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Geosyntec consultants

AECOM

SCS ENGINEERS Environmental Consultants and Contractors

The Metropolitan Water District of Southern California

OC SAN Orange County Sanitation District

carollo®

BLACK & VEATCH

CDM Smith®

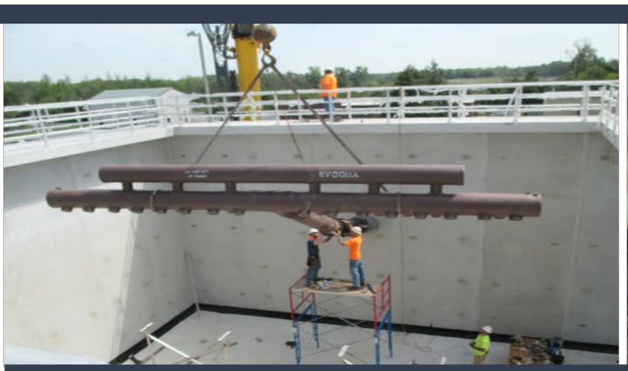
DSWA Delaware Solid Waste Authority

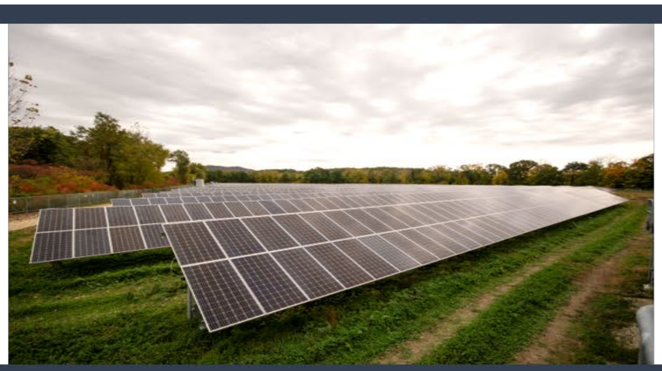
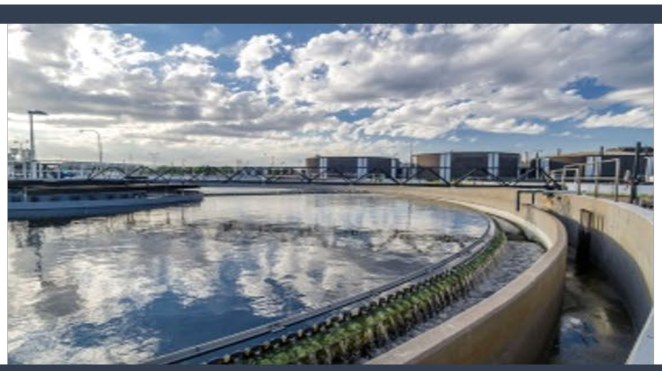
Los Angeles County Sanitation Districts Converting Waste Into Resources

Stanley Consultants

LA DWP Los Angeles Department of Water & Power

We will begin our presentation in a few minutes…



Leadership and Excellence in Environmental Engineering and Science

APPLICATION OF AI/ML FOR ENGINEERING SOLUTIONS IN THE WATER SECTOR

Aryan Emaminejad –AI/ML Engineer at Black & Veach, Chicago

AAEES

July 2nd 2025

Section I: General Discussion

Why Now? The Pressures Driving AI Adoption in Water

Aging Infrastructure

Decades-old water infrastructure is struggling to keep up with demand, leading to inefficiencies and failures. Artificial Intelligence (AI) can help monitor and predict maintenance needs.

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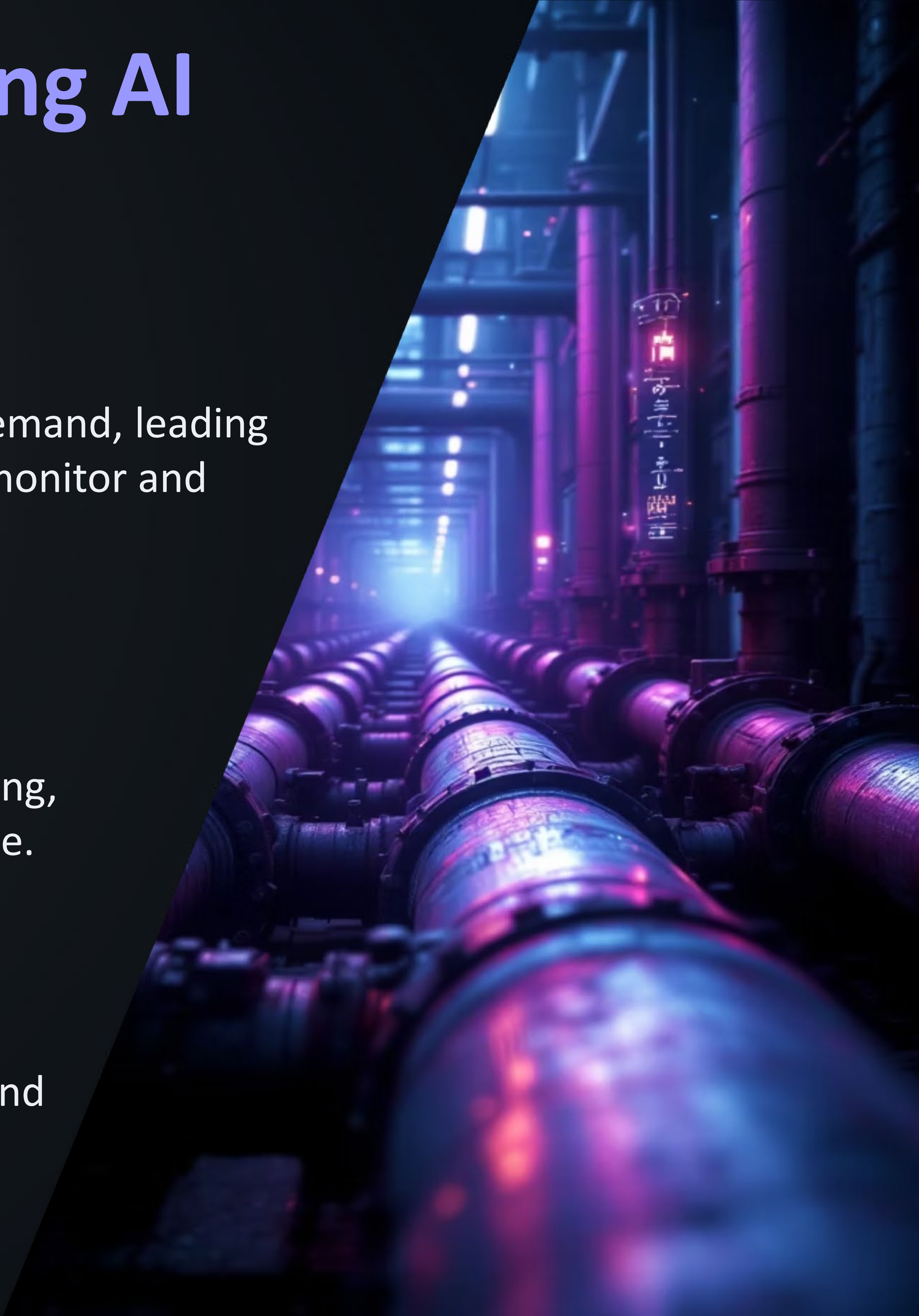
Regulatory Complexity

Evolving environmental regulations demand more precise data and reporting, areas where AI excels in ensuring compliance and transparency.



Digital Water Promises

Operational Efficiency and Cost Reduction

Real-Time Monitoring & Automation

Continuous oversight of water systems, automating processes and responding instantly to operational changes.

