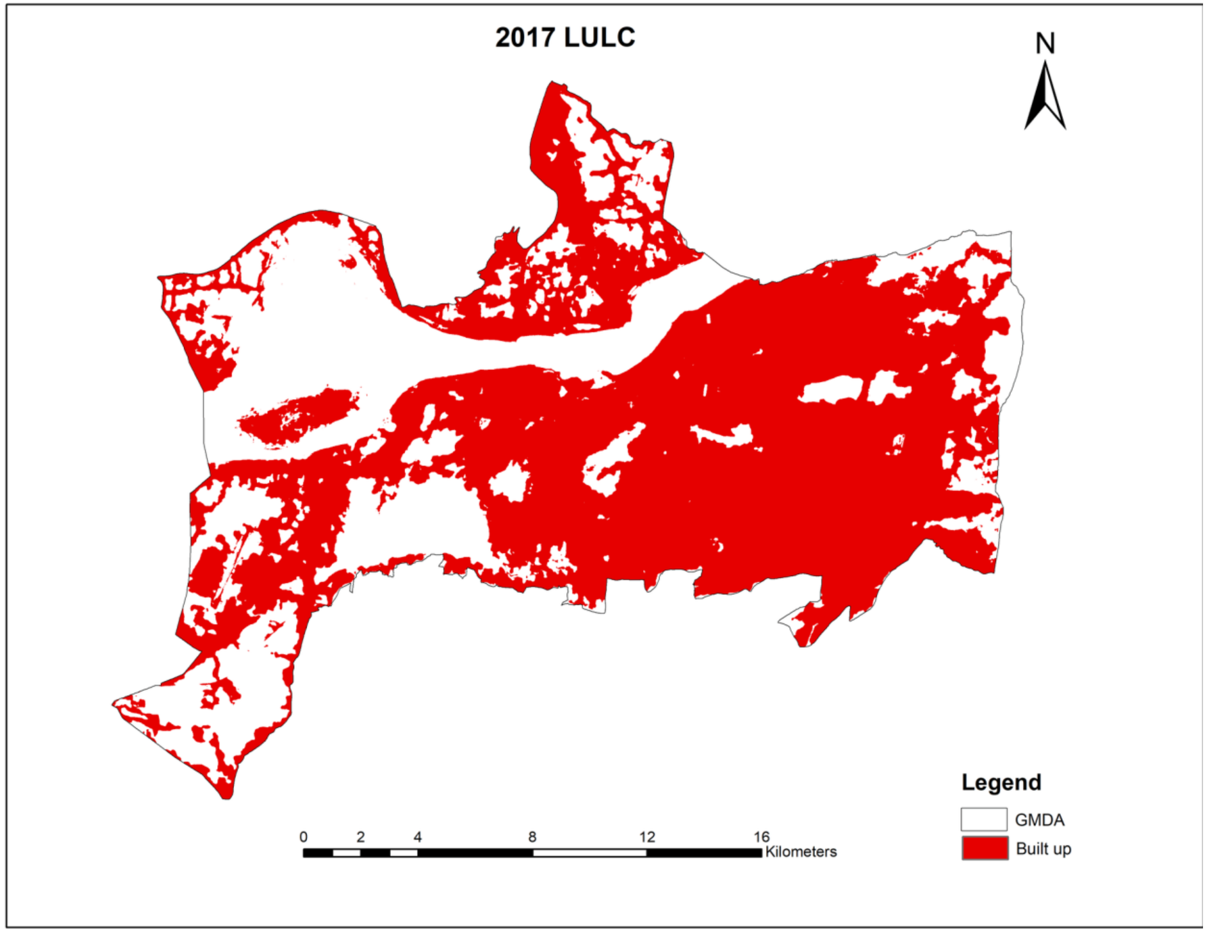
Mapping and Forecasting Groundwater Vulnerability in Guwahati- A Multi-Source Approach using earth observation, GIS and Machine Learning

