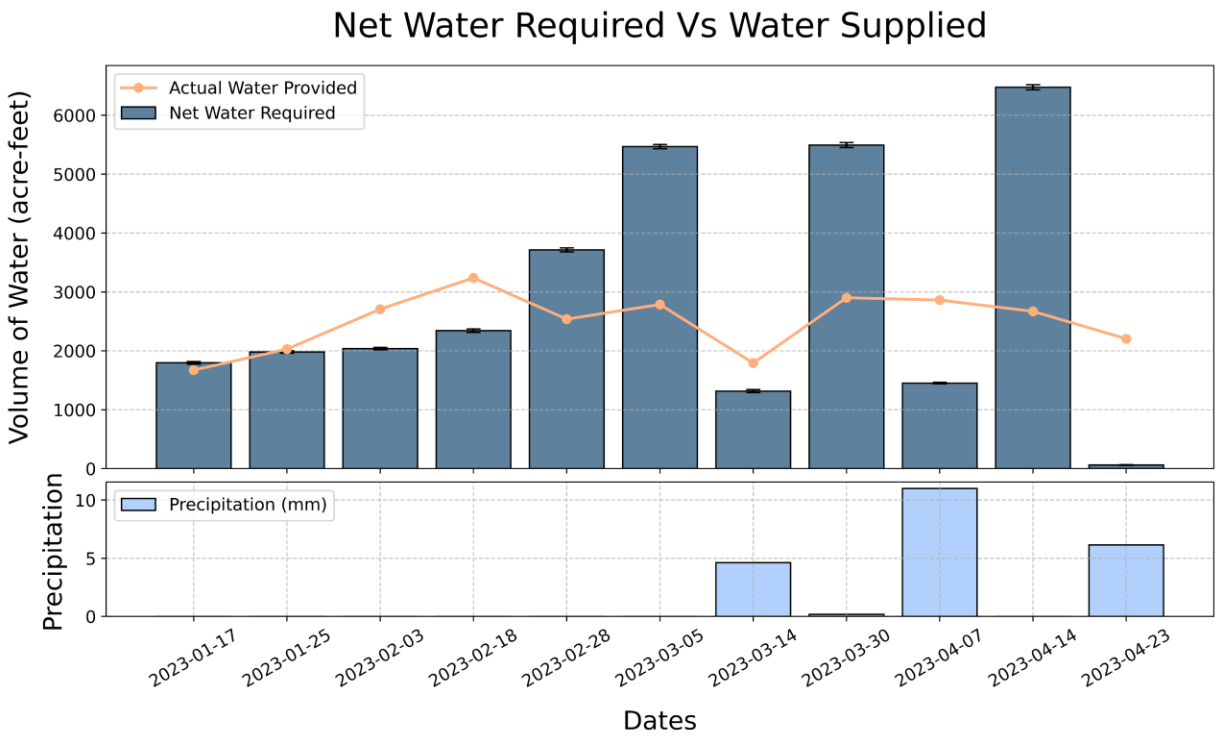
GLUE (Generalized Likelihood Uncertainty Estimation)

Parameters perturbed in Monte Carlo Simulations

Sr. No	Parameter	Range
1	Normalized Difference Vegetation Index (NDVI)	±20% from estimated
2	Albedo	±20% from estimated
3	Leaf Area Index (LAI)	±20% from estimated
4	Surface Roughness	±20% from estimated
5	Aerodynamic Resistance	±20% from estimated
6	Emissivity	±20% from estimated