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Plant-Wide Cost Savings

AI algorithms precisely control chemical dosages in treatment processes, ensuring water quality while minimizing chemical waste.

Digital Water Risks

Navigating the Challenges of AI in Water

Cybersecurity Threats

Increased network exposure creates new attack surfaces, risking operational disruptions and sensitive data breaches.

LLMs: Large Language Models

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Operational Risk & Expertise Loss

Over-reliance on AI may diminish hands-on skills, causing challenges during system upsets.

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Regulatory & Ethical Concerns

Some AI applications, particularly LLMs, raise privacy, data governance, and ethical questions that need careful consideration.

LLMs: Large Language Models

The AI Spotlight: Why is Now Different?

AI/ML has been around for decades…

Lower Barrier to Entry

AI/ML frameworks are now more accessible, moving from complex academic environments to user-friendly platforms.

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ChatGPT's Impact

The advent of LLMs has significantly boosted public and industry awareness.

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Using LLMs Safely & Effectively

Retention	LLMs store data and may use it for future training.
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Privacy	Remove identifying details before sharing any information with LLMs.
Security	For organization handling sensitive data, enterprise solutions offer enhanced security.
Bias	Confirmation bias is a real issue and always be considered.

Using LLMs Safely & Effectively

Common Pitfalls

- Uncritical acceptance of AI responses
- Lack of citation verification
- Overconfidence in AI-generated content

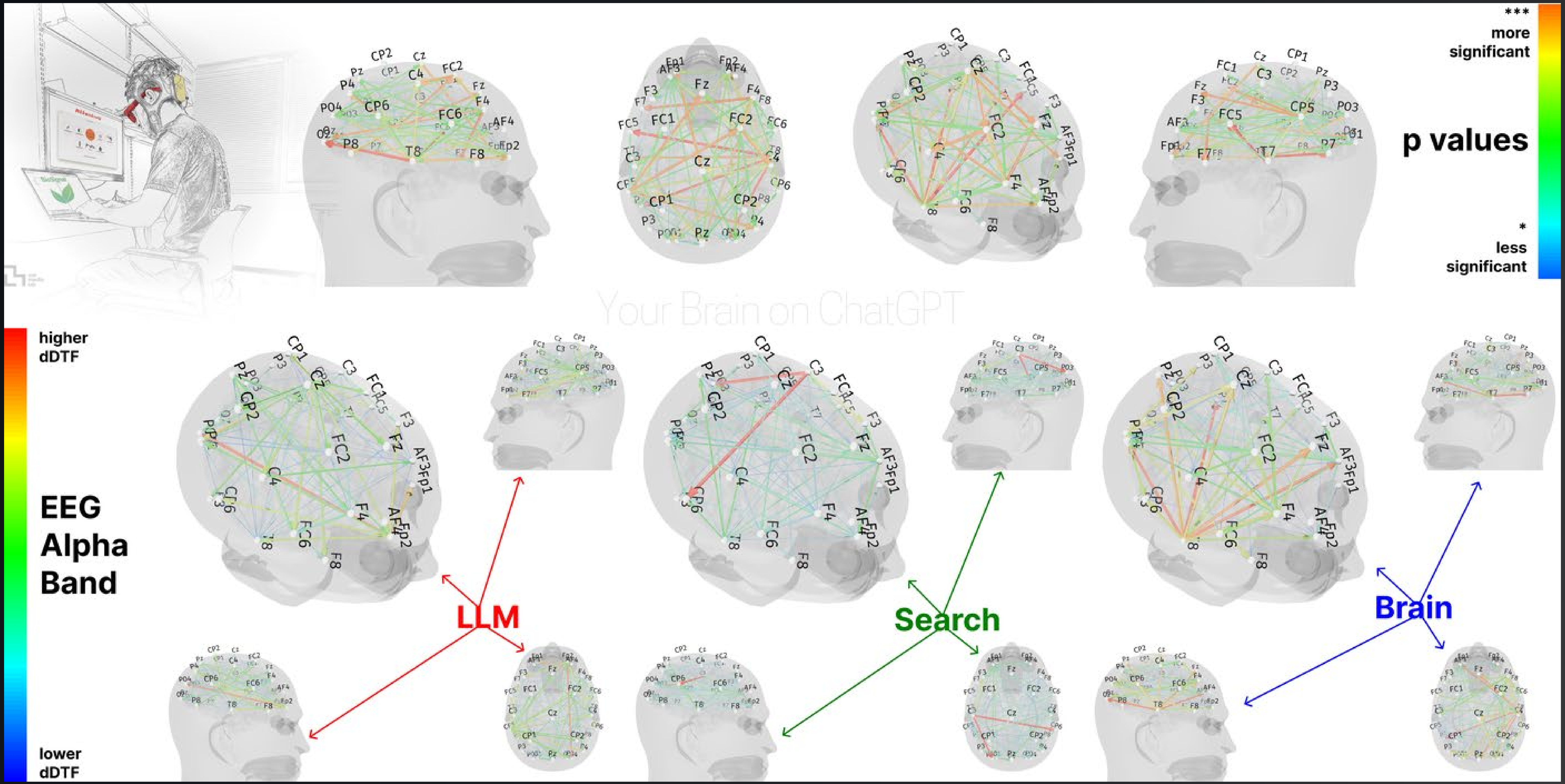
Best Practices

- Cross-reference information with trusted sources
- Verify facts before incorporating into work
- Use AI responses as starting points, not final products

Using LLMs: Augmentation vs. Replacement

What LLMs Can Do:	Human Expertise:
Process and summarize vast amounts of information	Domain-specific knowledge and judgement
Generate initial drafts and prototypes	Contextual understanding and nuance
Automate routine cognitive tasks	Ethical decision-making

Using LLMs: The Cognitive Task



The dynamic Direct Transfer Function (dDTF) EEG analysis of Alpha Band for groups: LLM, Search Engine, Brain-only, including p-values to show significance from moderately significant (*) to highly significant (***). Credit: Nataliya Kosmyna

https://www.media.mit.edu/projects/your-brain-on-chatgpt/overview/

AI Application: From Academia to Industry

The “WHY” Problem?

The “HOW” Problem?

AI Application: From Academia to Industry

Environmental Science & Technology

pubs.acs.org/est

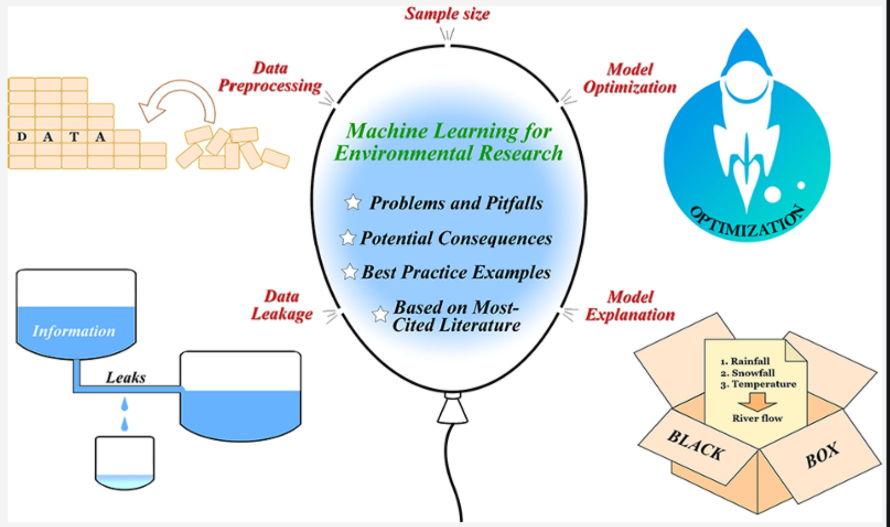
Critical Review

Machine Learning in Environmental Research: Common Pitfalls and Best Practices

Jun-Jie Zhu,* Meiqi Yang, and Zhiyong Jason Ren*

Cite This: *Environ. Sci. Technol.* 2023, 57, 17671–17689

ABSTRACT: Machine learning (ML) is increasingly used in environmental research to process large data sets and decipher complex relationships between system variables. However, due to the lack of familiarity and methodological rigor, inadequate ML studies may lead to spurious conclusions. In this study, we synthesized literature analysis with our own experience and provided a tutorial-like compilation of common pitfalls along with best practice guidelines for environmental ML research. We identified more than 30 key items and provided evidence-based data analysis based on 148 highly cited research articles to exhibit the misconceptions of terminologies, proper sample size and feature size, data enrichment and feature selection, randomness assessment, data leakage management, data splitting, method selection and comparison, model optimization and evaluation, and model explainability and causality. By analyzing good examples on supervised learning and reference modeling paradigms, we hope to help researchers adopt more rigorous data preprocessing and model development standards for more accurate, robust, and practicable model uses in environmental research and applications.