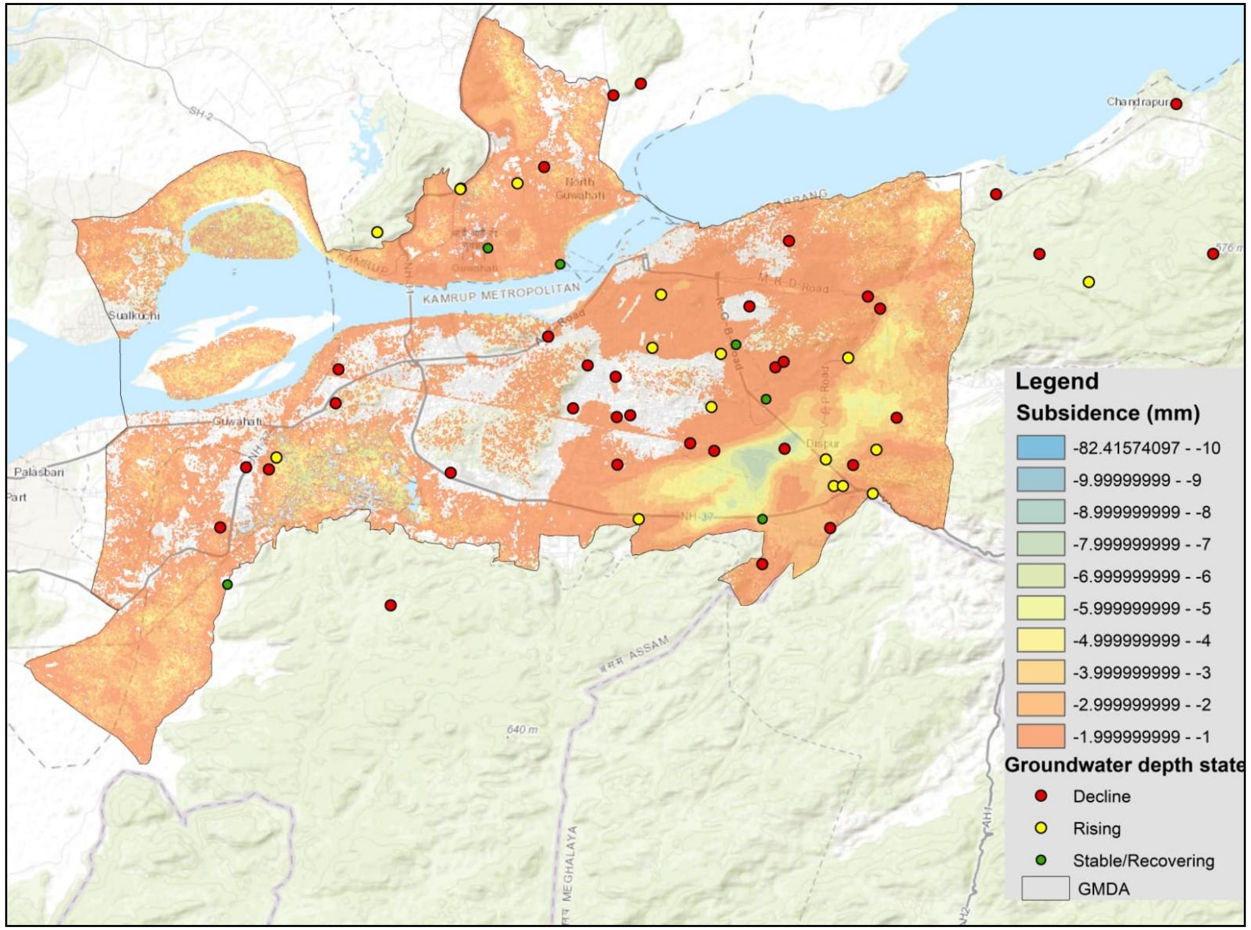
Santanu Das

North Eastern Space Applications Centre, Department of Space, Govt of India

GENESIS & PROBLEM STATEMENT



Urbanization in Guwahati (2017-2025)

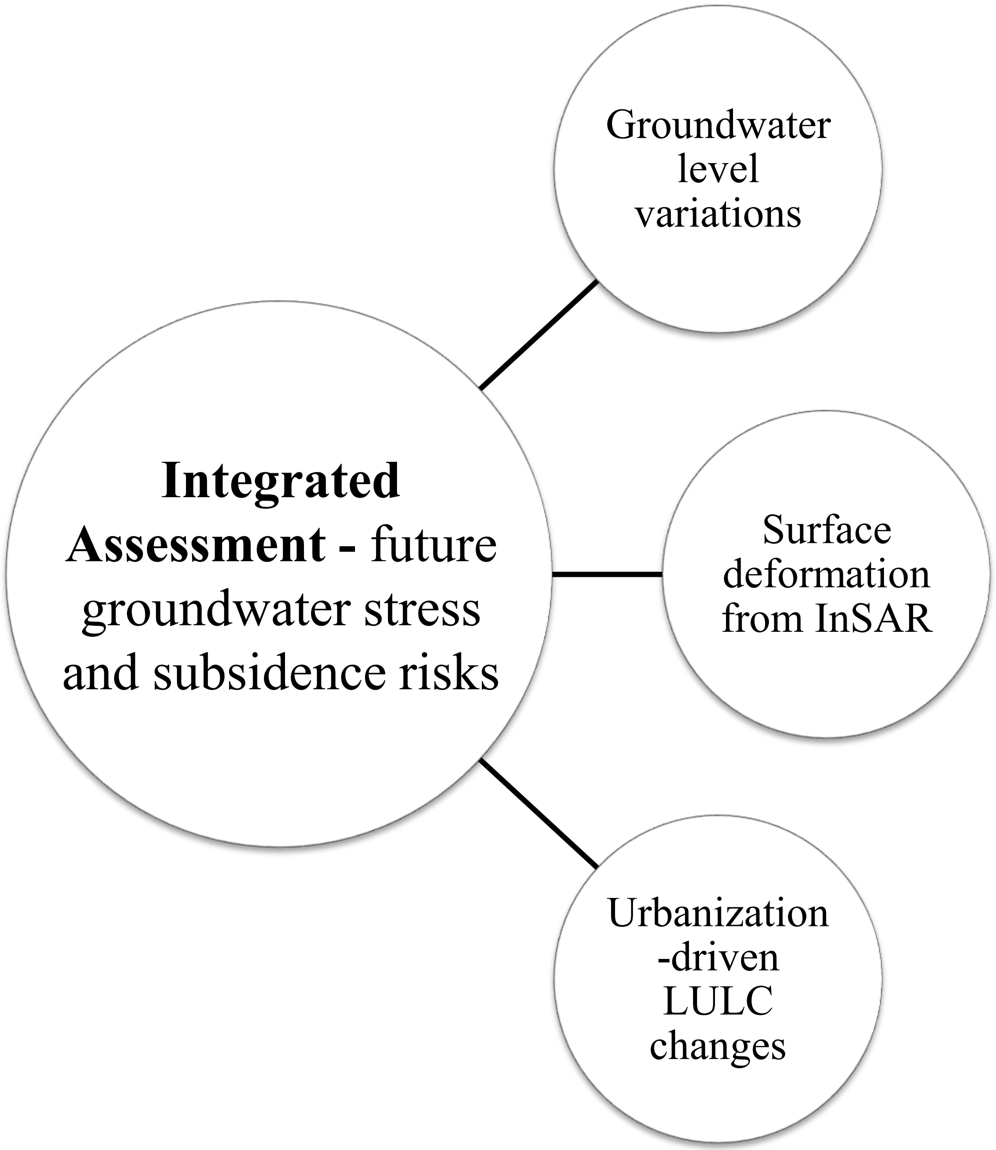


Mean subsidence (2017-2025)

