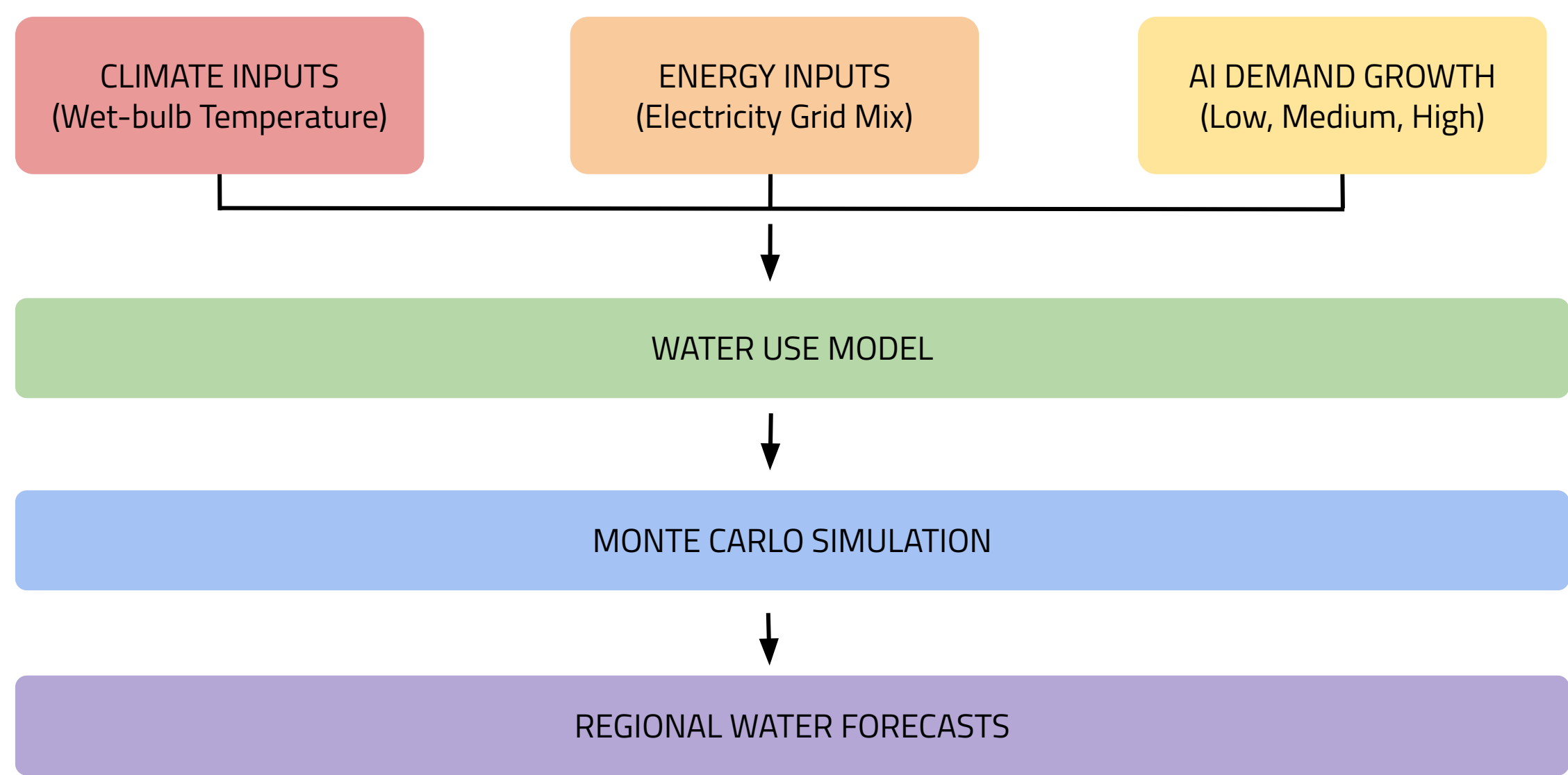


REGIONALIZED FORECASTING OF AI DATA-CENTER WATER USE UNDER UNCERTAINTY

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VISUAL MAP



BACKGROUND & RESEARCH GAP

ISSUE STATEMENT

Increasing AI-driven water demand is intensifying regional water stress and straining limited freshwater resources

