

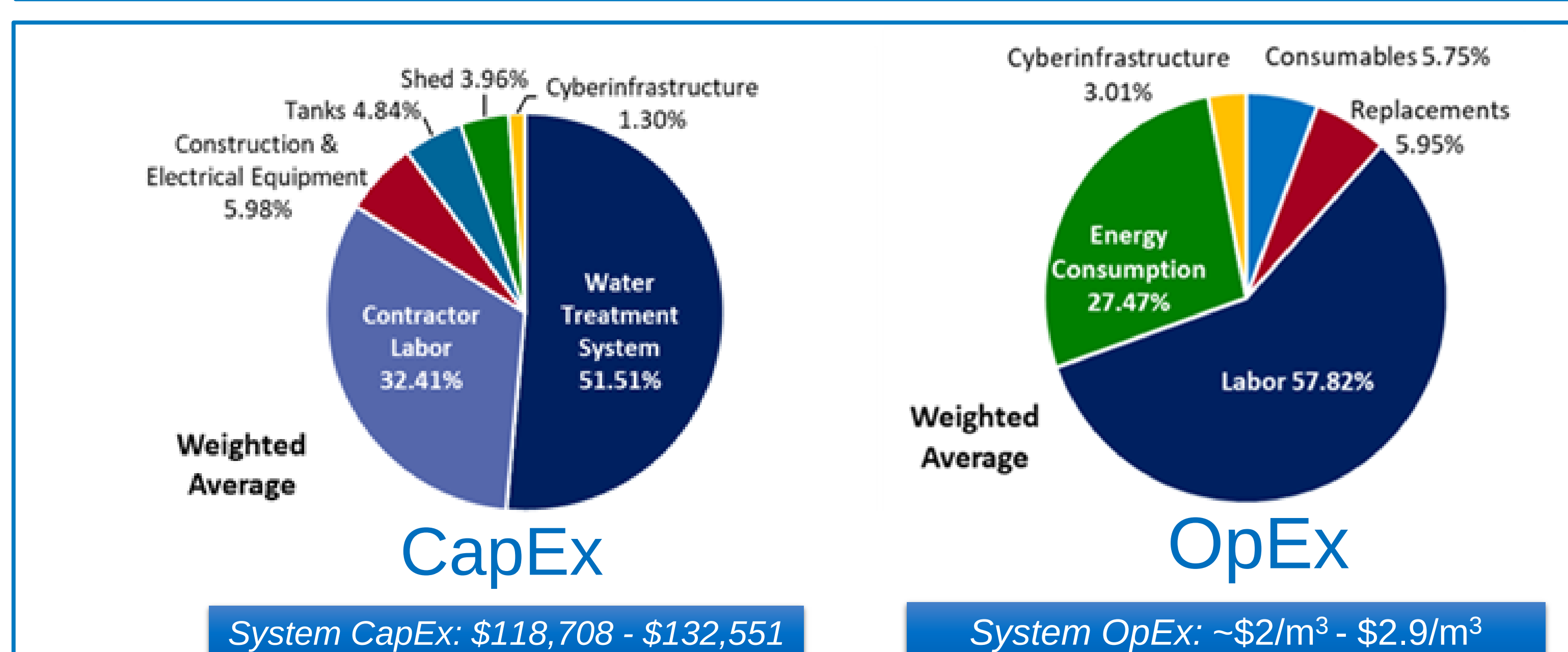