GROUND WATER DEPLETION ⟷ DRIVER OF LAND SUBSIDENCE

Lack of spatio-temporal correlation

GENESIS & PROBLEM STATEMENT



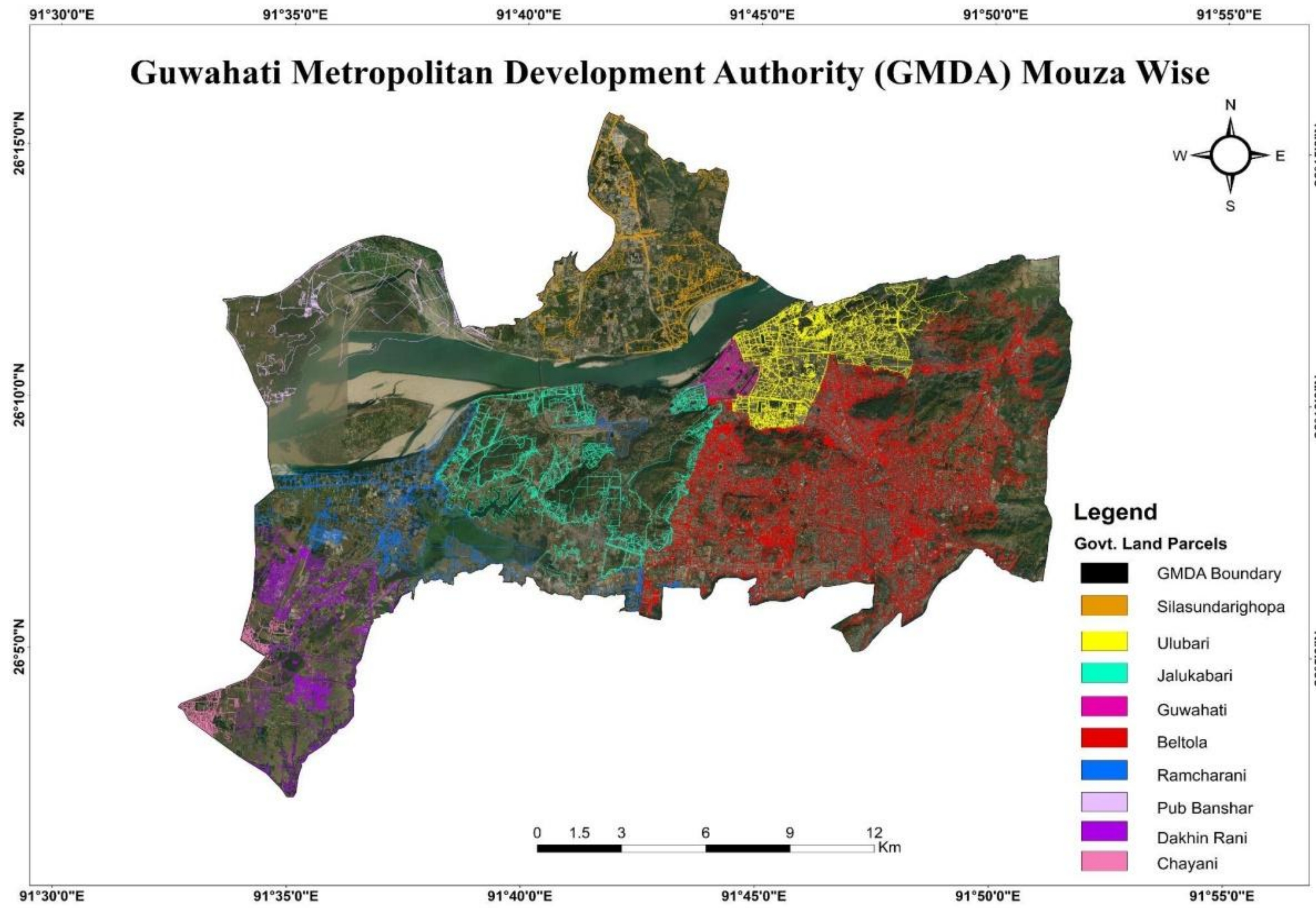
Objectives:

- To analyse spatio-temporal trends in groundwater depth (2017-2025)
- Quantification using InSAR derived surface displacement (Subsidence)
- Assess correlation between groundwater decline and subsidence
- Examine the role of LULC transitions, especially urban growth
- Predict future groundwater depth under different scenarios

CURRENT LIMITATIONS AND ON GOING RESEARCH

1. Integration of hydrological, hydro-geomorphological Models.
2. Identification of recharge zones, impervious surface expansion from vertical development, floodplain dynamics, and structural load impacts.
3. Integration of historical rainfall data.
4. Application of Enhanced Predictive Analytics - multi-variable relationships-to model and predict aquifer stress

STUDY AREA



About GMDA

(Guwahati Metropolitan Development Authority)

Districts : **2**

Circles : **6**

Mouzas : **9**

Total GMDA Area: **~378 Sq Km**

DATA USED

- **Land Use/Land Cover Dataset:**
  ESRI Global Land Use/Land Cover datasets (2017–2025)

- **Land Use/Land Cover Driving Factor:**
  Elevation (**SRTM-30m Resolution**), Slope, Distance to CBD (**Open Street Map**)
  Distance to Transportations Including Roads, Airport, Railway Stations (**Open Street Map**)

- **Groundwater Depth Dataset:**
  Well-wise groundwater depth measurements obtained from **Central Ground Water Board (CGWB)**

- **InSAR Displacement Dataset:**
  Sentinel-1 SAR–derived surface displacement products generated using **ASF InSAR On-Demand** processing (Alaska Satellite Facility)

Methodology – Future Land Use Generation (GEOSOS-FLUS)

GeoSOS- FLUS simulates future land use by coupling Human and Natural effects.

Key Components :

- **Markov Chain –** Predicts future land use distribution based on past trends.
- **Artificial Neural Network (ANN)** – Estimates land use transition probabilities based on driving factors.
- **Cellular Automata (CA) –** Simulates spatial evolution of land use using neighborhood effects.

Unique Features :

- Uses **roulette wheel selection** and **competitive mechanism** for cell allocation.
- Captures **spatial constraints** and **driving forces** dynamically.
- Provides more **realistic and accurate** land use predictions.