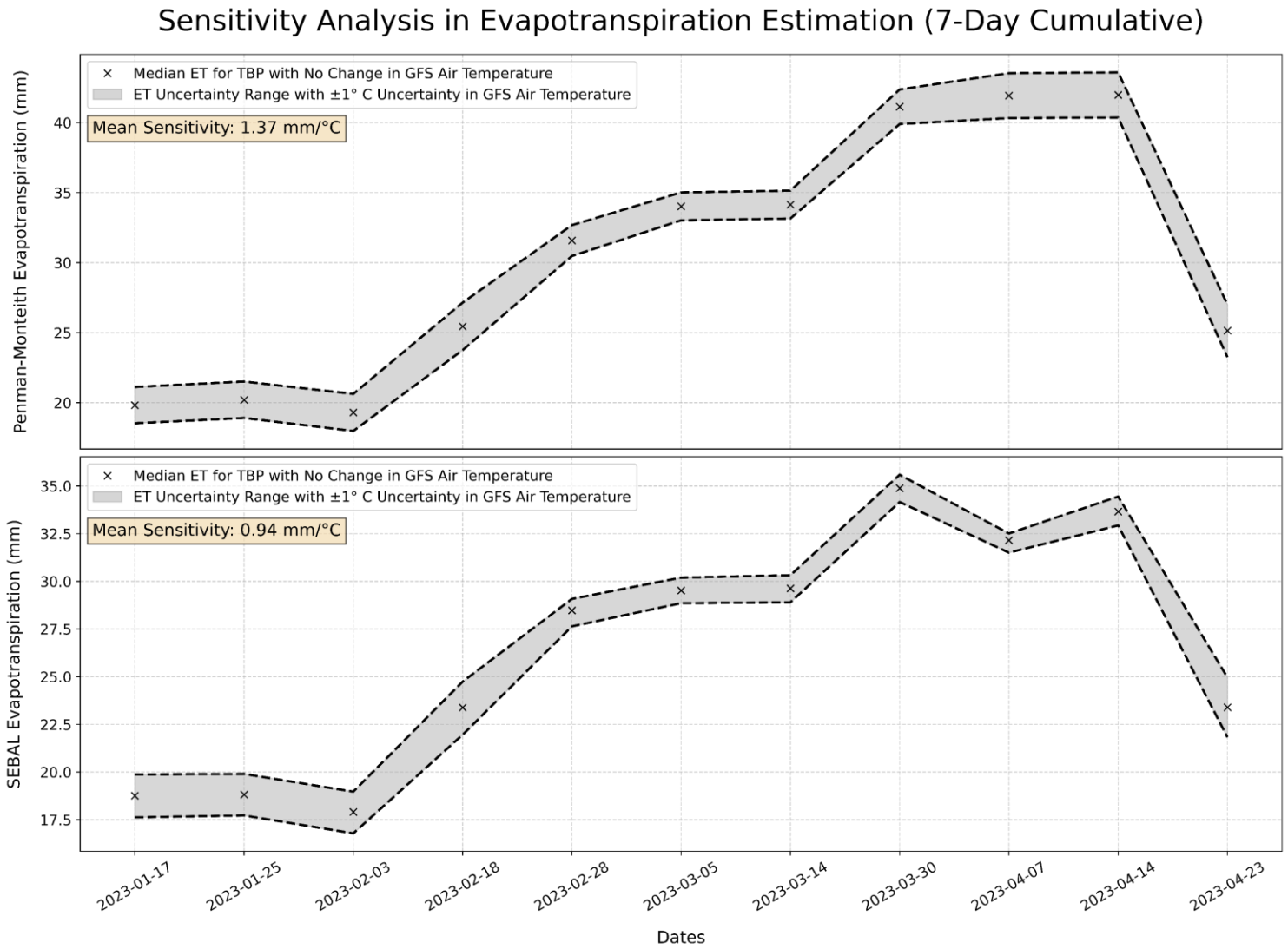
GLUE (Generalized Likelihood Uncertainty Estimation)