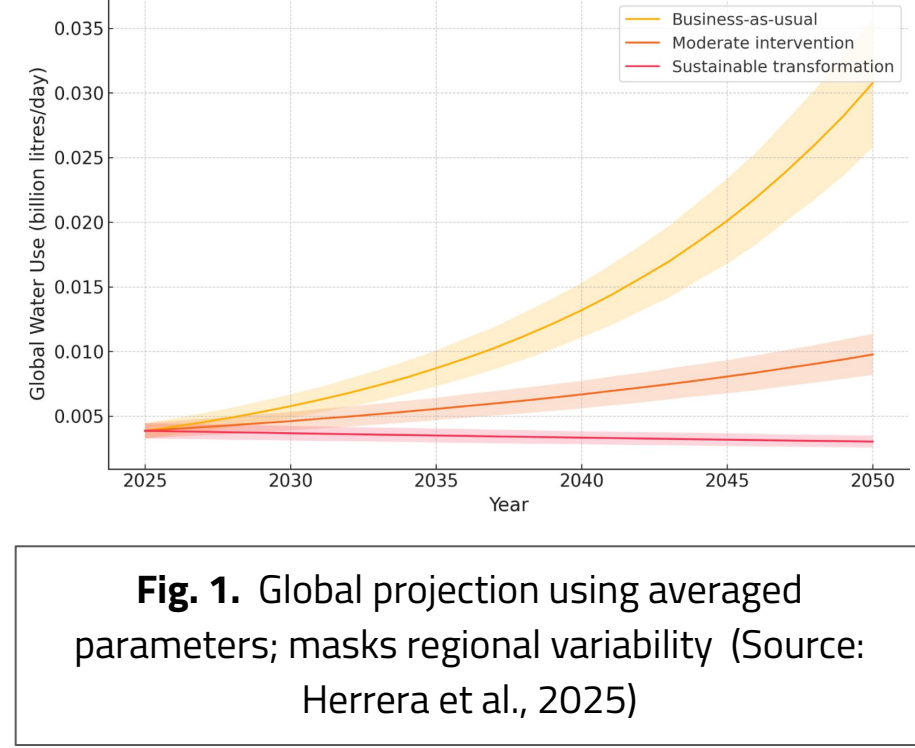
- Around 4 billion people experience severe water scarcity at least one month per year (Mekonnen & Hoekstra, 2016)
- Data center water use is rapidly increasing due to AI-driven compute demand
- AI workloads are growing around 40–60% annually
 - This increases cooling and electricity needs
- Around 20% of data centers are located in water-stressed regions and half of servers are powered by power plants located in water-stressed regions (Siddik et al., 2021)
- Cooling systems rely heavily on freshwater (especially in hot climates)

Current projections do not account for where and how this water demand will occur.

CURRENT FORECASTING METHODS

Aggregated Regional Models

- Farfan and Lohrmann (2023):
 - Projects water use in Europe by 2030
 - Based on:
 - Population growth
 - Data demand
- Limitation:
 - Treats Europe as a single homogeneous region



Global Forecasting Models

- Herrera et al. (2025):
 - Scenario-based projections of global data center water use
 - Use global averages
- Limitation:
 - Treat water consumption as spatially uniform

By relying on averaged assumptions, existing models overlook regional climate and electricity grid factors that determine water use (Lei et al., 2025), masking variability.

RESEARCH QUESTION

How do regional climate conditions and electricity grid structures influence the projected water consumption of AI data centers under different futuristic-growth scenarios?

SIGNIFICANCE

Understanding how water use varies by region is critical for sustainable data center development.

- Helps identify locations where data centers may increase water stress
- Supports better decisions on where and how to deploy AI infrastructure
- Highlights the role of energy systems in driving indirect water use
- Can inform policies to reduce environmental impact of digital growth

METHODOLOGY

Water use is modeled as a function of climate-driven cooling and electricity-driven energy consumption under different growth scenarios

Step 1: Regional Inputs

By using **wet-bulb temperature** and **local energy grid composition** info to calculate WUE(po) and PUE(px), **regional variation** is incorporated into the model.