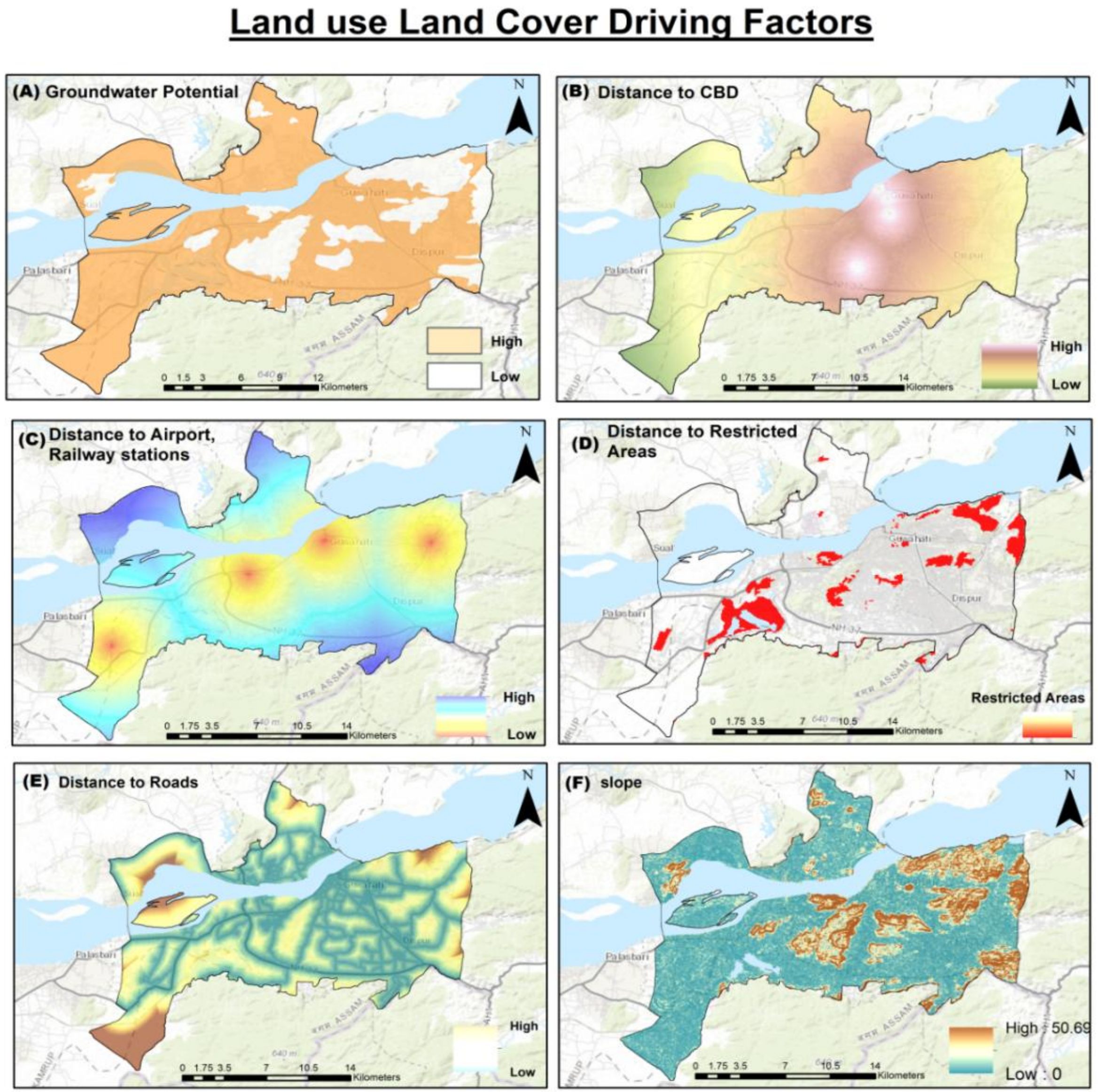
Temporal analysis with Markov chain

1. It uses historical land use data to estimate probability of a cell changing from one land cover type to another.
2. But it only quantifies change, doesn't show where the change will occur. So, it is integrated with cellular automata to overcome this problem.

ANN (Artificial Neural Networks)

- **Input** : ANN takes all the parameters and land use datasets as input.
- **Layered Processing :** Using Hidden Layers
- **Output Generation :** Computes the transition probability of each land use type.
- **Training with back propagation :** Readjusts weight values
- **Integration for simulation:** Suitability Probability + CA

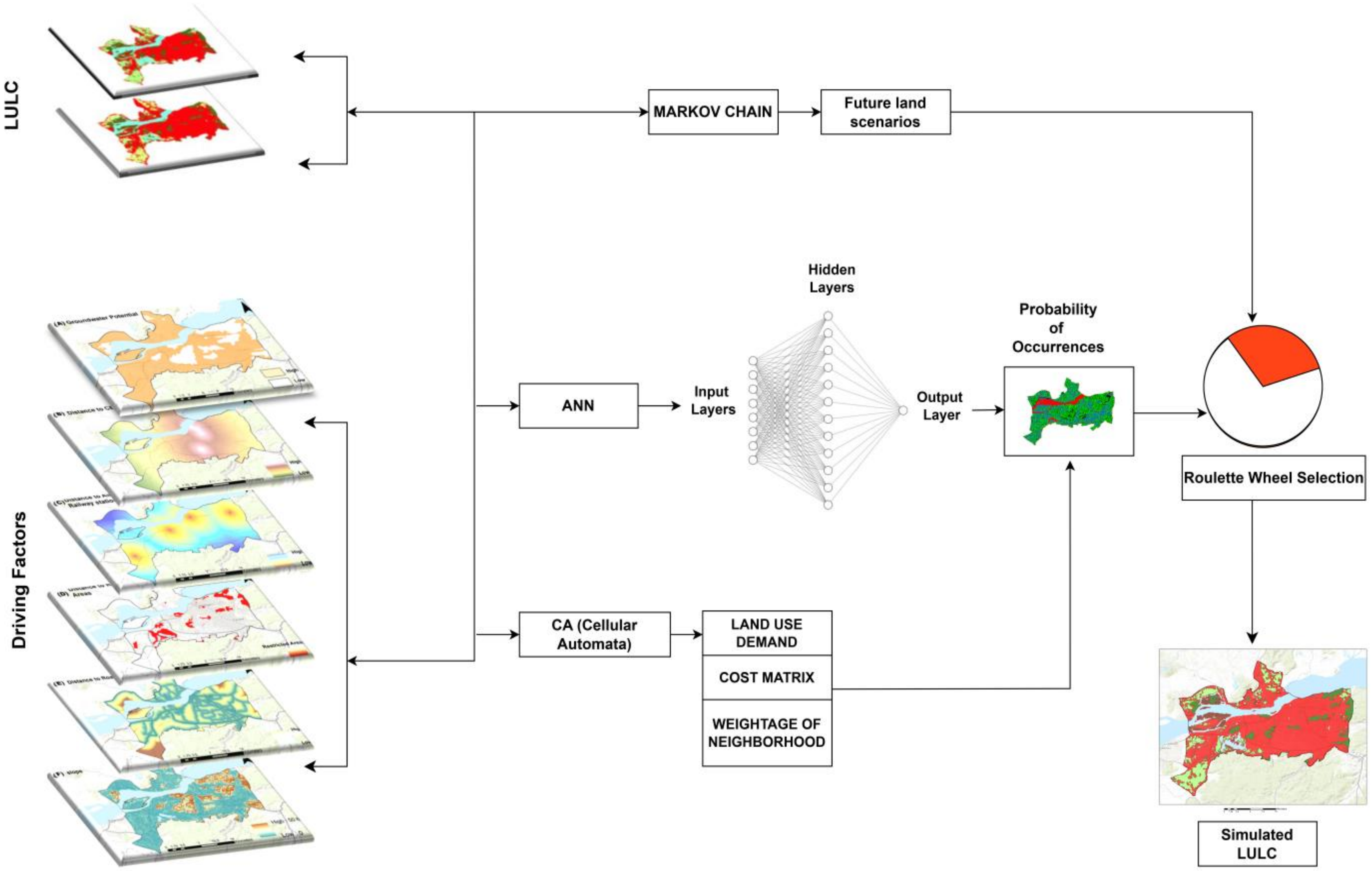
Driving factors – Future Land Use Generation (GEOSOS-FLUS)