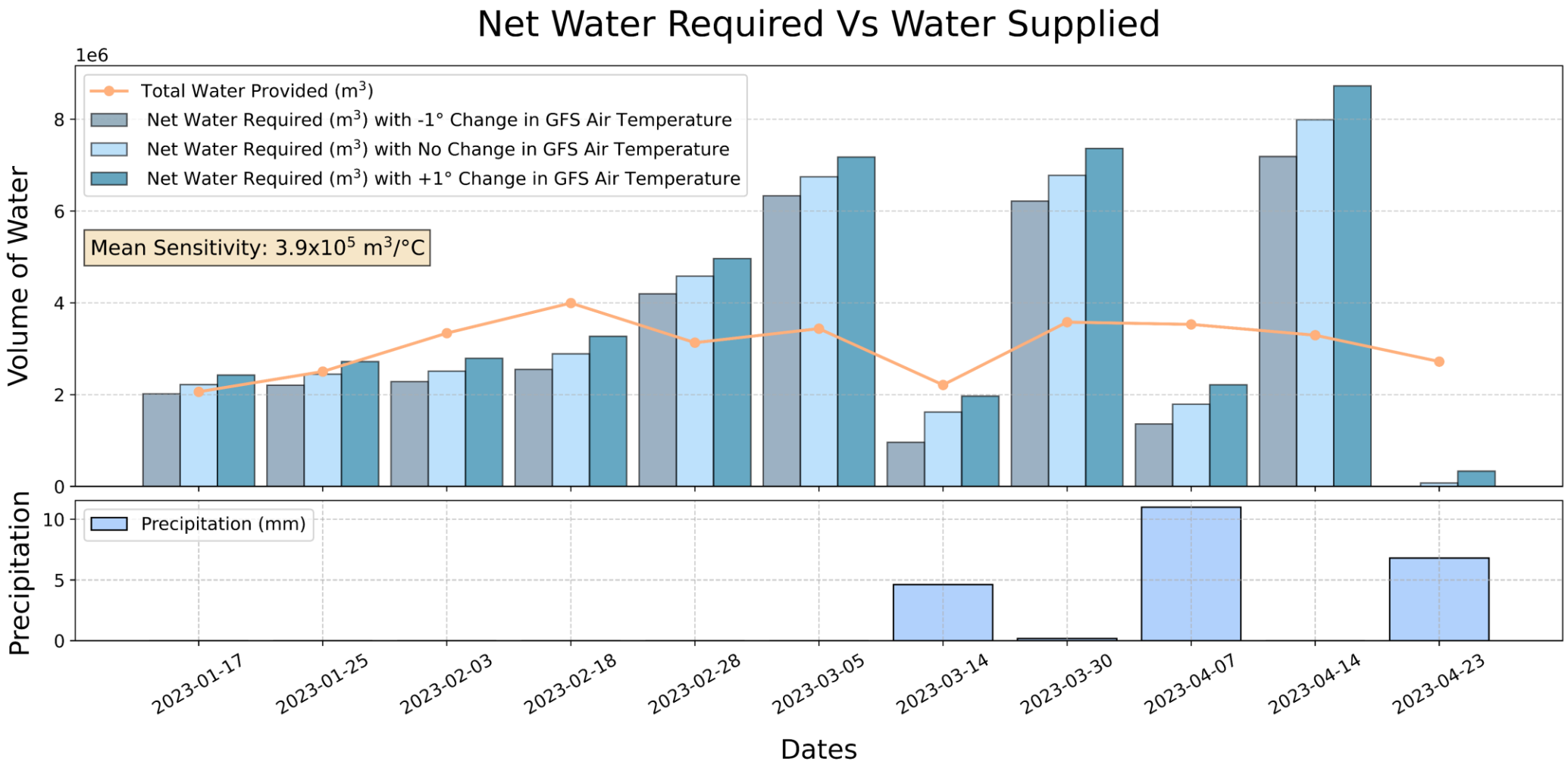


NWR: ~<5%

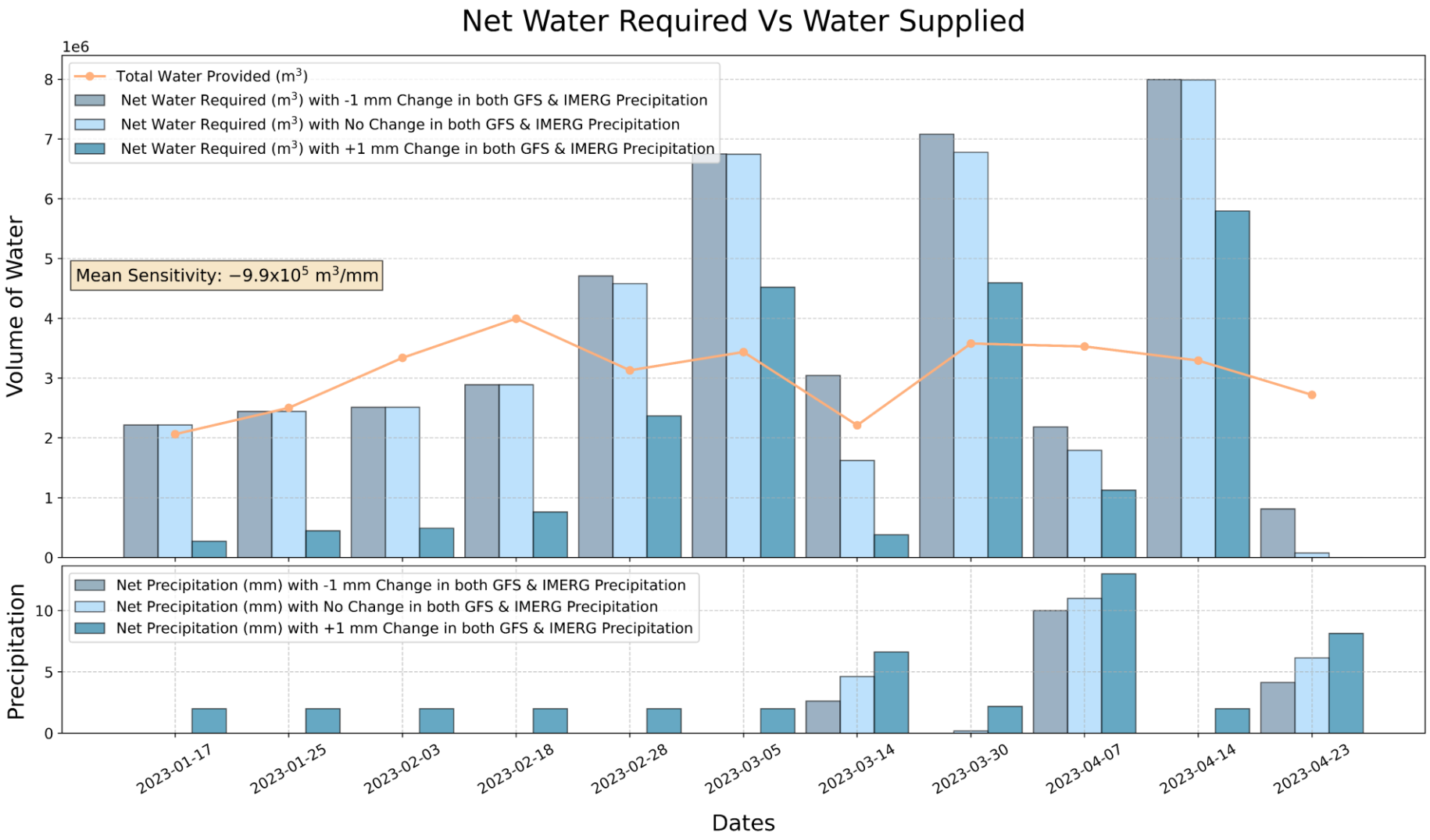
Sensitivity Analysis - Temperature