Cooling water use varies with temperature

Wet-bulb Temperatures (T_w) (12 baseline)
po - using formula (a)
(12 baseline)

Electricity-related water use depends on grid composition

Energy mix (ek) Water intensity (wk)
px - using formula (b)

* θ and e are retrieved from existing literature

* To model improvement over time, an improvement rate of 0.75% is applied to po, θ , and px

Step 2: Model Structure

$$W_o(r, t) = e(r, t) \cdot \rho_o(T_w(r, t))$$

On-site cooling water use Off-site water use from electricity generation

$$W_x(r, t) = e(r, t) \cdot \theta(r, t) \cdot \rho_x(r, t)$$

$$W_{tot}(r, t) = W_o(r, t) + W_x(r, t)$$

Total data-center water footprint at a given region r and year t

W_{tot} Total water use (L/year)
 W_o On-site water use (L/year)
 W_x Off-site water use (L/year)
 e Server energy consumption (kWh/year)
 ρ_o Water Usage Effectiveness (L/kWh)
 T_w Wet-bulb Temperature (°C)
 ρ_x Energy Water Intensity Factor (L/kWh)
 θ Power Usage Effectiveness (dimensionless)
 e_k Electricity generation from energy source k
 w_k Water footprint of energy source k

$$\rho_o, baseline = -0.0001896 \cdot (T_w(r, 2025, m))^2 + 0.03095 \cdot T_w(r, 2025, m) + 0.4442$$

$$\rho_x, baseline = \frac{\sum_k e_k(r, 2025) \cdot w_k}{\sum_k e_k(r, 2025)}$$

Step 3: Model Dynamics

Growth Scenarios:

To account for increasing AI-driven compute demand, W_{tot} is analyzed under three growth scenarios. Applied to server energy consumption (e)

1. **Business As Usual (10%)** → rapid AI growth
2. **Moderate (5%)** → controlled growth
3. **Sustainable (0%)** → no growth

Temporal Modeling:

To preserve regional climate effects, a monthly resolution was used.

- Model evaluated using monthly wet-bulb temperature (T_w)
- Cooling water use varies by month due to seasonal climate changes
- Annual water use calculated as the sum of monthly values

This method captures seasonal variability that is lost in annual averaged

Step 4: Uncertainty Modeling

Define baseline energy demand

Randomly sample energy demand (e)

Compute water use using model equations

Repeat sampling (500 iterations)

Generate distribution (Mean, P5, P95)

RESULTS

Fig. 2. Projected Water Consumption in Phoenix until 2050 (Student Generated):

Phoenix shows rapid growth in water use under BAU, with strong seasonal fluctuations. The region's total usage is lower than Mumbai.