Factors	Description	Sources
Slope	Derived from CartoDEM (Digital Elevation Model), resolution 10m	Bhoonidhi.nrsc.gov.in
Distance to Central Business District (CBD)	Proximity of each cell to the CBD, which is critical driver of urban expansion	Guwahati Metropolitan Development authority (GMDA) Masterplan-2025
Distance to mobility services	Proximity to Airport, Railway stations, bus stations	Open street Maps
Distance to roads	Proximity to all kinds of roads (Highways, secondary highways, link roads, trunk roads, residential roads etc.)	Open street Maps
Groundwater Potential	Groundwater potential areas indicated areas are prone to urbanization	Bhukosh.gsi.gov.in & cgwb.gov.in
Restricted Areas	Areas with restriction such as Defense land and Reserve forest	Open street Maps

- **Groundwater potential** : derived from rock types where sedimentary rocks which can store water in high quantity are classified as high potential, and hard igneous rocks which stores comparatively less water are classified as low potential.
- **Restricted areas** including defense lands and protected reserve forests.

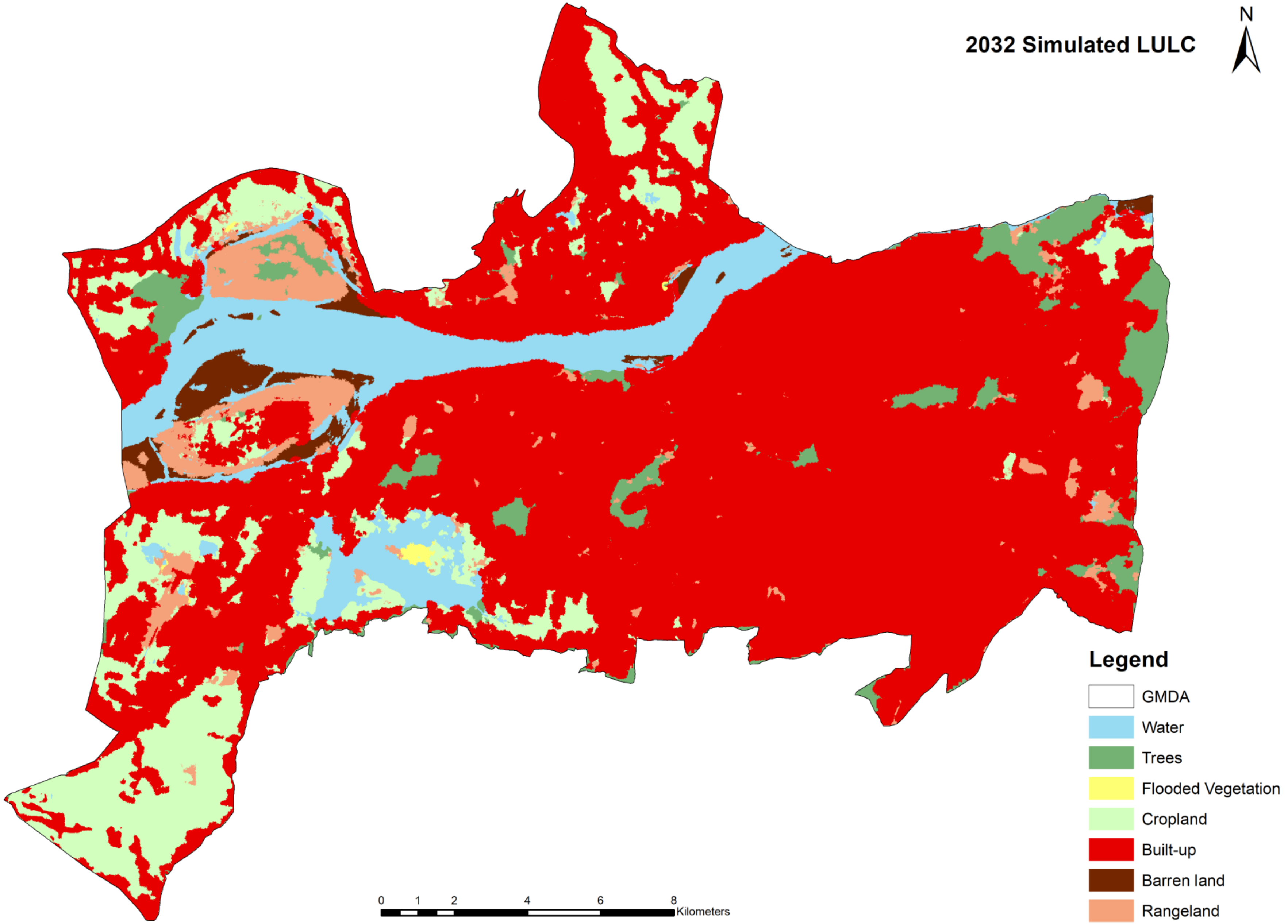
Methodology – Future Land Use Generation (GEOSOS-FLUS) ..continue