KEYWORDS: *Machine learning, supervised learning, environmental research, data preprocessing, data leakage, hyperparameter optimization, model explainability, causality*

https://pubs.acs.org/doi/full/10.1021/acs.est.3c00026

The "iPhone Plateau" for AI?

A period of exponential growth is usually followed by a stabilization in innovation and adoption…

iPhone 1st gen

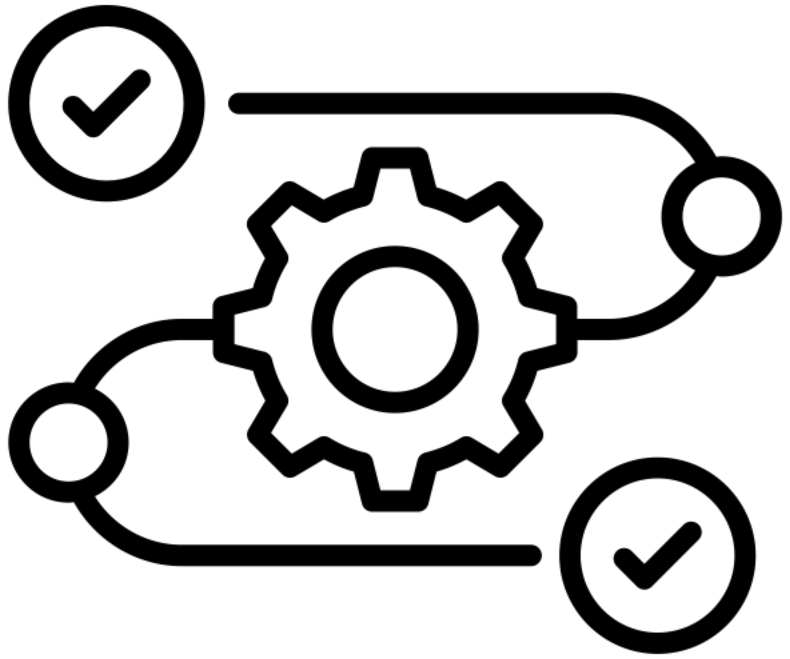
iPhone 7

iPhone 11, 12, 13, 14, 15, 16…

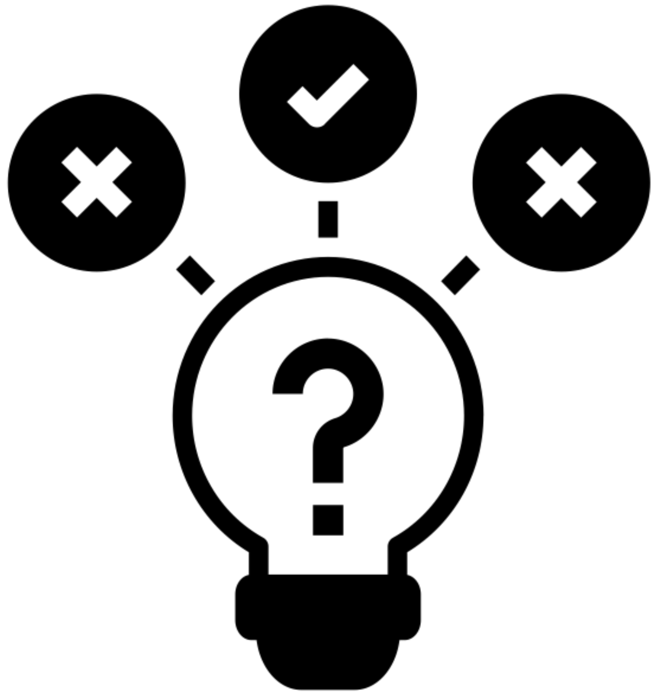
Section II: Engineering Case Studies

Mechanistic Models: Activated Sludge Model (ASM)

Fundamental Principles

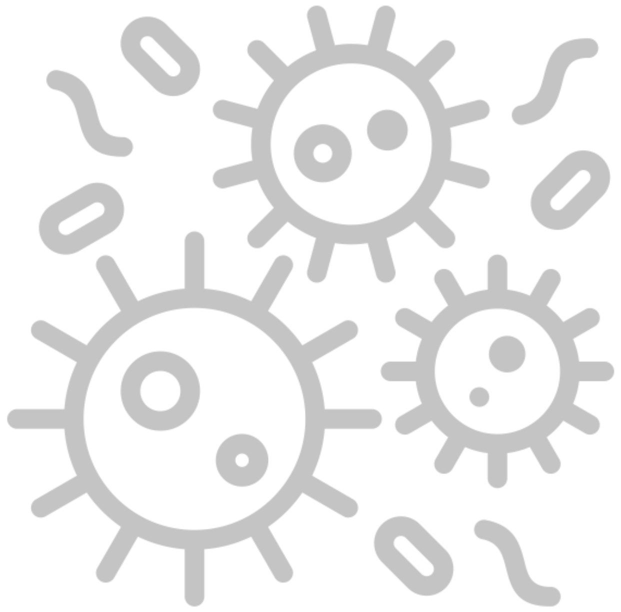


Describe Underlying Physical Process

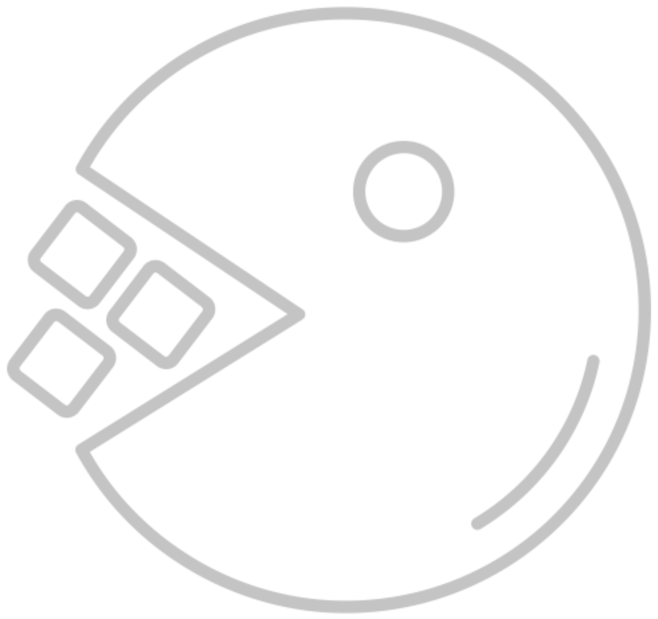


Require a Deep Understanding

Mechanistic Models: Activated Sludge Model (ASM)



