Satellite-Based Estimation of Soil Geologic Properties Using Physics-Guided Machine Learning

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Motivation: Need for Remote Estimation of Aquifer Properties

Source: cleanwater.org

Source: kompas.com

- $\text{Subsidence} \propto \frac{1}{\text{Coarse-grain ratio}} \times \text{Groundwater loss}$

- Subsidence sensitivity depends on **coarse-grain ratio (CGR)**

- Knowing the **CGR** helps in understanding better **the aquifer behavior**
  - Better **water-management**

- Traditional **borehole-based CGR measurements** are
  - **Costly**, **sparse**, and **geographically limited**

Source- USGS

Sky to Subsurface approach

- **How much** compaction occurs depends on **soil type** — specifically **coarse-grain ratio (CGR)**:

Soil Type	Behavior Under Stress	Observed Subsidence
Fine-grained (clays/silts)	Compressible — **inelastic** compaction	**Large**, often irreversible
Coarse-grained (sands/gravels)	Mostly **elastic** deformation	**Small**, recoverable

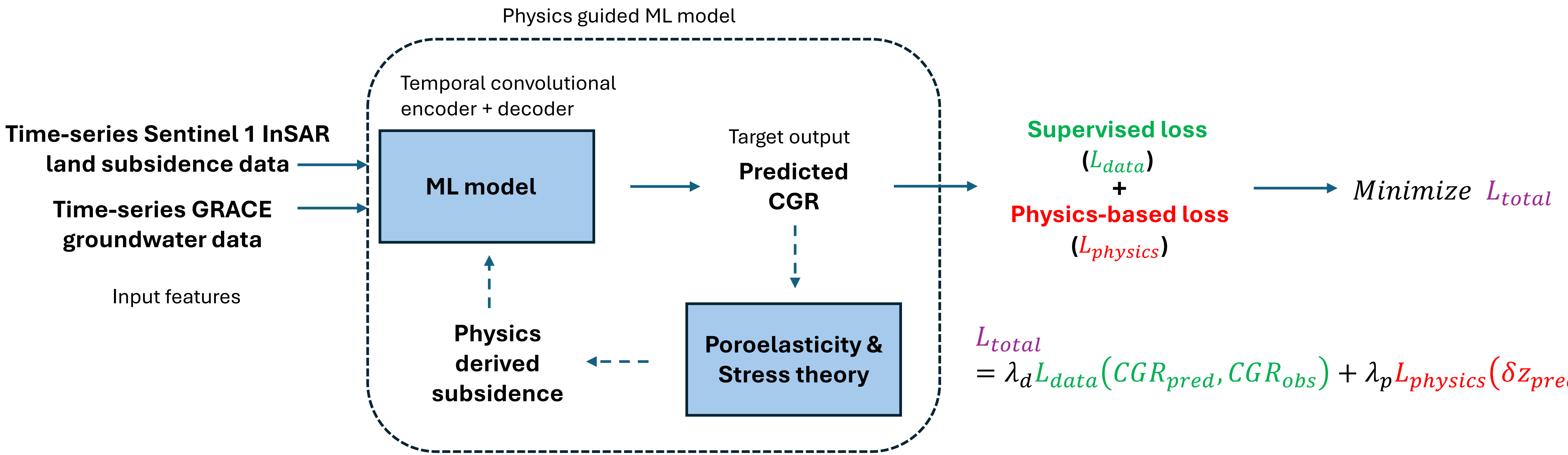
Subsidence response encodes geologic composition.

- Satellite data + Physics (poroelasticity + effective stress theory)

Input	What It Measures	Why It's Needed
Sentinel-1 InSAR	Land subsidence	Gives **compaction** signature (effect)
GRACE/GLDAS	Groundwater storage change	Gives **pore pressure change** signature (cause)

- California's Central Valley supports a quarter of U.S. food production and relies heavily on groundwater, supplying ~20% of national demand.
- **Intensive groundwater pumping** has led to significant **land subsidence** in California's Central Valley.