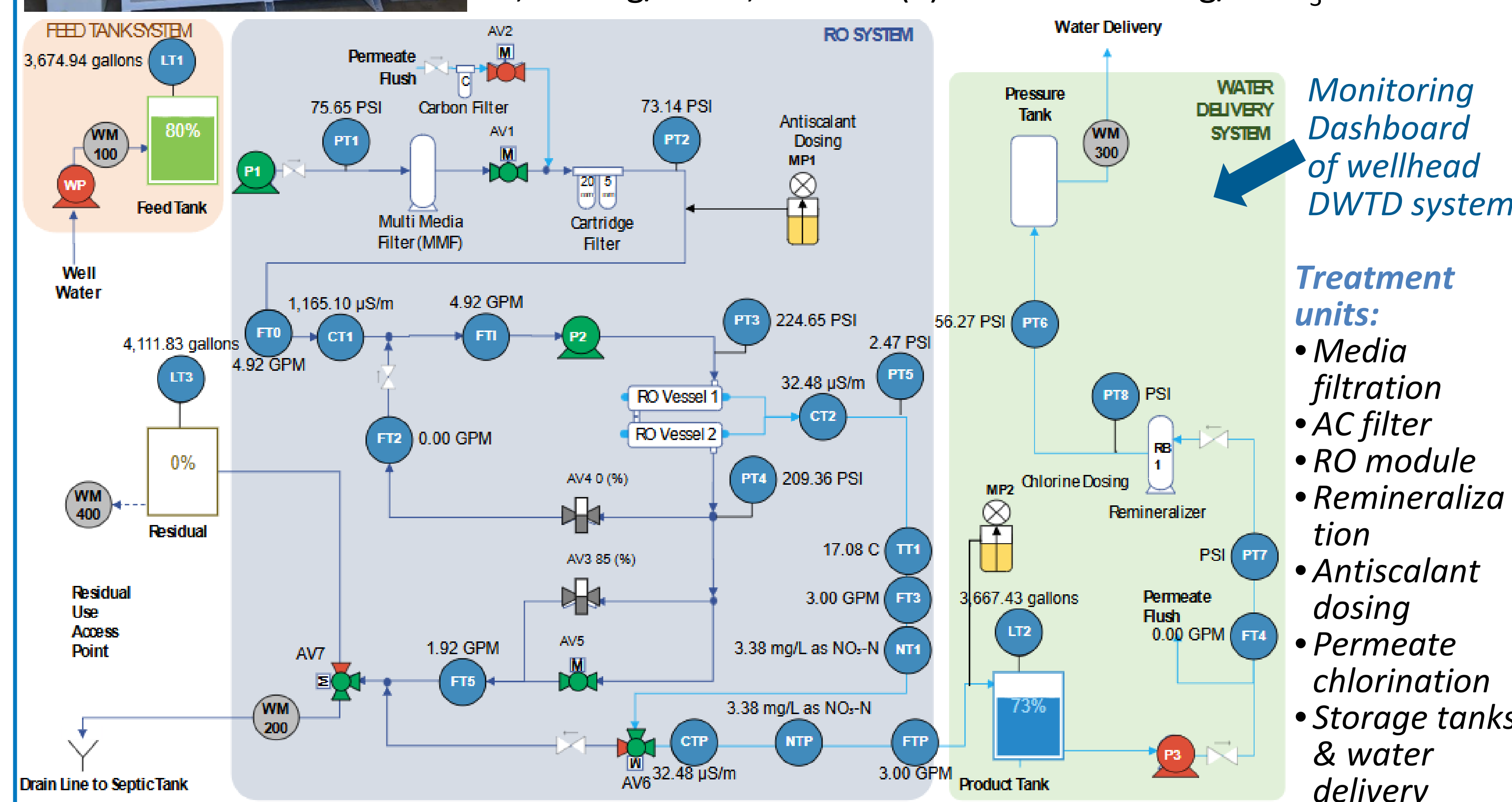
MOTIVATION AND OBJECTIVES