Microbial Growth and Decay



Substrate Consumption

Oxygen Consumption

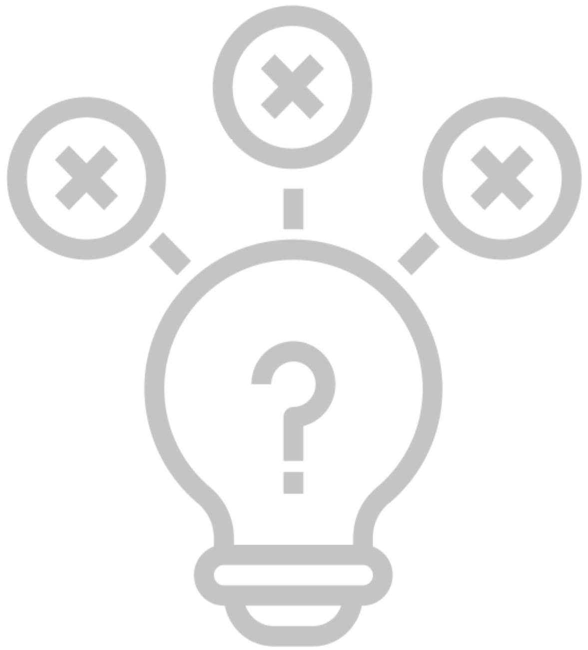
Nutrient Removal

sumo

GPS-X™

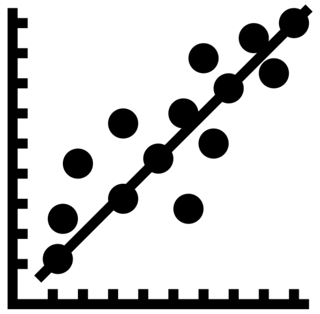
Machine Learning (ML) Models

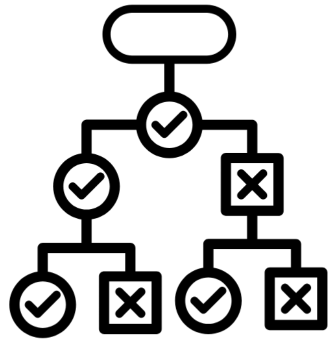
Mathematical Algorithms

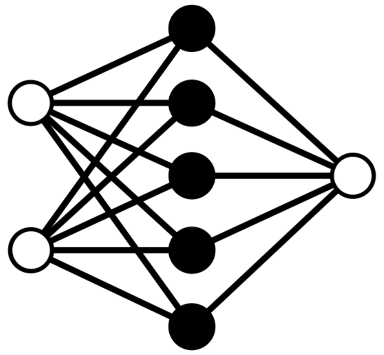


System Assumptions: Not Required

Physical Process Knowledge: Not Required







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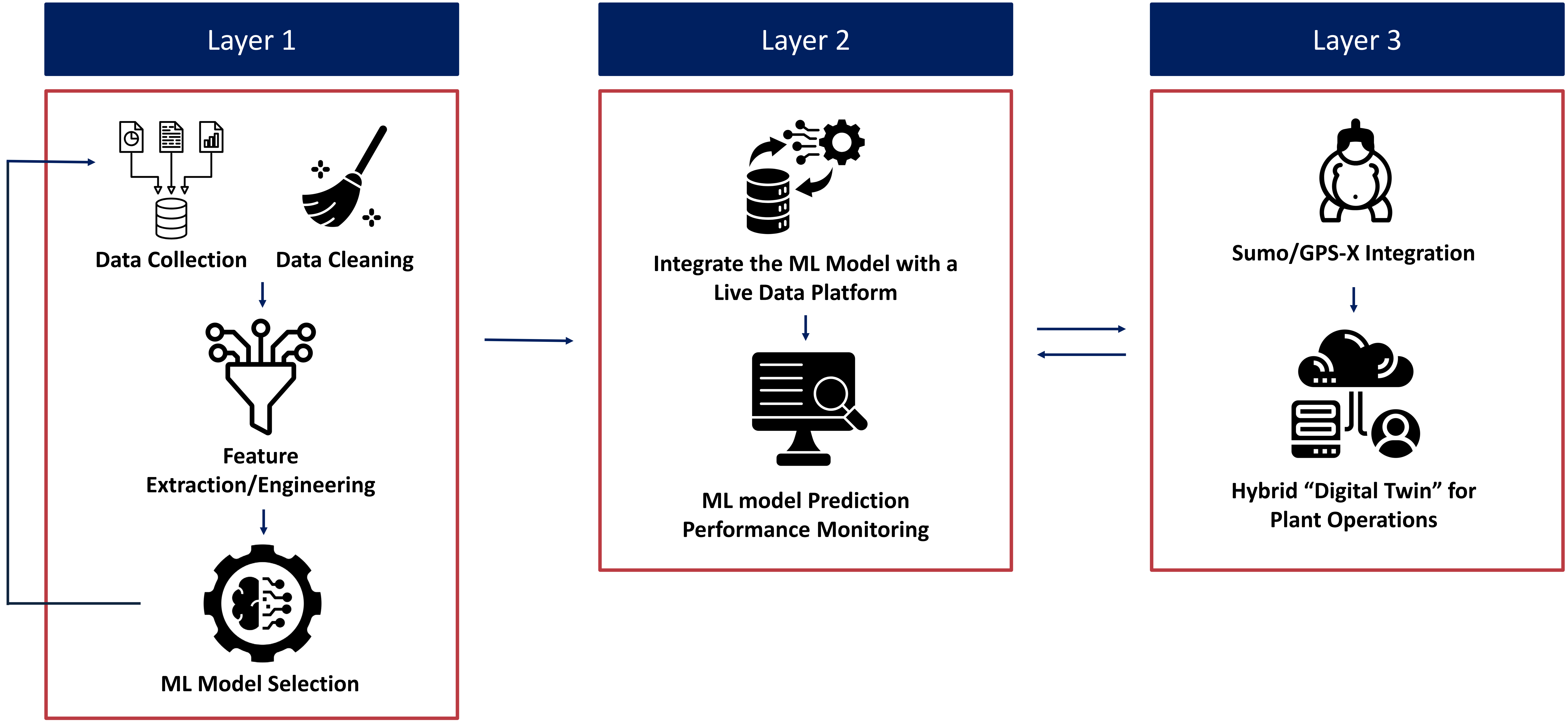
Architecture of an Integrated ML Model