Sensitivity Analysis - Temperature



Sensitivity Analysis - Precipitation

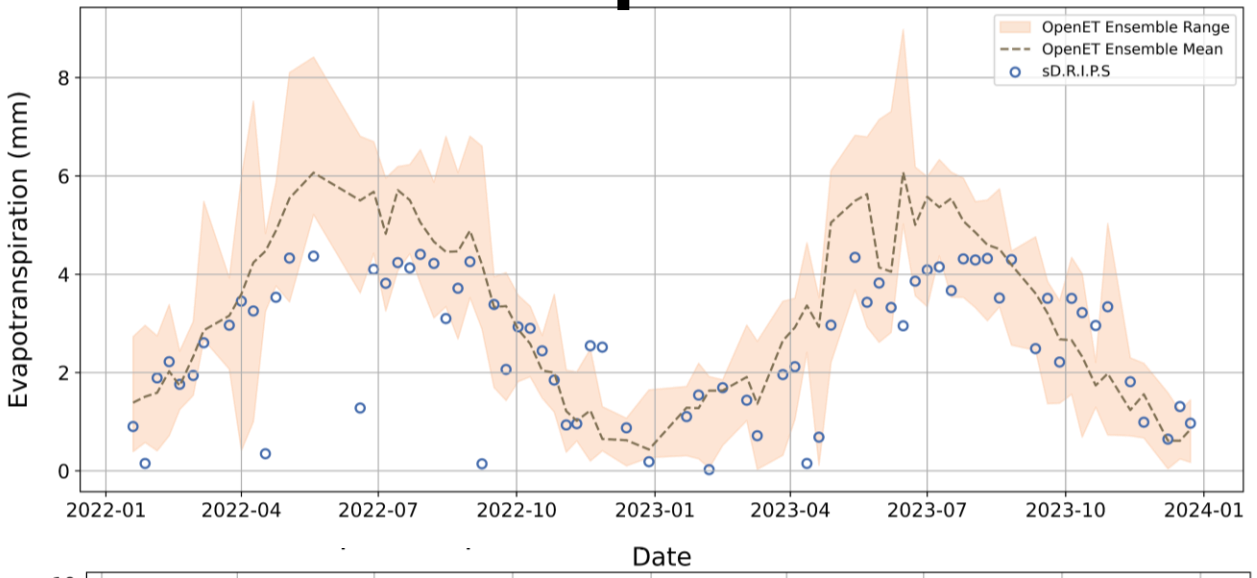


Comparing Framework Estimates with OpenET Data