Physics Guided ML approach



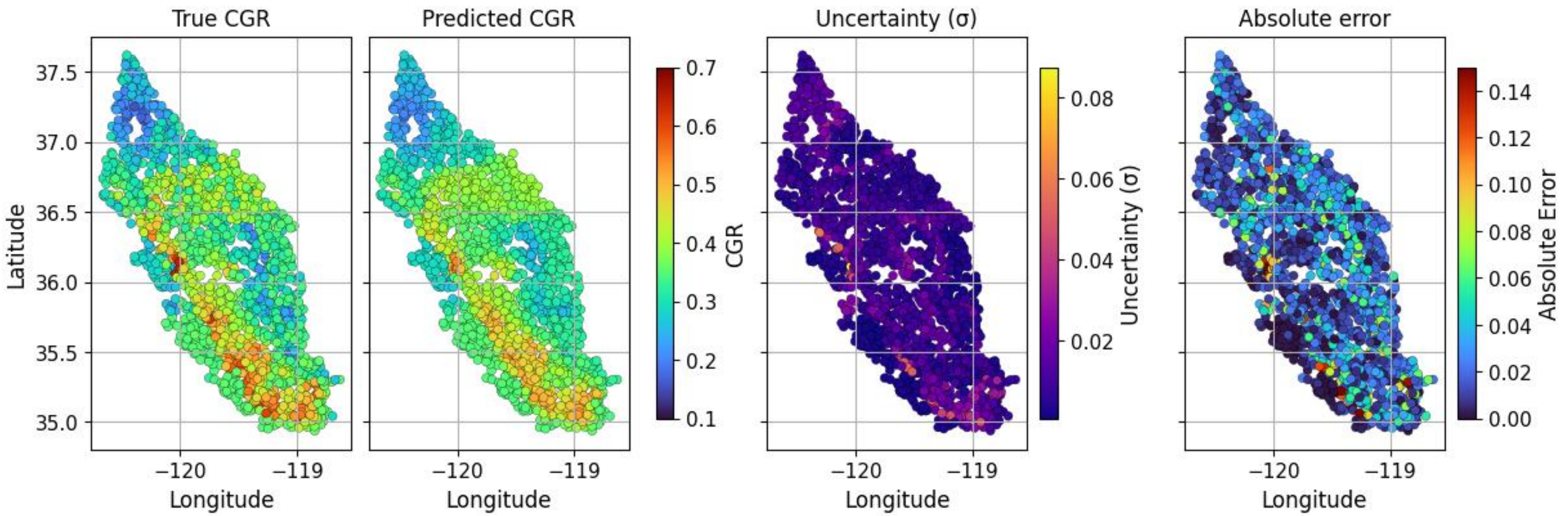
$$L_{total} = \lambda_d L_{data}(CGR_{pred}, CGR_{obs}) + \lambda_p L_{physics}(\delta z_{pred}, \delta z_{obs})$$

$$S_{sk} = S_{sk,fine}(1 - CGR_{pred}) + S_{sk,coarse} CGR_{pred}$$

$$\delta z_{pred} = -\frac{S_{sk}}{S_s} \delta d_{gws}$$

Results

- **Case A**: Integrating poroelasticity theory with GRACE and Sentinel-1 data yields strong generalization

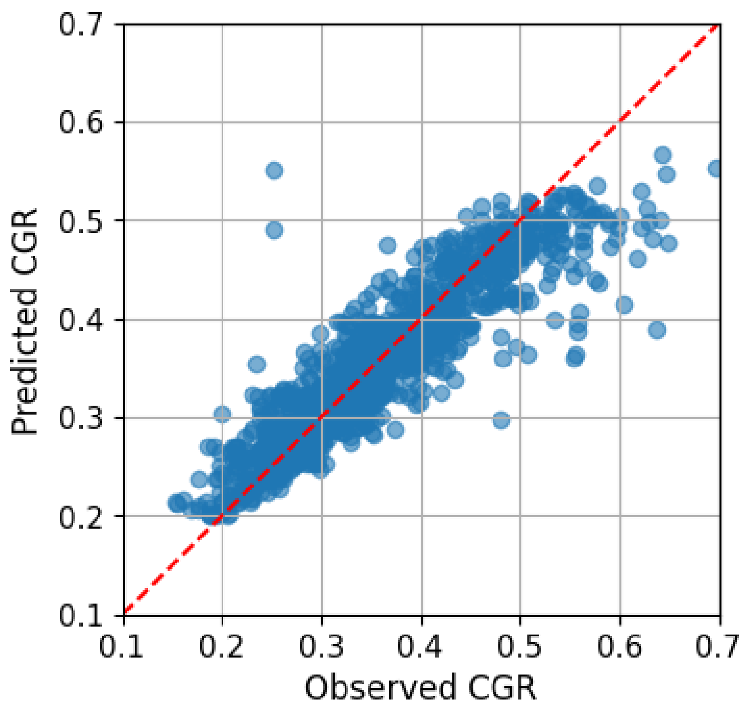


Mean Uncertainty: 0.011

Mean absolute error: 0.025

Results Continued…

- Case A: Integrating poroelasticity theory with GRACE and Sentinel-1 data yields strong generalization



Corr: 0.90, NSE: 0.81

Results Continued...

- **Case B**: Without physics, fit improves slightly (Corr: 0.92, NSE: 0.83, Mean Uncertainty: 0.0235) but model overfits noise and loses physical consistency.

- **Case C**: Embedding physics (GWS + poroelasticity) enforces causality, physical consistency, and lowers prediction uncertainty and extrapolation risk.

- **Case D**: Excluding location to test spatial generalization shows robust performance (Corr: 0.88, NSE: 0.76, Mean Uncertainty: 0.014).

Conclusion and Future Work

- **Remote estimation** of CGR, **scalable** approach
- Embedding **poroelasticity** theory improves physical **interpretability**

- Expanding to **additional locations**
- Extending training on **longer multi-year time series**
- Integrating InSAR data from NASA–ISRO’s **NISAR mission**

Thank You

Open to future opportunities

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For follow-up discussion, please contact:
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