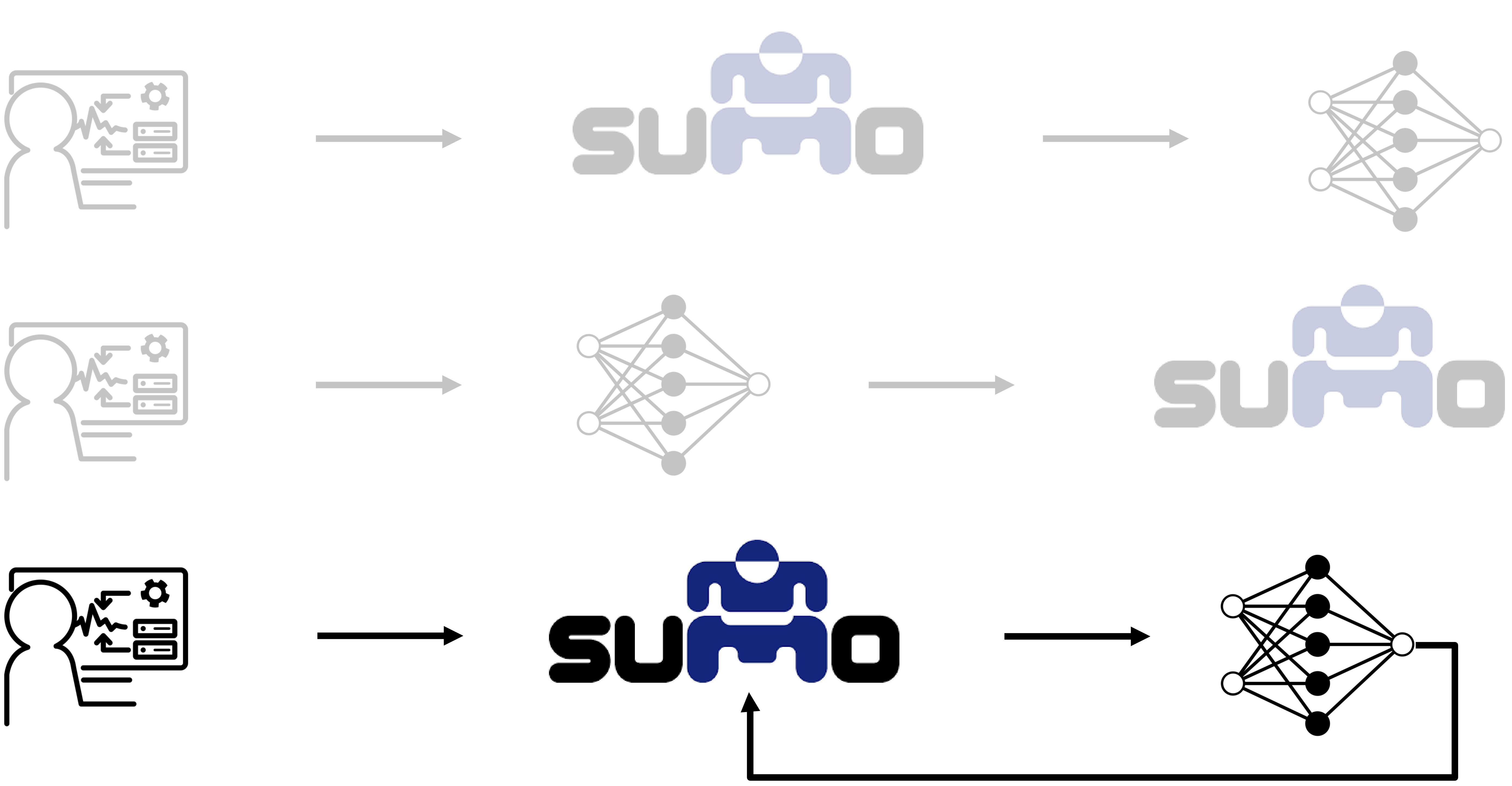


Mechanistic + ML Models: Hybrid Modeling

Mechanistic -> ML
e.g. Error Correction

ML -> Mechanistic
e.g. Soft Sensor

Mechanistic <-> ML
e.g. Emulator, Digital Twin



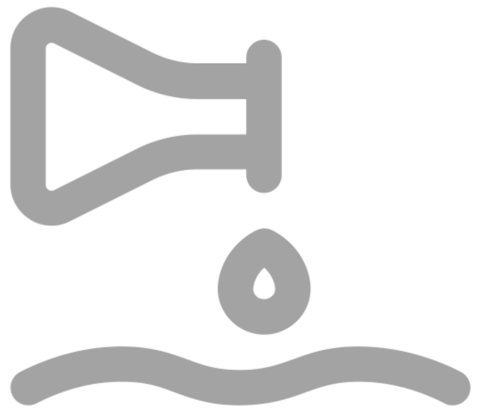
Case Study I:
HRSD - Nansemond

Background and Problem Statement

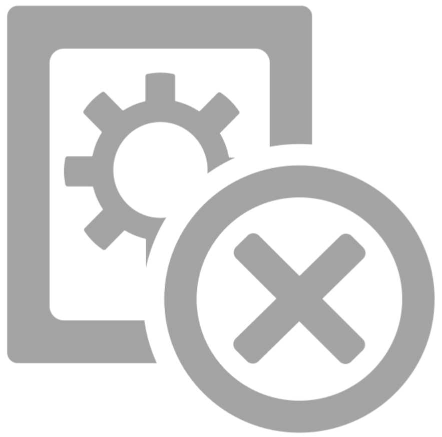
- Began Operation in 1983 and Treats 30 Million Gallons Per Day (MGD)
- 5-Stage Bardenpho® Process to Meet Biological Nutrient Removal (BNR) Standards
- Current Chlorination Process Utilizes Sodium Hypochlorite Dosing with a Feedback Control System.

Hampton Roads Sanitation District (HRSD) Nansemond Treatment Plant, Suffolk, VA

Background and Problem Statement: Permit Requirements



No More than 36 Exceptions with Chlorine Concentrations < 0.5 mg/L in a Month



No Violations with Chlorine Concentrations < 0.1 mg/L in a Month

Goal: Minimize Sodium Hypochlorite Usage While Meeting the Permit Requirements.

Background and Problem Statement: Desired Controller

Feedforward Component: Hybrid Mechanistic (Chlorine Decay) + Machine Learning (ML) Models

Feedback Component: Chlorine Sensor Measurements

Mechanistic Model Development

Parallel First-Order Decay Model for Chlorine

$$C(t) = \left(C_0 \times x \times e^{-k_1 \times t}\right) + \left(C_0 \times (1-x) \times e^{-k_2 \times t}\right)$$

10-Minute Resolution Data (Nov 2022 to Feb 2024): **C_t** and **C_0** Concentrations, CCT **HRT** Values

→

Bi-weekly **Nelder-Mead** Parameter Fitting: Find Values for **x**, **k_1**, and **k_2**