Cellular Automata

- **Local transition rules :** CA uses simple rules – often applied to a 3 * 3 grid
- **Integration with other models** The CA model uses suitability probabilities from the ANN and overall land demand forecasts from the Markov model to guide which cells change.
- **Adaptive mechanism : A** roulette wheel selection randomly chooses cells based on their suitability, ensuring that conversion reflects both local conditions and overall demand.
- **Realistic spatial patterns**

Results: Simulation of Land Use in GMDA (2025-2032) & Net change



LULC CLASSES	Net Change (Sq.km)
1. Water	- 11.89
2. Trees	-16.45
3. Flooded Vegetation	-2.37
4. Cropland	-15.74
5. Built-up	+56.48
6. Barren land	-1.85
7. Rangeland	-8.18

GROUNDWATER DEPTH ANALYSIS

- Compilation of **well-wise groundwater depth data** from CGWB (CSV format)
- Temporal trend analysis of groundwater depth at **individual observation wells** (2017–2025)
- Statistical analysis to identify **areas exhibiting persistent groundwater decline**
- No spatial interpolation applied; analysis performed at **well locations only**

Interferometric Synthetic Aperture Radar (InSAR) Analysis

Data Acquisition

- Sentinel-1 SLC (IW Mode), Descending Orbit, **2017–2025,**
- Data accessed and processed using **ASF InSAR On-Demand** services

1. Orbit Correction & Co-registration
2. Interferogram Generation
3. Topographic Phase Removal (DEM)
4. Filtering, Coherence & Phase Unwrapping
5. Displacement estimation & Geocoding

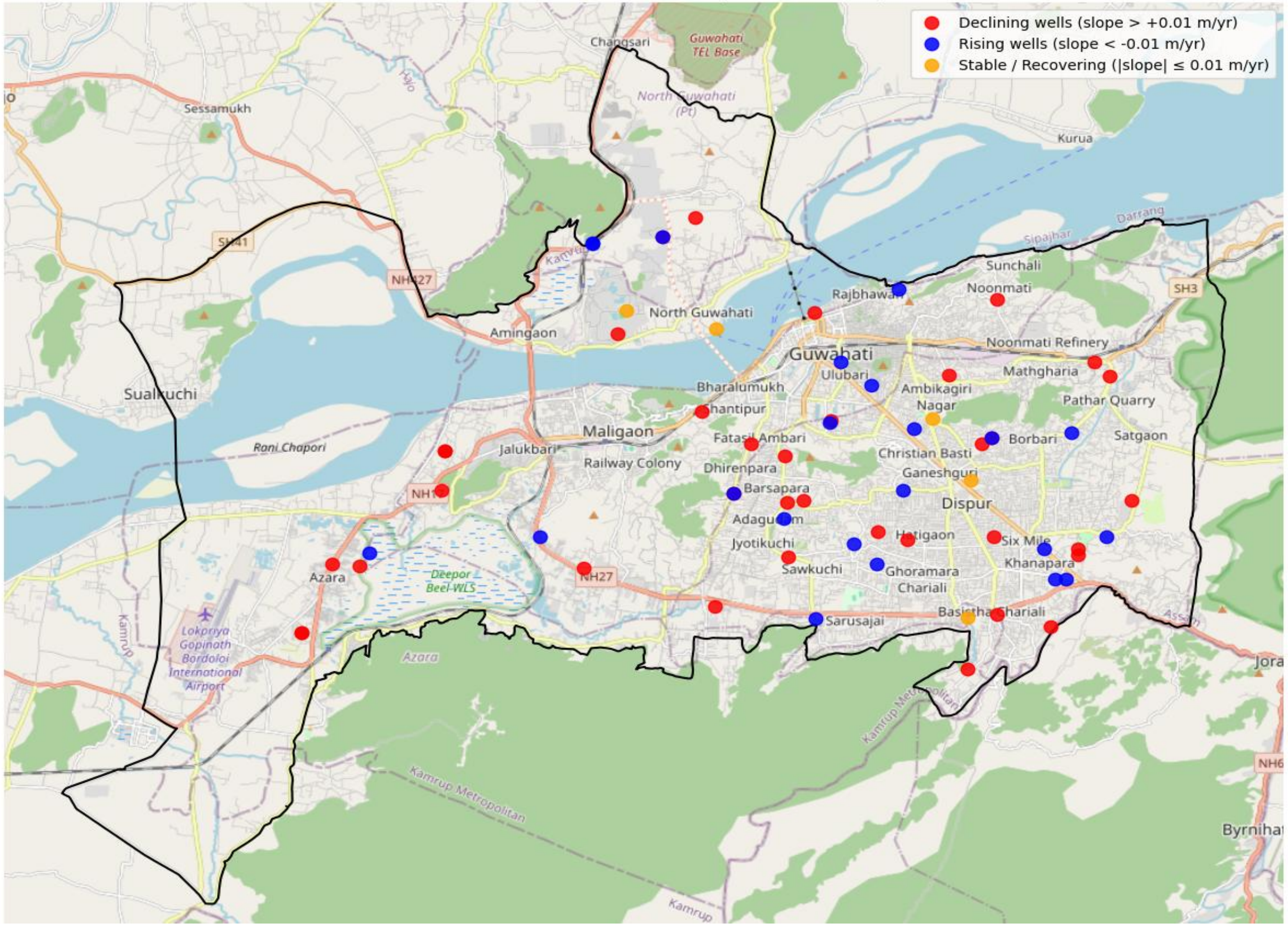
InSAR Processing

1. Precise orbits and accurate image alignment
2. Isolates deformation-related phase
3. Removes terrain-induced phase
4. Noise reduction and phase continuity
5. Surface movement estimation and mapping