Integration of machine learning models with deterministic models (domain knowledge) for process automation, decision support and process optimization → Autonomous and robust self-adaptive Distributed Water Treatment and Desalination (DWTD) systems.

Application Space: Treatment and desalination of brackish groundwater, agricultural drainage water, industrial water, seawater and municipal wastewater treatment systems of varying sizes.

Water Treatment and Desalination (DWTD) Systems

(a) Three field deployed wellhead DWTD systems (located in Salinas Valley, CA): capacity of 2,500-5,800 gallons/day; and (b) Containerized DWTD mobile system (Capacity: 30,000 GPD) located in the Western side of the San Joaquin Valley, CA. Source water quality: Salinity: (a) ~600-1,600 mg/L TDS, (b) ~11,000 - 19,000 mg/L TDS; Nitrate: (a) nitrate 12-80 mg/L NO₃-N.

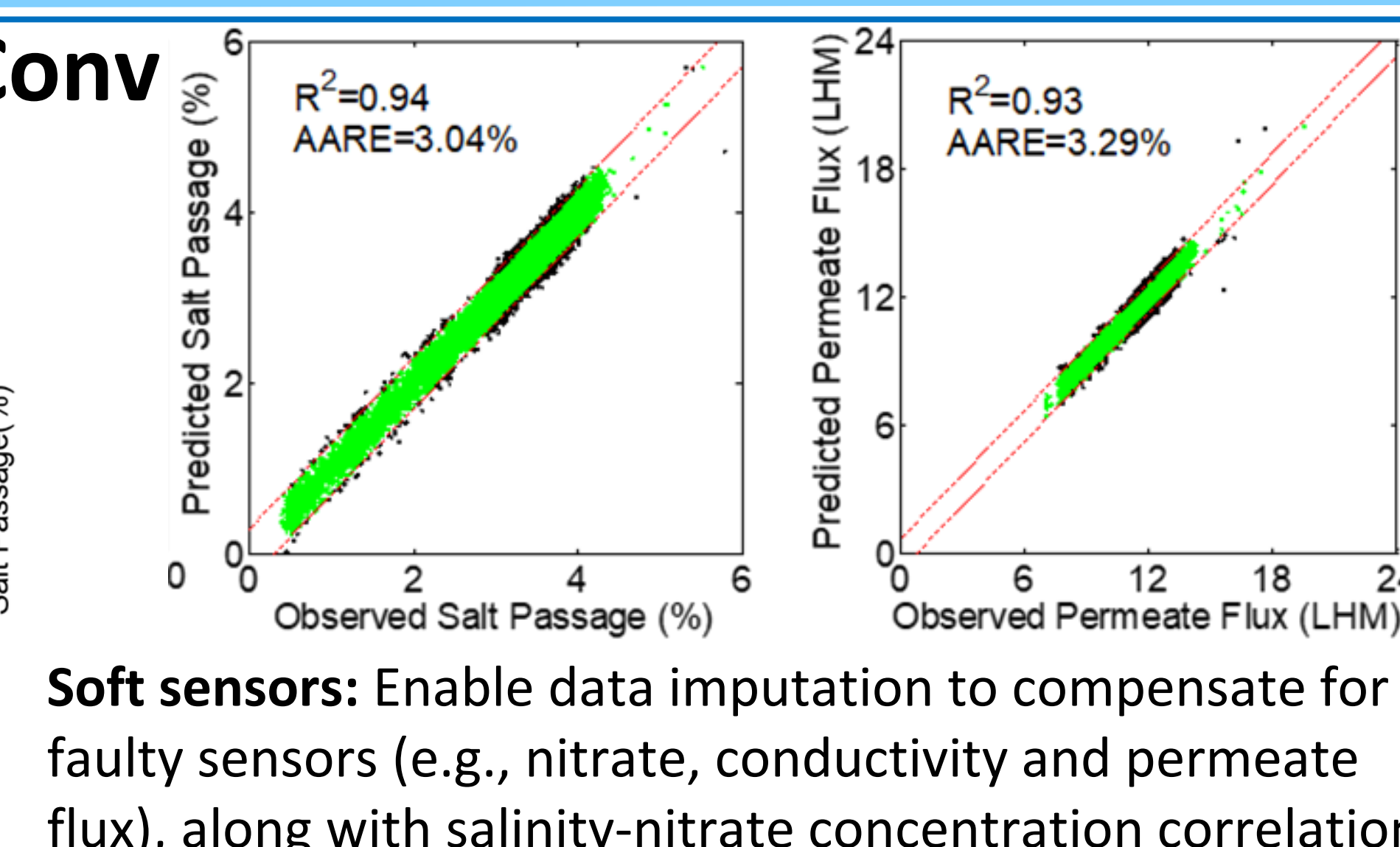
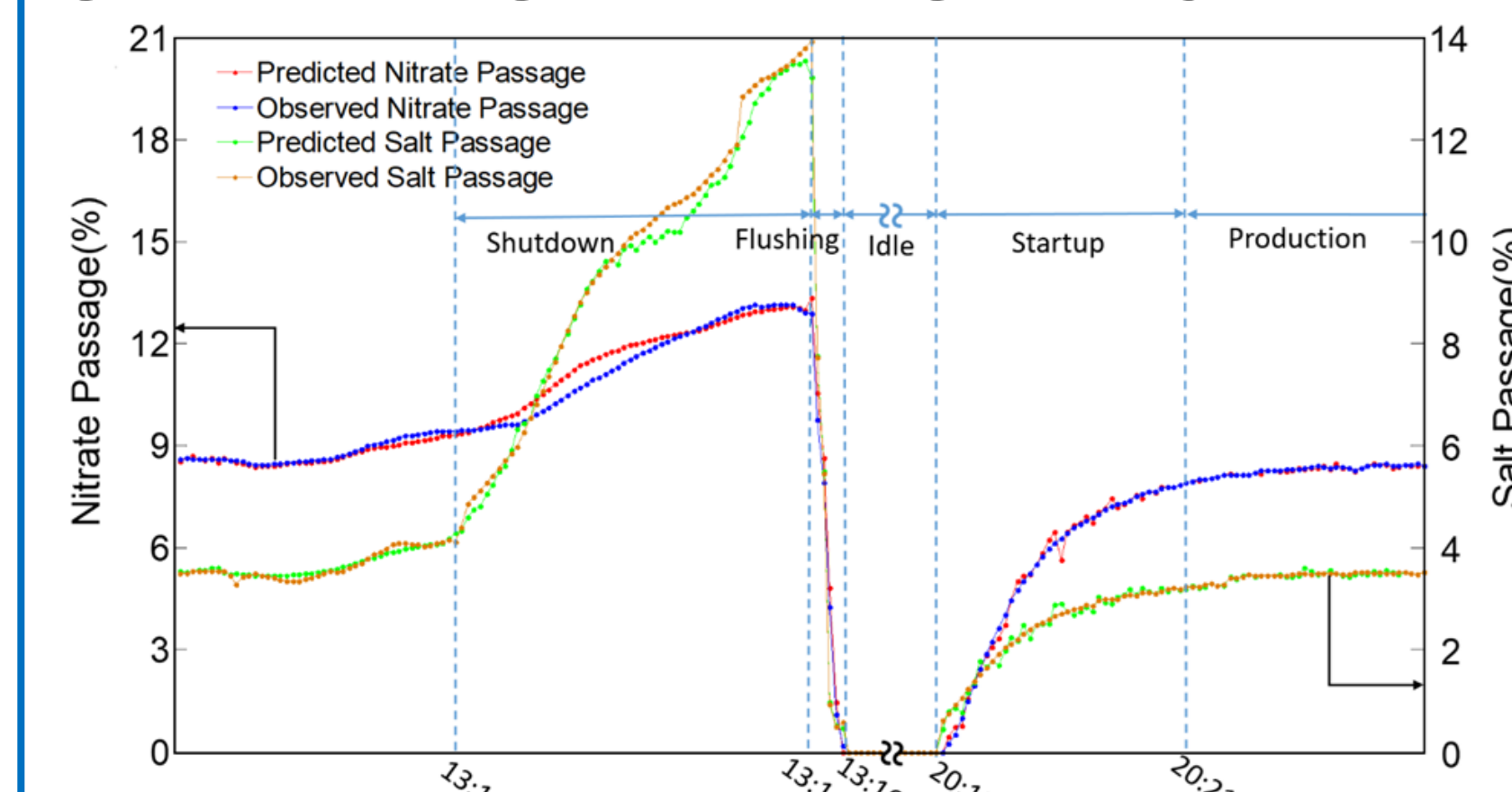


- DWTD treated water: ~\$2.0-2.9/m³ (\$39-70 per month per residential unit)
- Metered water in California: ~\$2-6/m³ (Salinas Valley: ~\$2-4/m³)
- Bottled water: \$258-413/m³

LIFE-CYCLE ASSESSMENT

- Electricity consumption drives ~50% of emissions.
- 30% reduction in GHG emissions is possible via treatment optimization based on grid GHG emissions.