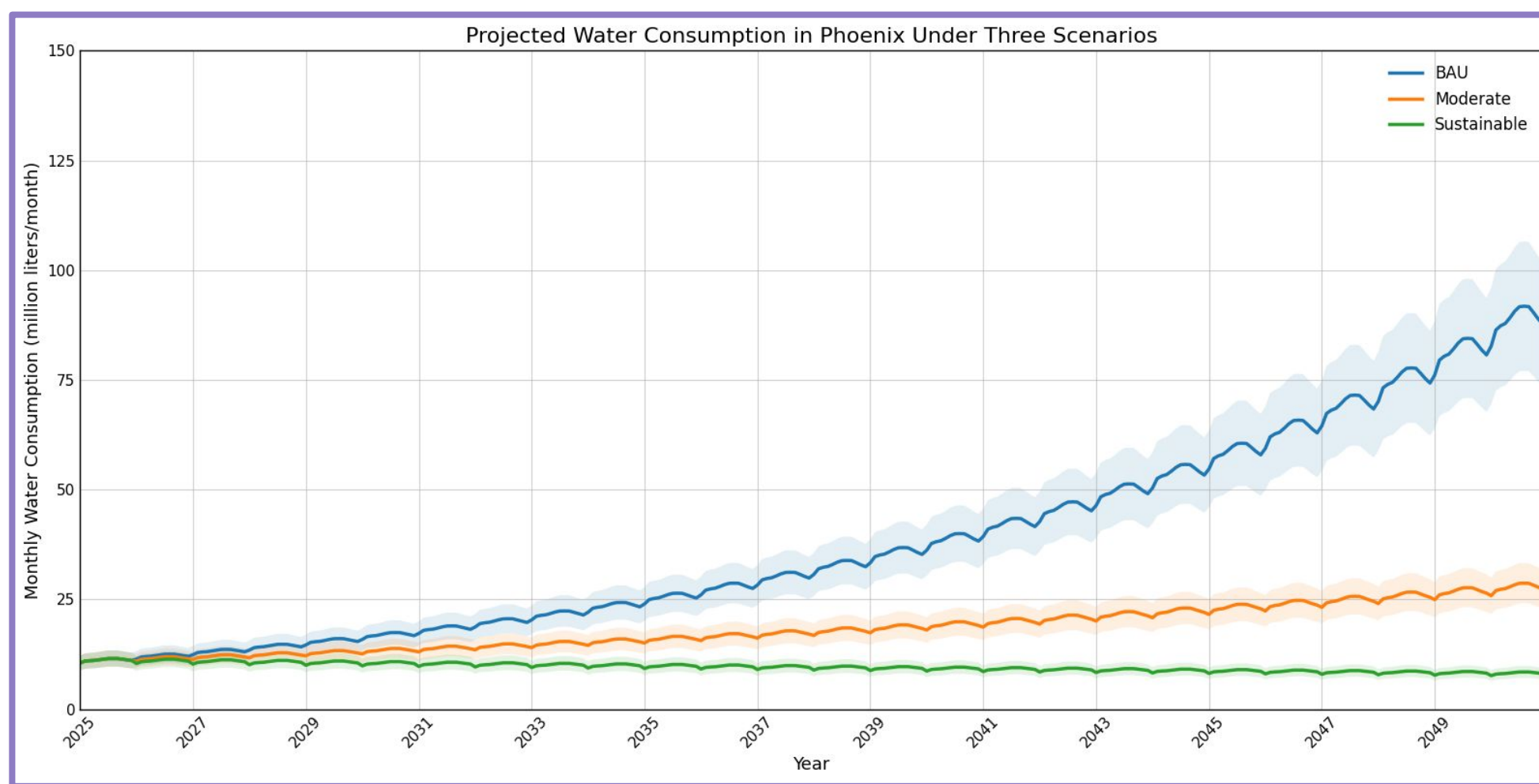


Fig. 3. Projected Water Consumption in Mumbai until 2050 (Student Generated):

Mumbai exhibits the highest overall water use across all scenarios, driven by the region's high energy demand and warmer climate. The wider uncertainty range indicates greater sensitivity to future growth in demand.