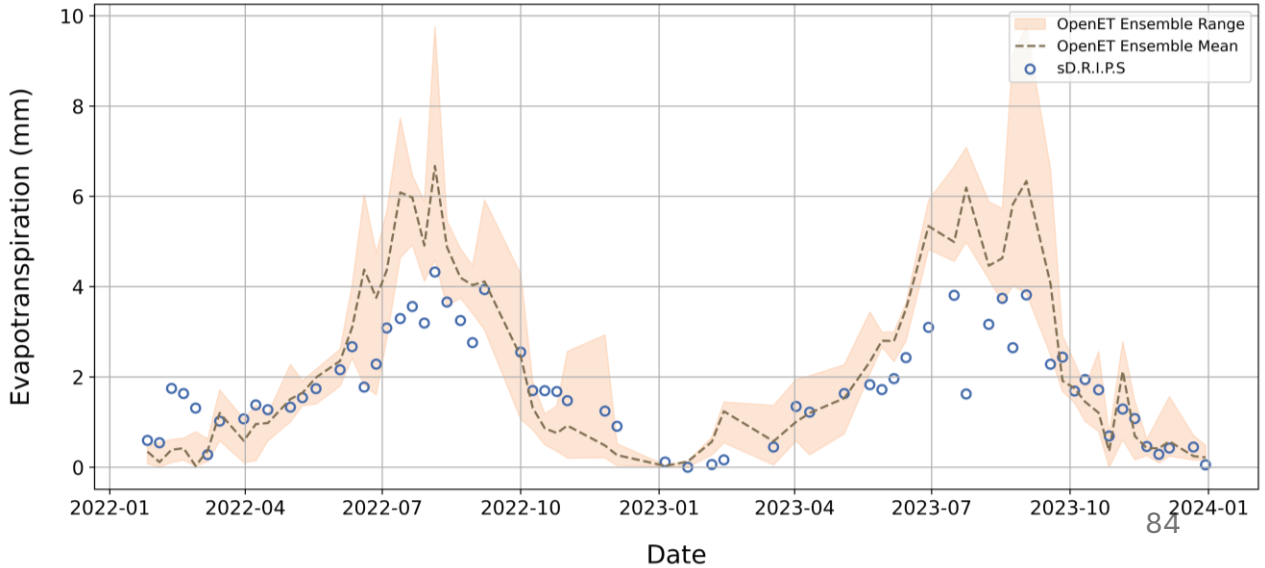
OpenET employs **six state-of-the-art** satellite-based energy balance models