SYSTEM RNN-LSTM and GATConv OPERATIONAL MODELS



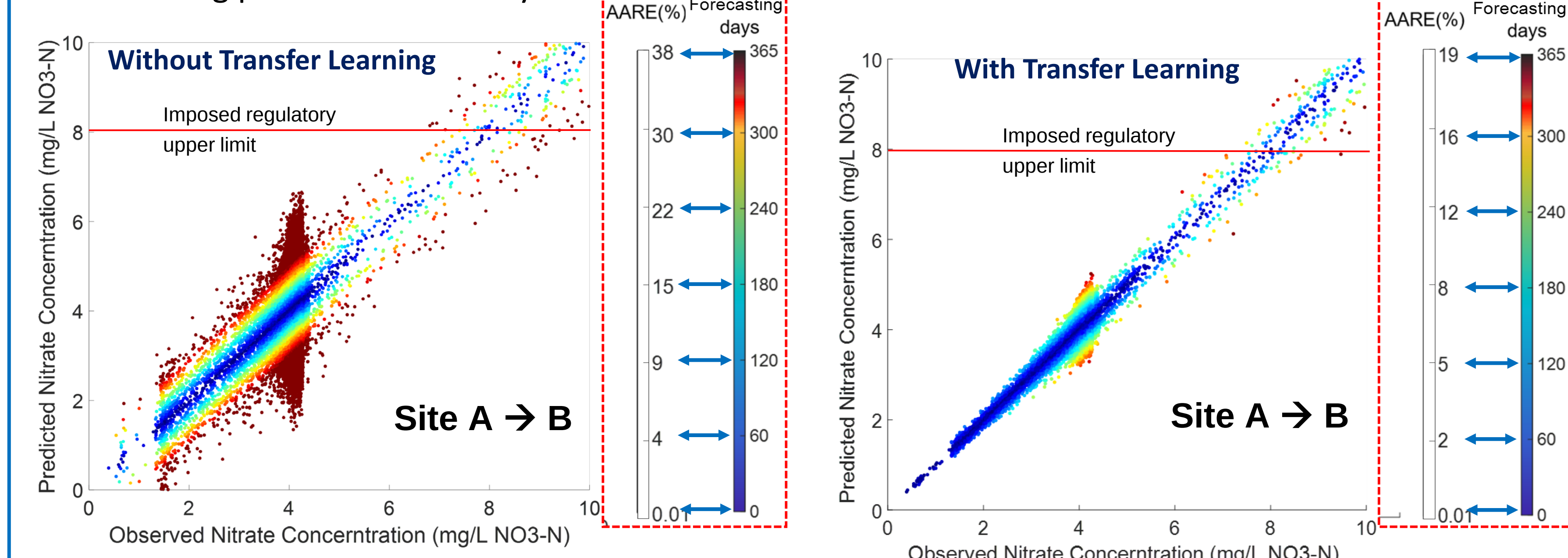
Soft sensors: Enable data imputation to compensate for faulty sensors (e.g., nitrate, conductivity and permeate flux), along with salinity-nitrate concentration correlation

ADAPTIVE LEARNING

Model adaptation accounts for new operating conditions and changes in DWTD system components/configuration, to retain model forecasting performance with a smaller dataset.