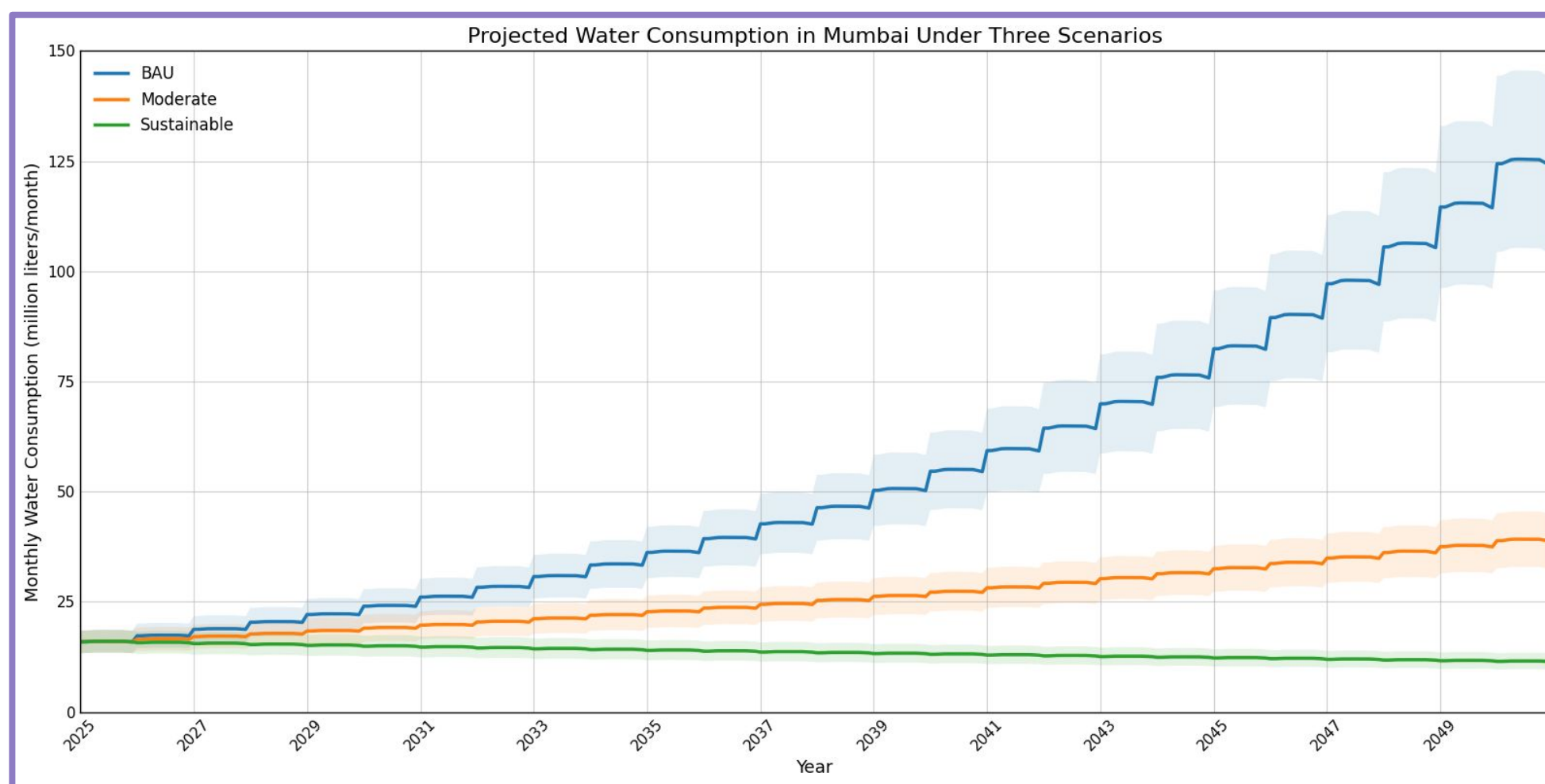