Subsidence Estimation

1. Vertical displacement products
2. Date-wise coherence masking (≥ 0.4)
3. Reliable subsidence mapping

Results: Groundwater Depth Trend Analysis



Wells inside AOI: 63

Groundwater Depth Trend Summary

Decline wells	:	36
Rising wells	:	22
Stable/Recovering wells	:	05

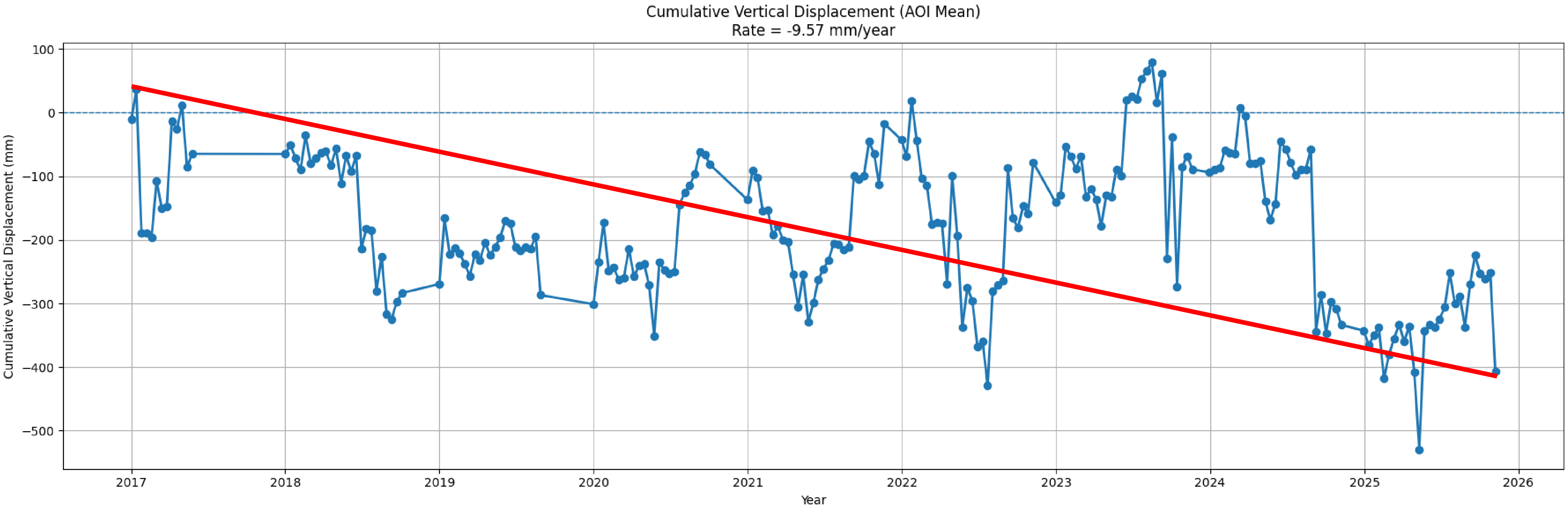
Linear Regression Slope Interpretation

Positive slope(Declining wells) = 57.14%

Negative slope(Rising wells) = 34.92%

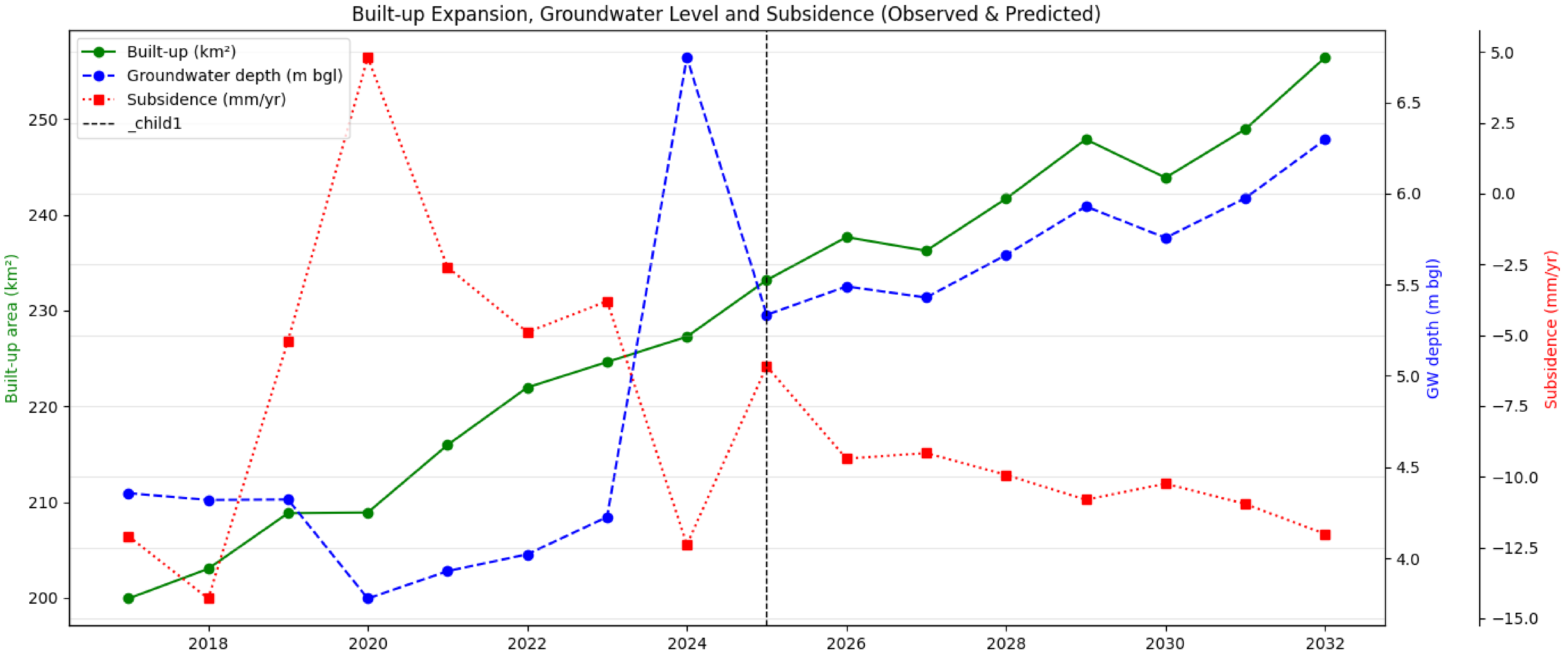
Near Zero slope(Stable/Recovering) = 7.94%