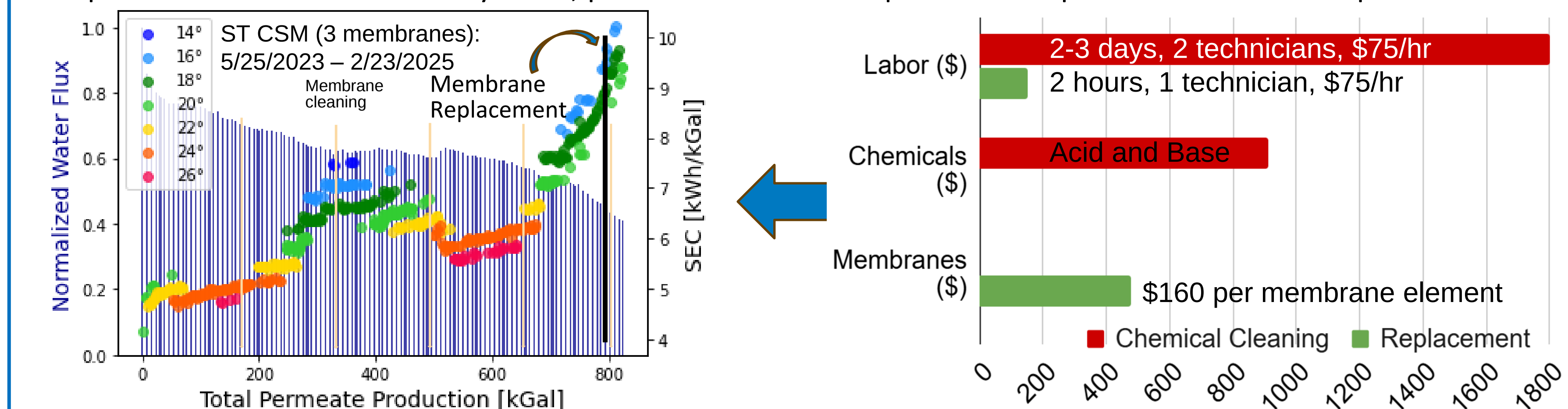
TRANSFER LEARNING (TL)

- ML models of the operation of DWTD system at a given site served as baseline models to develop new operational models for different systems in different geographical locations.
- TL accelerated commissioning period shortening the approval of new systems for delivery of safe potable water from 6 to 1-2 months.
- Forecasting period: ~50-100 days.



MEMBRANE CLEANING-IN-PLACE (CIP) VERSUS REPLACEMENT

- Membrane performance is impacted by membrane fouling, temperature and age.
- The common approach of assessing membrane performance degradation via ASTM normalization is insufficient to account for the impact of temperature and membrane aging.
- An approach was developed to establish the optimal timing for membrane replacement versus cleaning-in-place (CIP), considering the progression of membrane performance degradation and CIP cost relative to membrane replacement. For small DWTD systems, periodic membrane replacement is preferred to more frequent CIP.



KEY FINDINGS AND CONCLUSIONS

- Upgrading of impaired groundwater of small communities for potable use is affordable providing leveled water cost in the range of metered water (and lower) in the study region (Salinas, CA).
- Treated water produced by wellhead DWTD systems was shown to be affordable owing to autonomous system operation and remote monitoring & management which were enabled via: (a) DWTD cyberinfrastructure; and (b) ML models in support of operational decision making.

Major Accomplishments

- Forecasting the reliable performance of newly installed DWTD systems via transfer learning facilitated shortening of systems commissioning period from 6 to 1-2 months.
- Demonstration of DWTD systems robustness and performance reliability justified issuance of a General Waiver by for installation of *all* CA wellhead membrane-based water treatment systems of up to 10,000 gallons/day capacity with concentrate discharged to local community septic tanks.
- High-resolution operational data was acquired for 3 years of multi-mode operation of 3 DWTD systems (90M data samples each consisting data from of 22 sensors and 11 process tags).
- Over the project study period over 6,000,000 gallons of safe potable water were delivered to three DACs.

Next Steps

- Establish fault detection and decision support based on self-organizing maps and GATConv operational models.
- Explore opportunities for technology transfer/market development.

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