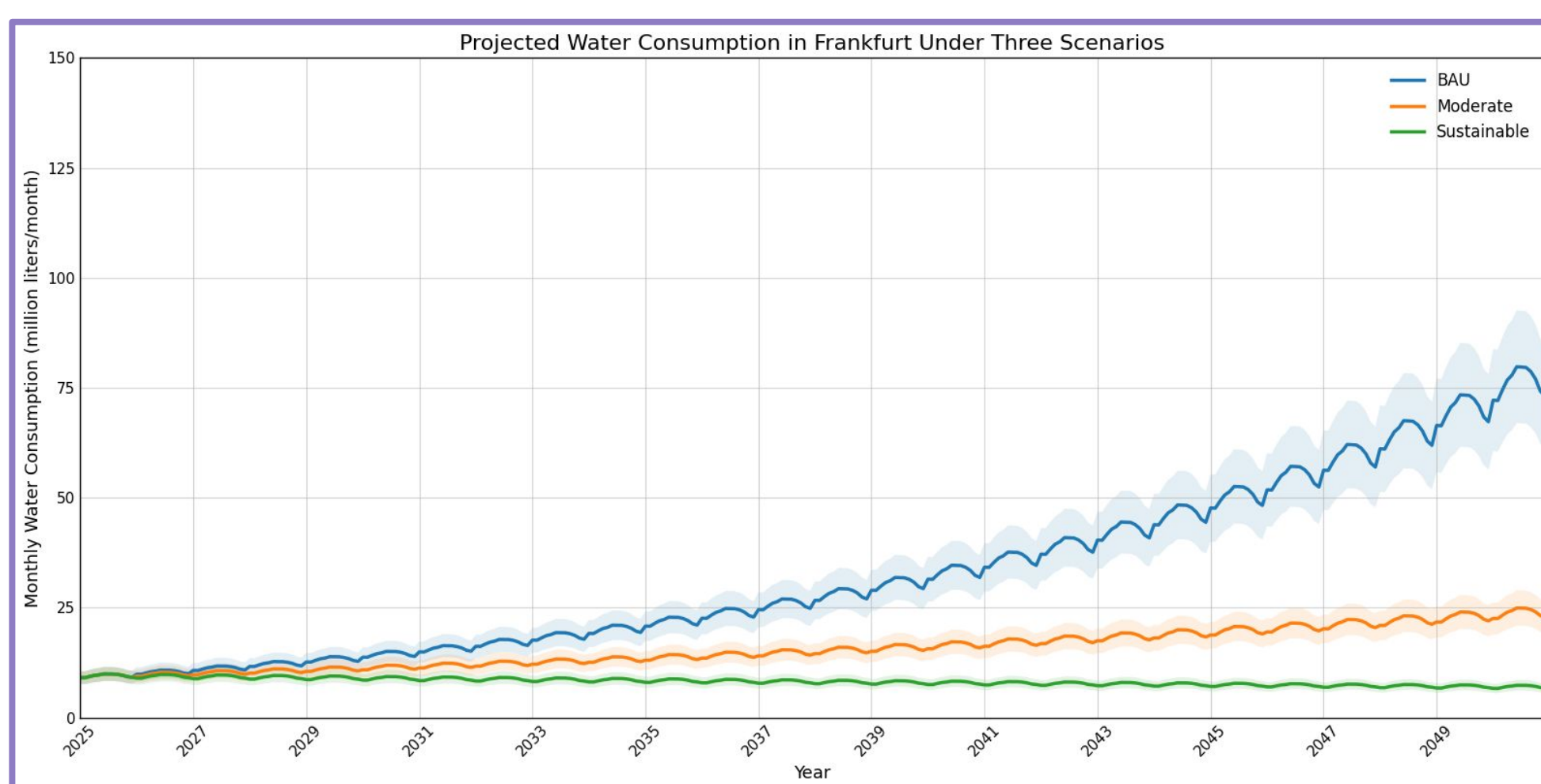