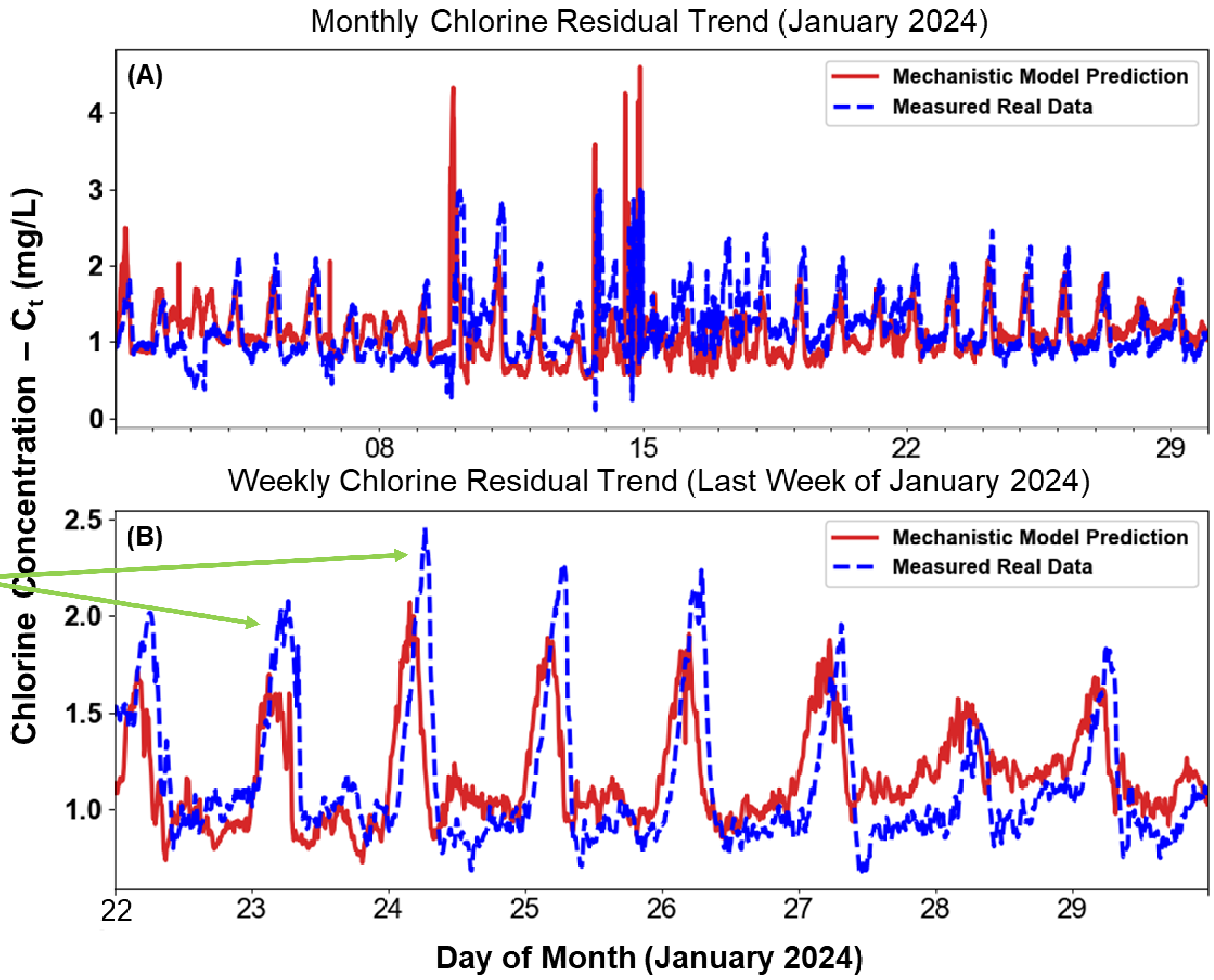
→

Estimate the **Chlorine Decay Function** Given the **Fitted Parameters** and Recorded **HRT** Values

CCT: Chlorine Contact Tank
HRT: Hydraulic Retention Time

Mechanistic Model Predictions: Error is Observed Between the Measured and Predicted Chlorine Concentrations

Observed Error Between the Measured and Predicted Chlorine Concentrations



Integration of Mechanistic and ML Models

C_0 Concentration, Picked by Plant

CCT HRT

C_t Concentration, Sensor Measurement

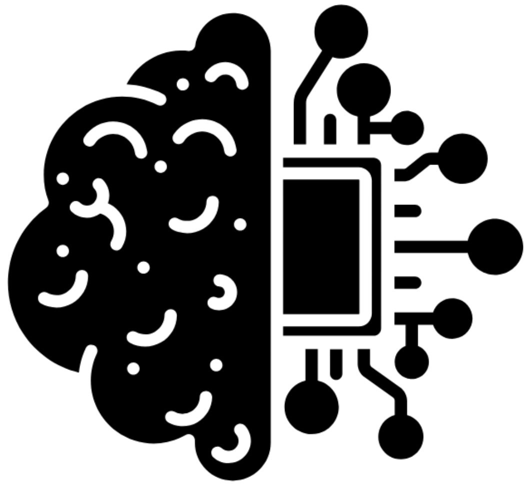
C_0 Concentration, Back-Calculated

Chlorine Decay Function

C_t Concentration, Sensor Measurement

Observed Error Between the Recorded and Back-Calculated C_0 Values

Advanced ML Error Correction Models



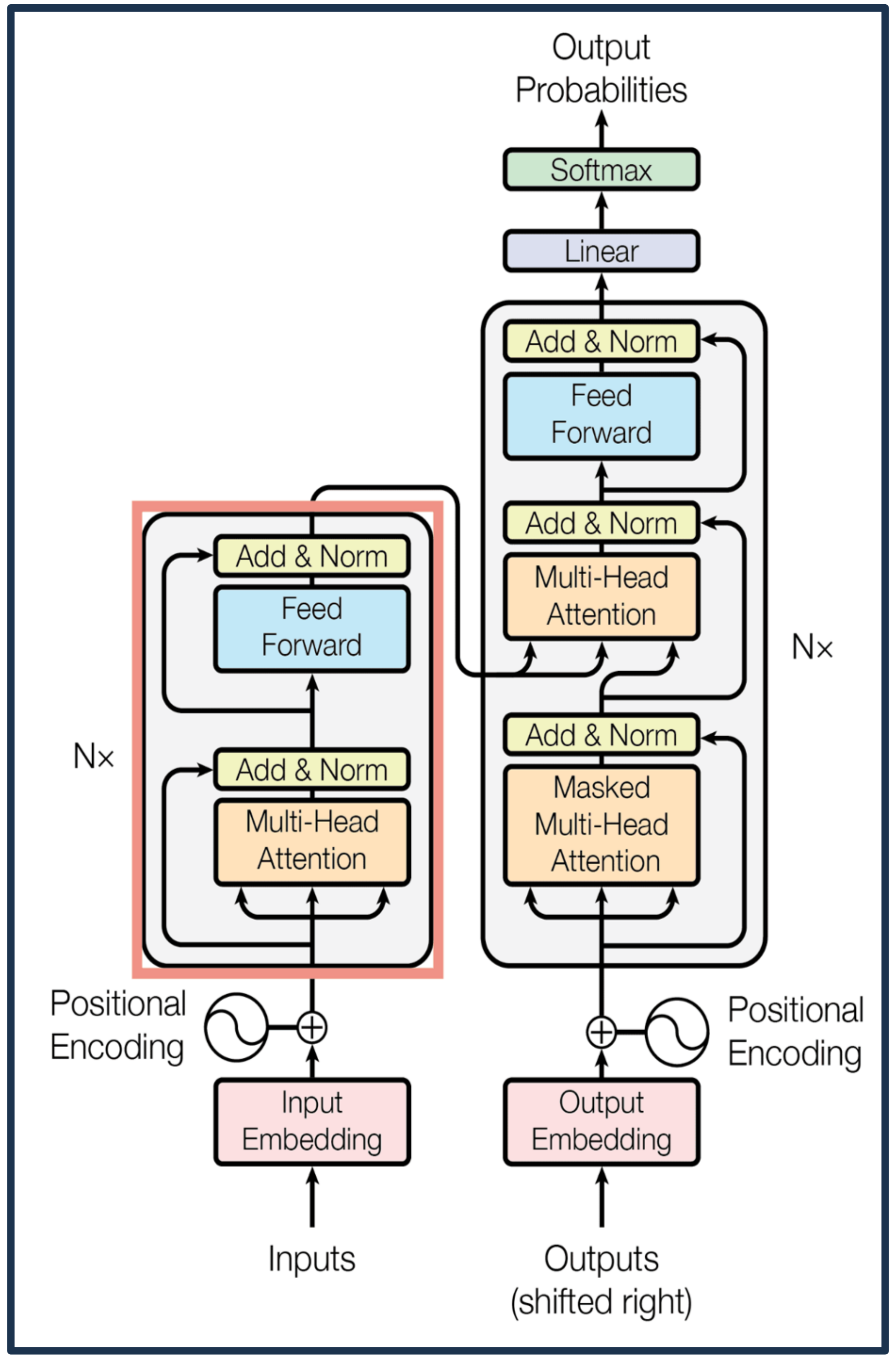
- Neural Prophet (Enhanced Facebook Prophet)
- Transformers (Building Blocks of ChatGPT)