Results: InSAR based displacement analysis



- The figure shows the AOI-averaged cumulative vertical displacement derived from InSAR time-series analysis,
- A **net downward displacement trend** is observed over the study period
- The estimated **mean subsidence rate is −9.57 mm/year**
- Temporal variations and episodic displacement fluctuations are evident throughout the time series

Results: Linear regression between Groundwater depletion vs. Urbanization (LULC) vs. Subsidence



Results: Linear regression between subsidence vs. Urbanization

The **empirical relationship** between **built-up area and groundwater depth** indicates that urban expansion leads to progressive groundwater level decline, with an average increase of **~4.3 cm** in groundwater depth **per square kilometer of built-up** growth. The **second relationship** demonstrates a negative linear response between groundwater depth and land subsidence, wherein a **1 m decline in groundwater level** results in approximately **3.3 mm of subsidence**. Together, these equations illustrate the indirect control of urbanization on land subsidence through groundwater depletion.

Empirical Equations Used ---(1)

$$\text{GW depth (m)} = 0.0429 \times \text{Built-up} - 4.7076$$

This is an **empirical linear relationship** derived from observed data (2017–2025) linking **urban expansion** to **groundwater depth** at a stressed monitoring well.

Slope = 0.0429
For every 1 km² increase in built-up area, groundwater depth increases by ~0.043 m (≈ 4.3 cm).
Intercept = -4.7076,
Represents the baseline groundwater depth when built-up is hypothetically zero
Has no direct physical meaning, but is necessary for linear fitting

Results:

Empirical Equations Used ----(2)

$$\text{Subsidence (mm/yr)} = -3.3042 \times \text{GW depth} + 8.7779$$

This equation links groundwater level decline to land subsidence rate, derived from InSAR-observed subsidence.

Slope = -3.3042

A 1 m increase in groundwater depth results in approximately 3.3 mm increase in land subsidence.

Intercept = +8.7779

Built-up expansion
↓
Groundwater depletion
↓
Land subsidence

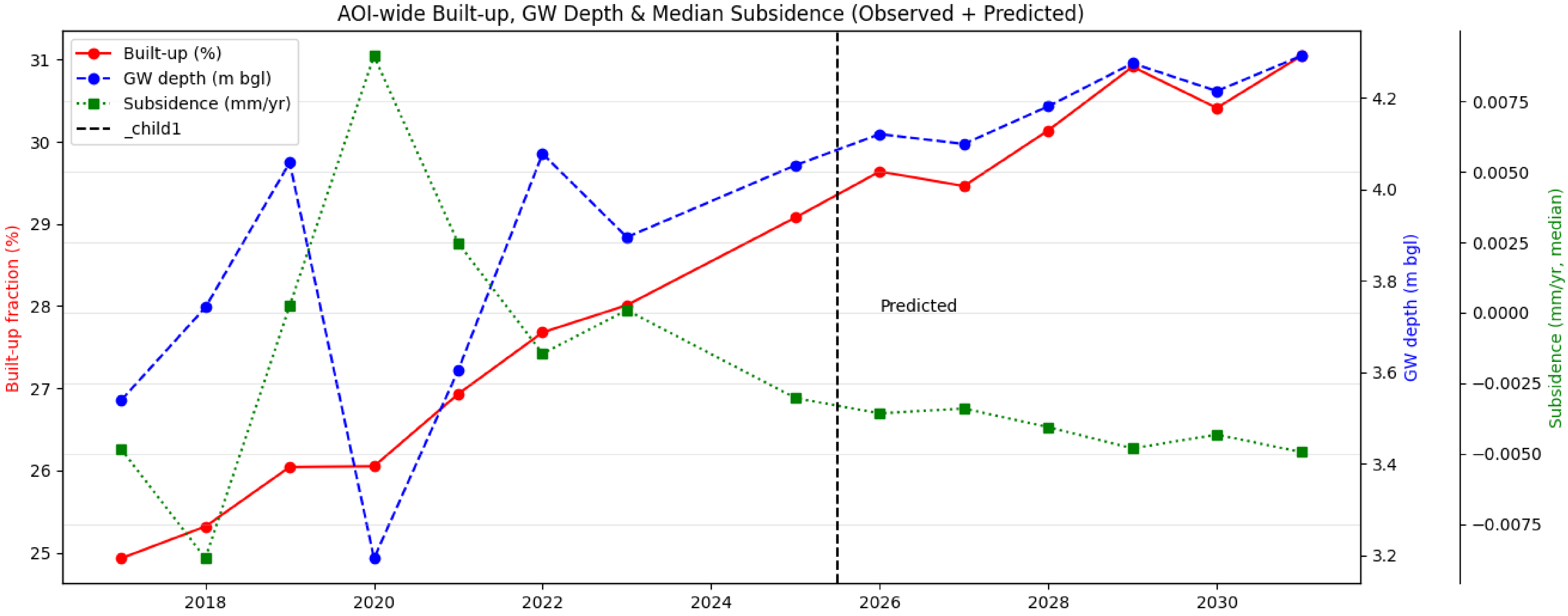
How the both equations worked together

Substituting Equation 1 into Equation 2:

$$\textit{Subsidence} = -3.3042 \times (0.0429 \times \textit{Built-up} - 4.7076) + 8.7779$$

- Built-up affects subsidence indirectly
- Groundwater acts as the mediating variable

Results:



GW depth = f(Cumulative Built-up change) --- GW_Depth = 12.1444 * BU_change + 3.5488

Subsidence = f(GW depth) --- Subsidence = -0.0080 * GW_Depth + 0.0295

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