Fig. 4. Projected Water Consumption in Frankfurt until 2050 (Student Generated):

Frankfurt exhibits the lowest overall water use and reduced variability, showing the impact of cooler climate conditions on limiting cooling demand.



Higher AI growth amplifies regional differences in water use. Under growth scenarios, variations between regions become more pronounced, showing that climate and electricity grid composition strongly influence long-term projections. Across all regions, water use increases nonlinearly with higher growth, and uncertainty widens over time. In contrast, under the no-growth scenario, overall water use stabilizes and both uncertainty and seasonal variation decrease. This suggests that growth not only increases total water demand, but also magnifies the impact of regional factors over time.

STATISTICAL ANALYSIS

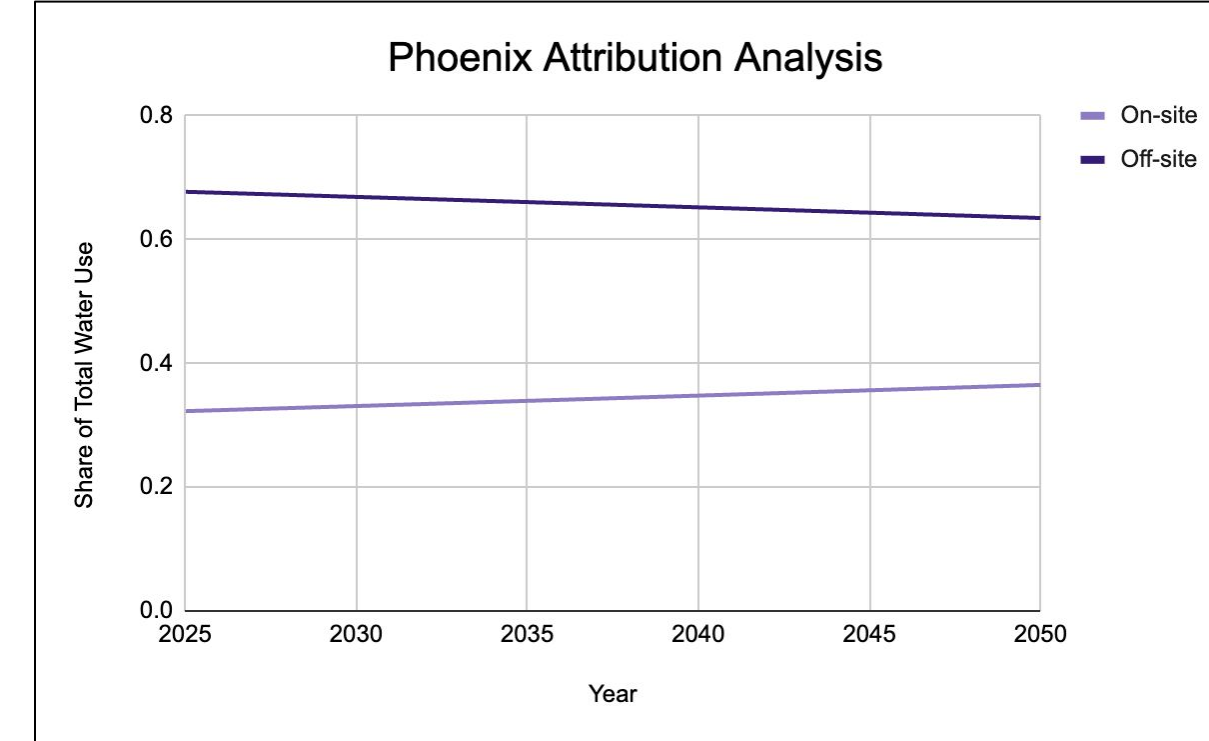


Fig. 5. Factor Attribution Analysis on Phoenix (Student Generated)

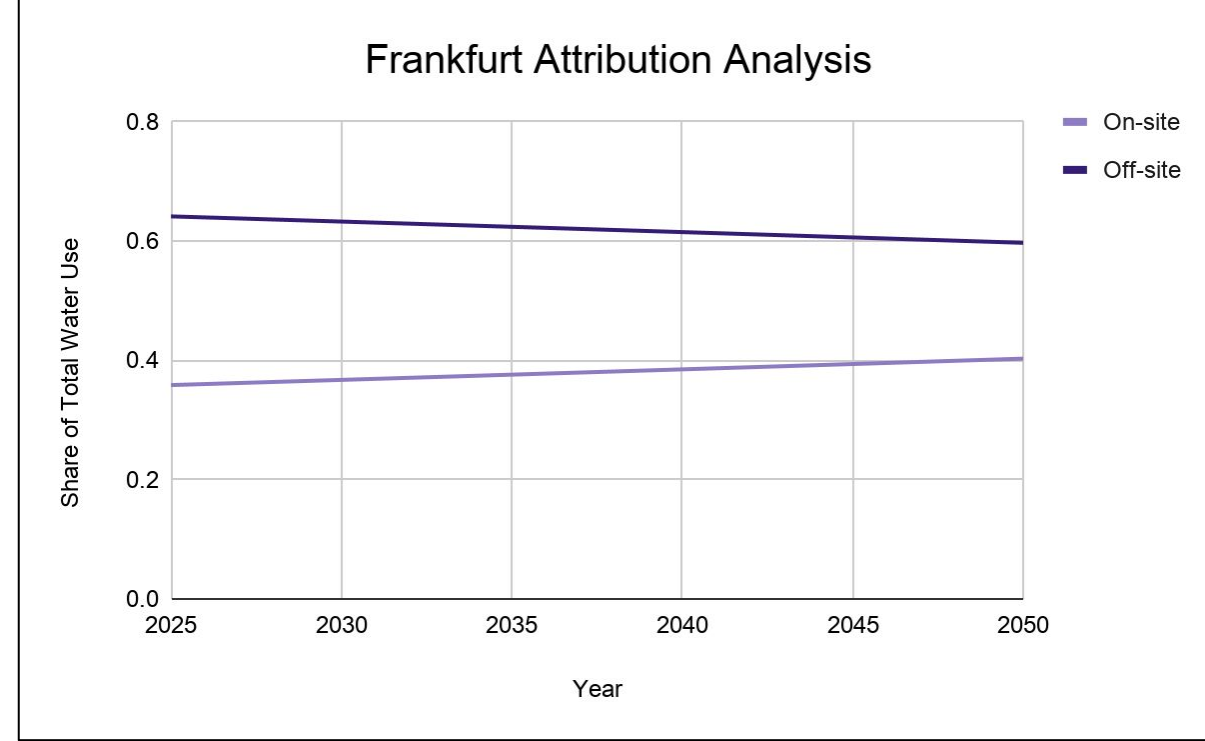


Fig. 6. Factor Attribution Analysis on Frankfurt (Student Generated)

Water use was decomposed into On-site(climate-dependent) and Off-site(electricity grid-dependent) using the model structure.