During peak periods (e.g., July), either sD.R.I.P.S estimates slightly underestimates ET, or OpenET slightly overestimates it.

California

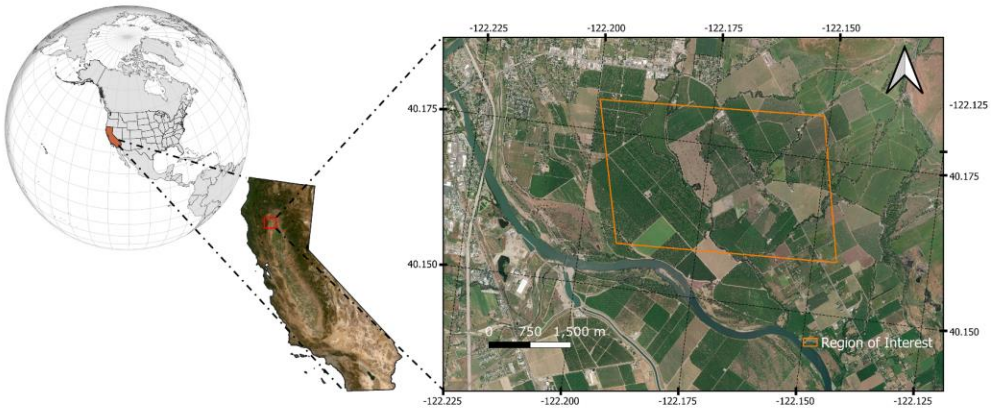


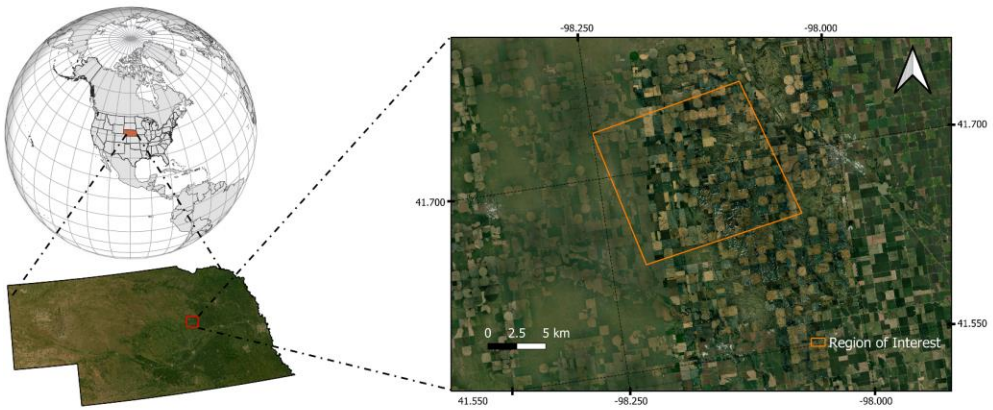
Nebraska

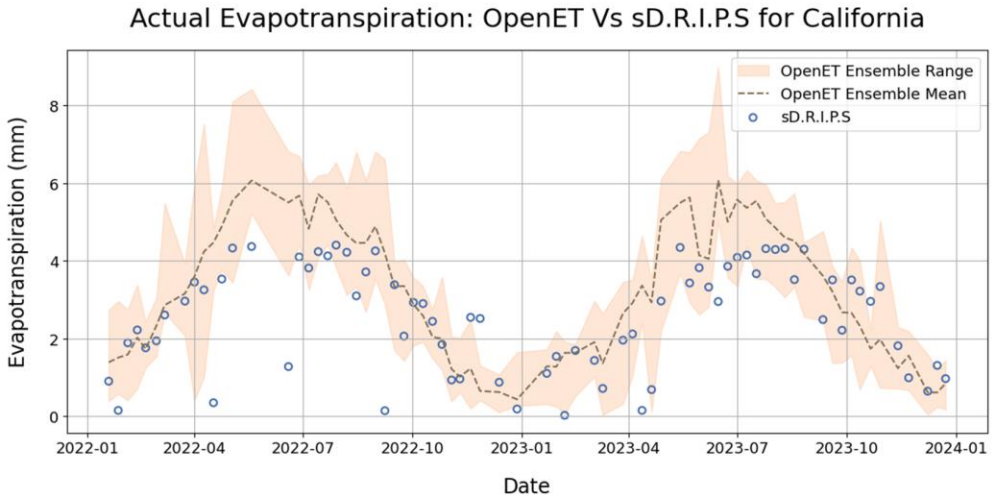


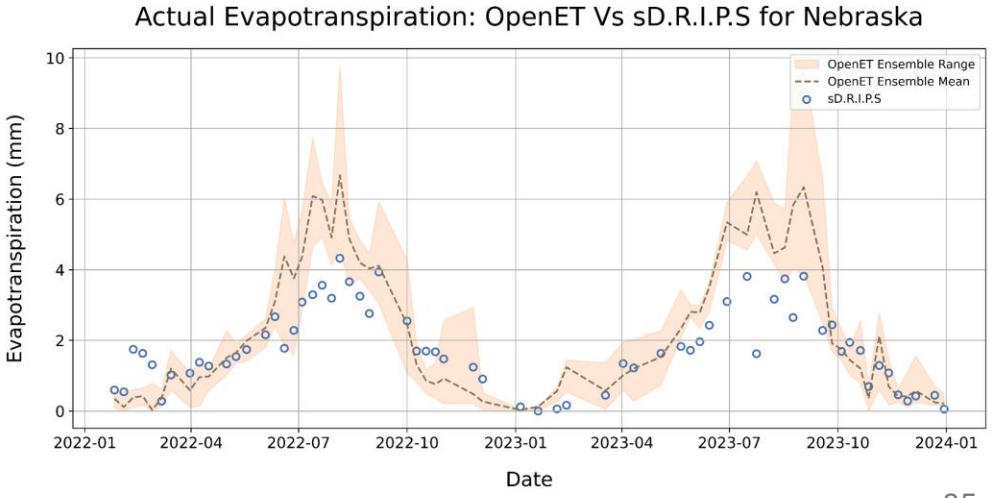
This variation likely stems from:
OpenET: Uses gridMET (4 km) and NLDAS (~13 km) products, **limited to the USA**.
sD.R.I.P.S: Relies on the **global** GFS product with a coarser resolution (25 km).