Neural Prophet vs. Transformers

Neural Prophet

- Statistical Models + Neural Networks
- Limited Scalability with Large Datasets

Transformers

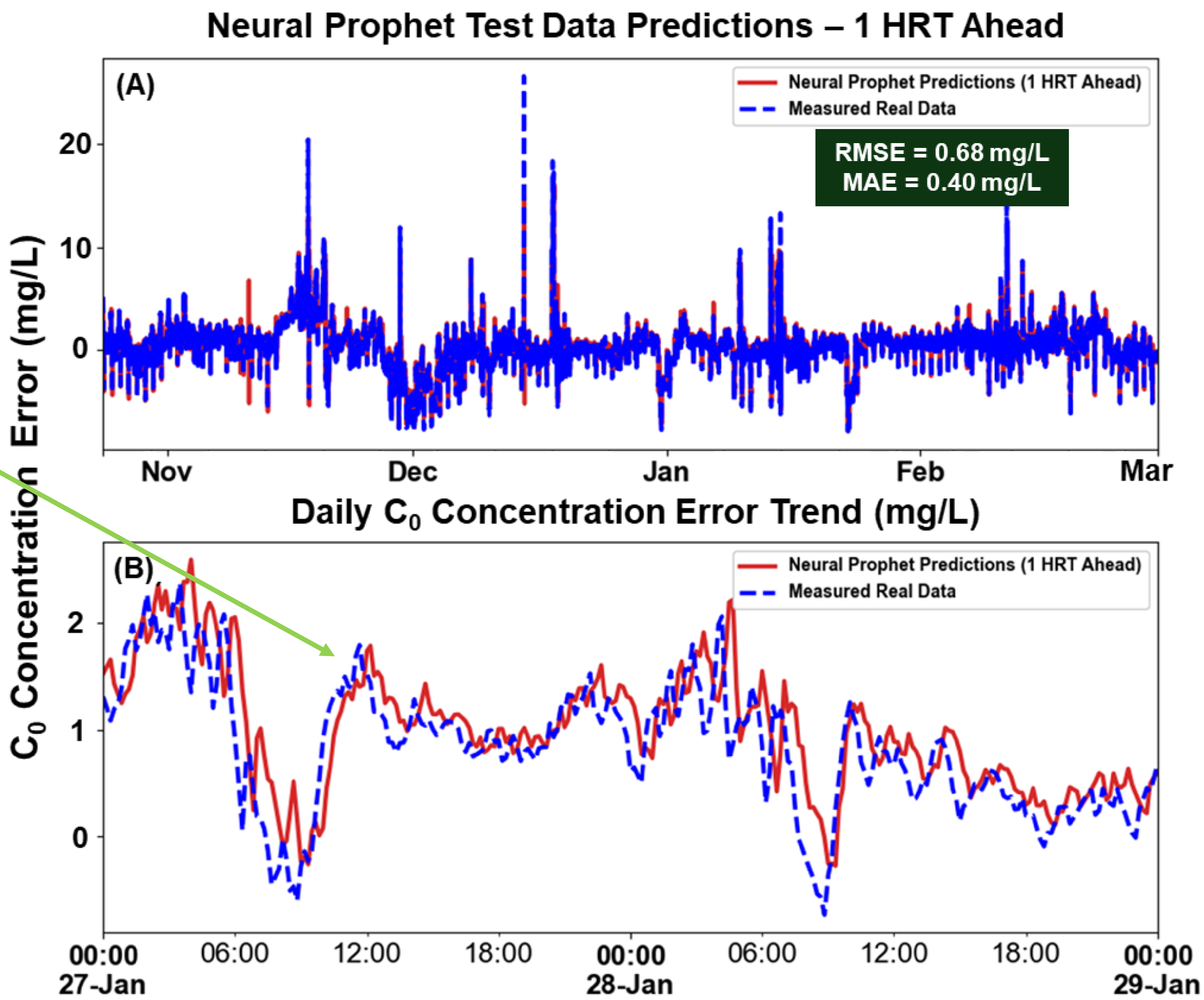


- Self-Attention: Captures Long-Range Dependencies
- Addresses the Temporal Evolution of Dynamic Systems
- High Computational Cost and Resource-Intensive

https://arxiv.org/abs/1706.03762

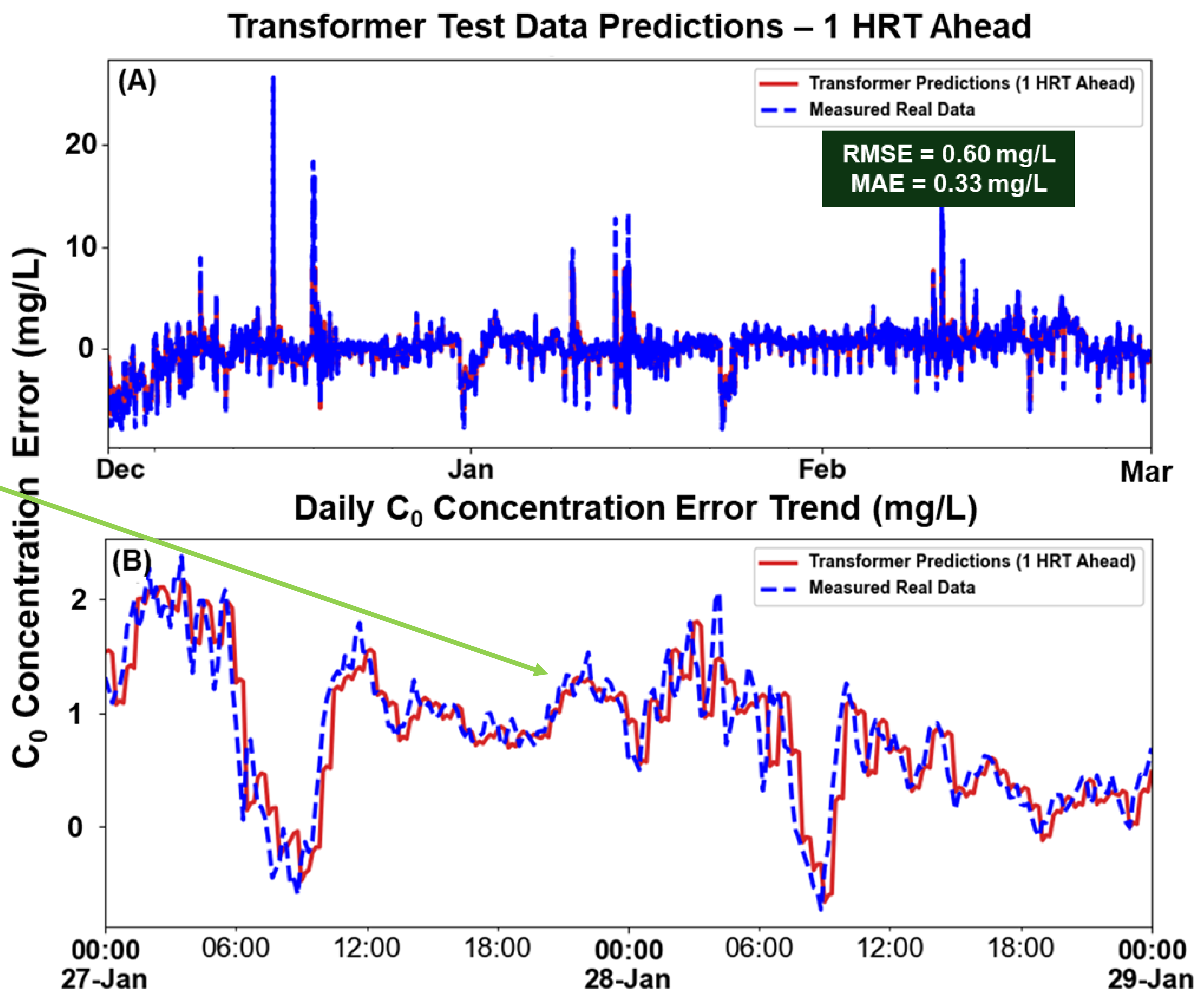
Neural Prophet Error Correction Results

- Neural Prophet Provided Accurate Predictions to Correct the Mechanistic Model Error.
- The Predictions Followed the Trend but Showed a Delay that Needed to be Properly Addressed.