Off-site water use has a much higher contribution across all years, indicating a stronger influence of the energy grid than climate. However, its **contribution decreases over time** while the **contribution of on-site increases**.

This suggests climate-driven cooling becomes more important in long-term projections, though electricity-related water use remains dominant overall.

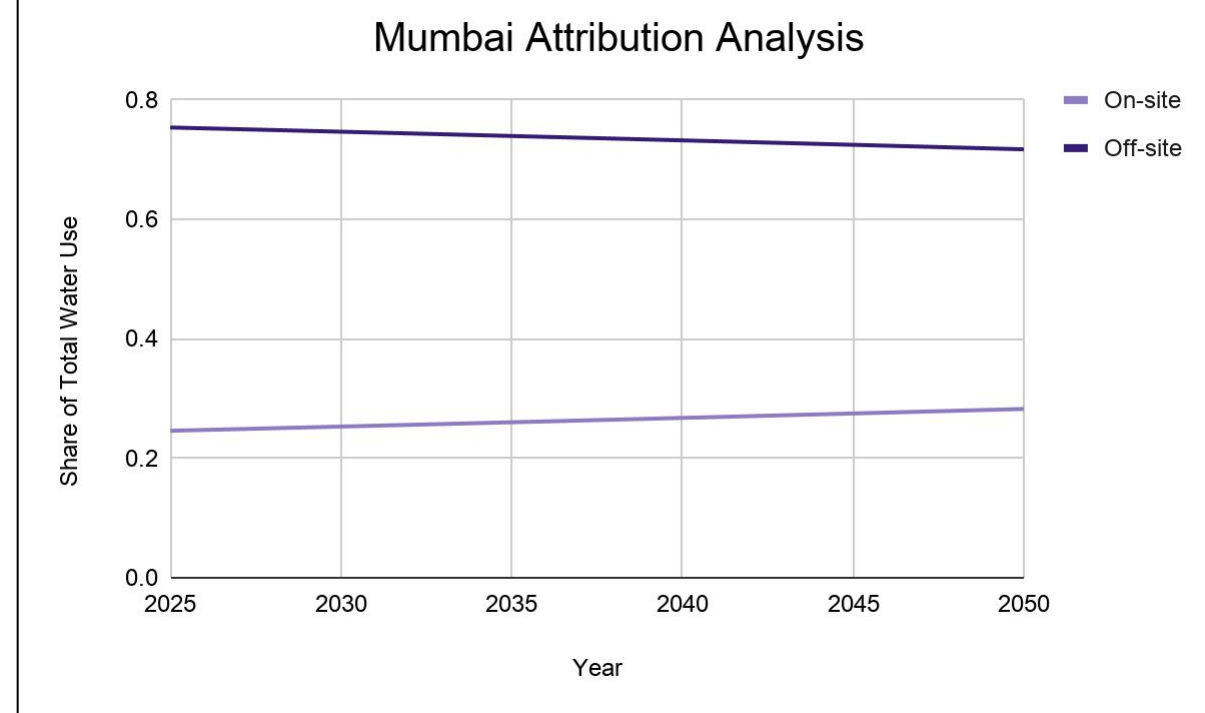


Fig. 6. Factor Attribution Analysis on Mumbai (Student Generated)

All analysis was done on BAU scenario because its most likely to occur if we follow current trends.

CONCLUSIONS

KEY FINDINGS

- **Water use varies significantly by region**, driven by differences in **climate (T_w)** and **electricity grid composition (EWIF)**
 - **Higher AI growth amplifies regional differences**, causing projections to diverge more over time
 - **Uncertainty increases under growth scenarios**, while stabilizing under no-growth conditions
- **EWIF has the strongest influence on total water use**, indicating that **electricity-related water use dominates overall impact**
- **Climate (WUE) plays a secondary but increasing role**, with its influence becoming more important over time due to rising cooling demand

LIMITATIONS & FUTURE WORK

Electricity grid composition is assumed constant over time

Future work can incorporate **dynamic grid transitions** (renewables)

Future climate change impacts on wet-bulb temperature are not modeled

Future work can integrate **climate projection scenarios**

REAL-WORLD APPLICATIONS

- Supports **data center site selection** based on regional water impact
- Identifies **high-risk regions** where growth may increase water stress
- Highlights **seasonal periods of higher operational impact**
- Provides a framework for **sustainable AI infrastructure planning**

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