Comparing Framework Estimates with OpenET Data

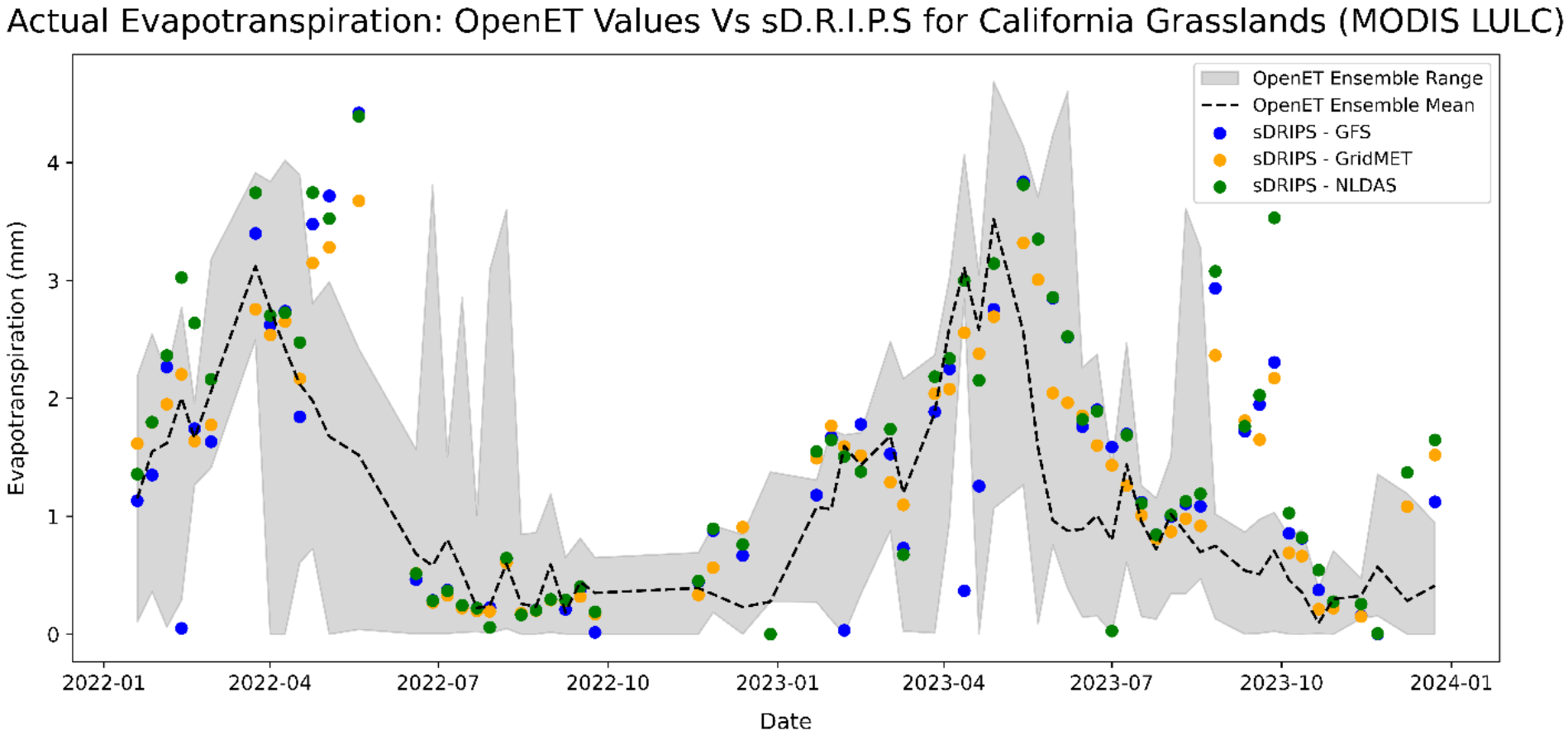




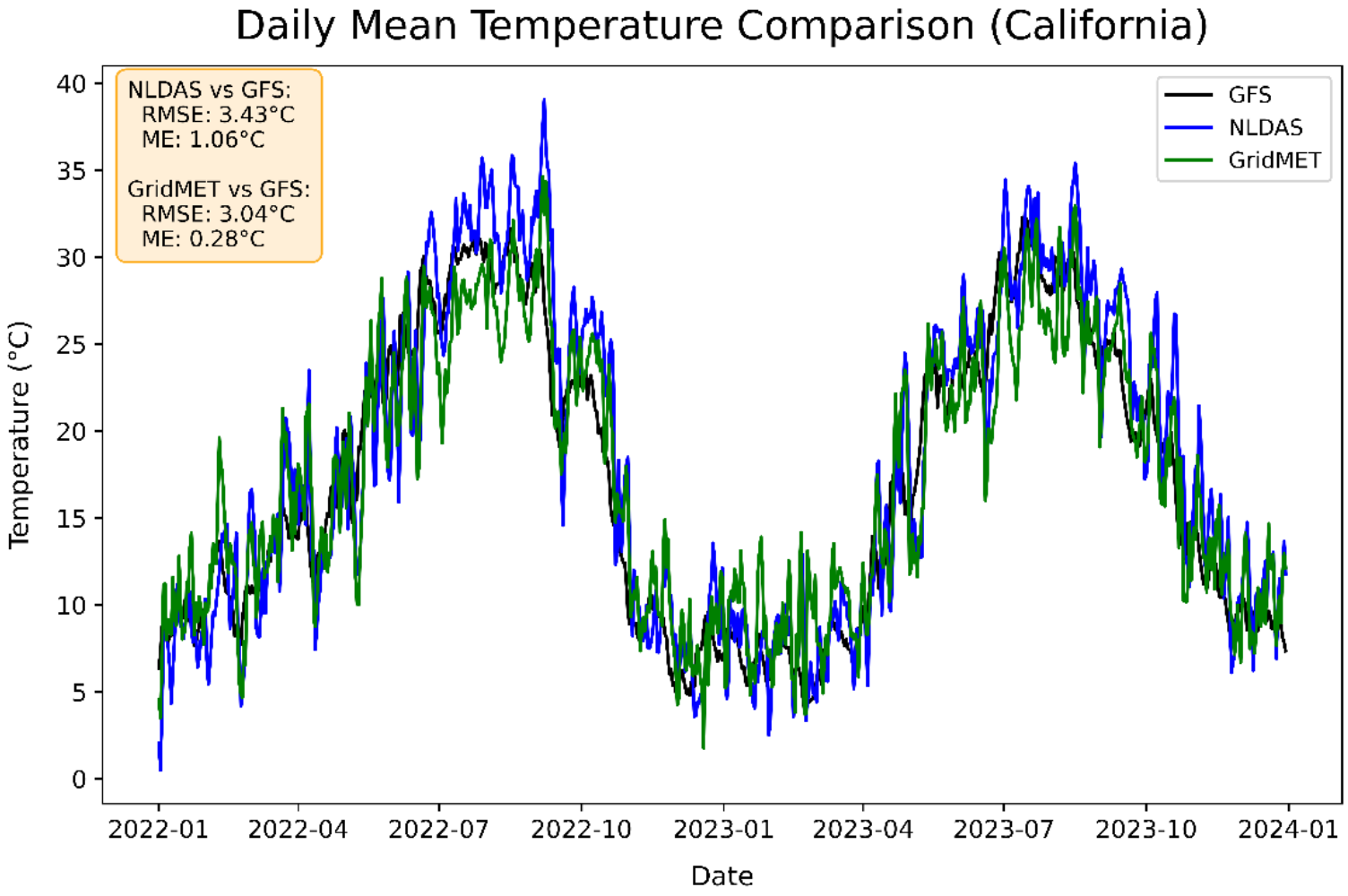




Comparing Framework Estimates with OpenET Data



Comparing Framework Estimates with OpenET Data



Challenges in Scaling

300 m

Husky Stadium

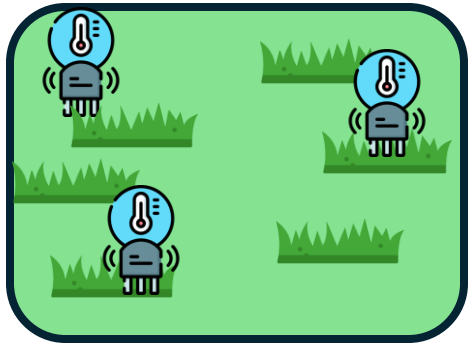
At **10 m** resolution

At **30 m** resolution

?

At **25 km** resolution

T



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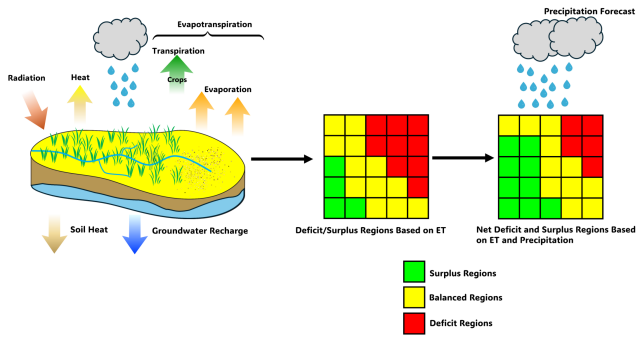


(Quasi) Impact Evaluation of sDRIPS-sense during Summer 2024 (June-Sept)

<u>Sensor (Rainier Vista Region):</u>

- Lack of metered irrigation data and in-situ ET data
- The red highlighted region experienced an average surplus (overwatering) of **47.28%** per week

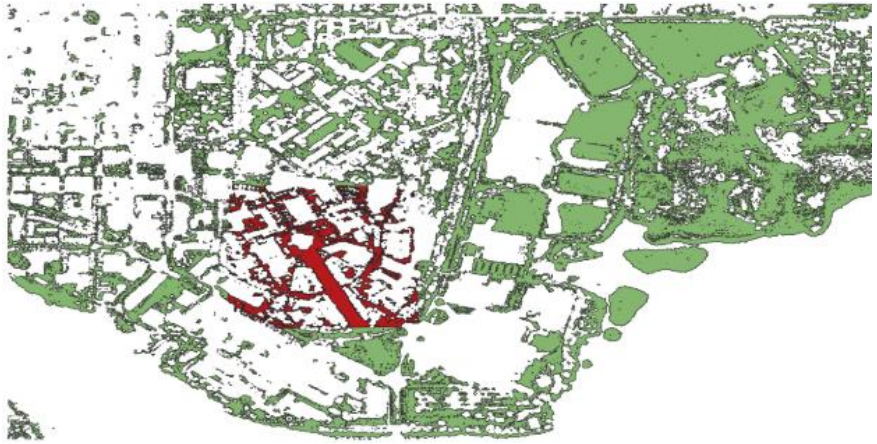
  Area: **17.60 acres**

  Potential Savings per week: **$3,160**

  Potential Summer Savings: **$34,762**

(Quasi) Impact Evaluation of sDRIPS-sense during Summer 2024 (June-Sept)

- Impact evaluation Sensored Region vs Non-Sensored Region



Sensored Region (Rainier Vista Region):

- Average % Deficit: 47.28% per week
- Likely realistic and actionable information

Non-Sensored Region (IMA Fields Region):

- Average % Deficit: 115.00% per week
- Likely highly uncertain information but still potentially actionable if applied with caution
- Further away from sensors mean higher uncertainty