Transformer Error Correction Results

- Transformers Further Improved the Neural Prophet Model Predictions.
- Additionally, Issues Related to the Delayed Predictions were Addressed.



Conclusions and Next Steps

- A Feedforward Component is Necessary to Create an Intelligent Chlorine Control System to Minimize Operational Costs and Maximize Process Stability.
- Using a Pure Mechanistic Approach Led to Inaccurate Sodium Hypochlorite Dosage Adjustments.
- The Hybrid AI/ML Models Fixed Mechanistic Errors and Accurately Adjusted the Dosage Rates.
- Next Step: Develop a Model Predictive Control (MPC) System to Minimize Costs.

2024 LIFT Intelligent Water Systems Challenge (2nd Place)
WEFTEC, New Orleans

https://www.waterrf.org/serve-file/2024_IWS-Challenge-Solution_Black-Veatch-HRSD.pdf

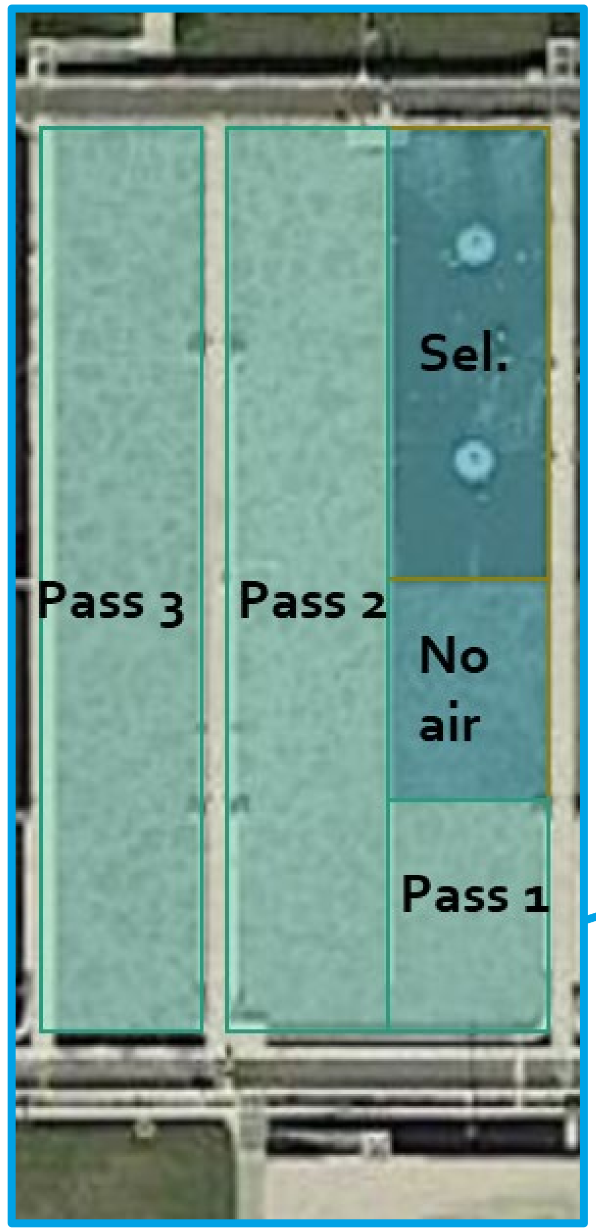
Case Study II: Fond du Lac

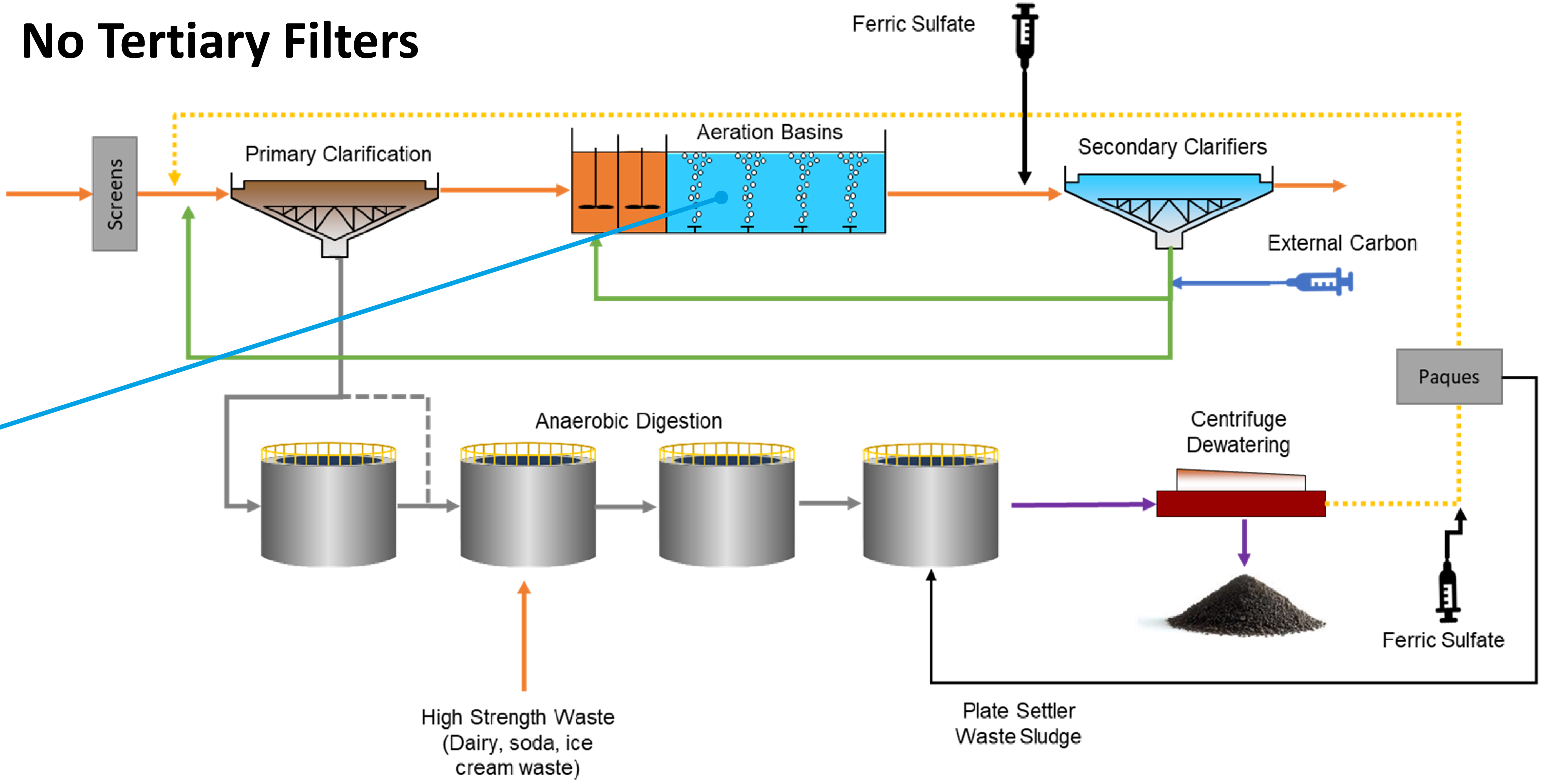
Fond du Lac Wastewater Treatment & Resource Recovery Facility

- Located 1.5 hours north of Milwaukee serving a population of **75,000**
- Resource Recovery Facility focus on sustainability
- Biggest challenge: **Effluent phosphorus (TP)** requirement of **0.17 mg/L** (pending)
- Inconsistent industrial contribution (dairy)
- Locally sourced waste carbon (expired soda)

Overview of the Fond du Lac Treatment Process

- **Anaerobic / Aerobic Process**
- **Ammonia Based Aeration Control**
- **Sidestream De-ammonification**
- **No Tertiary Filters**





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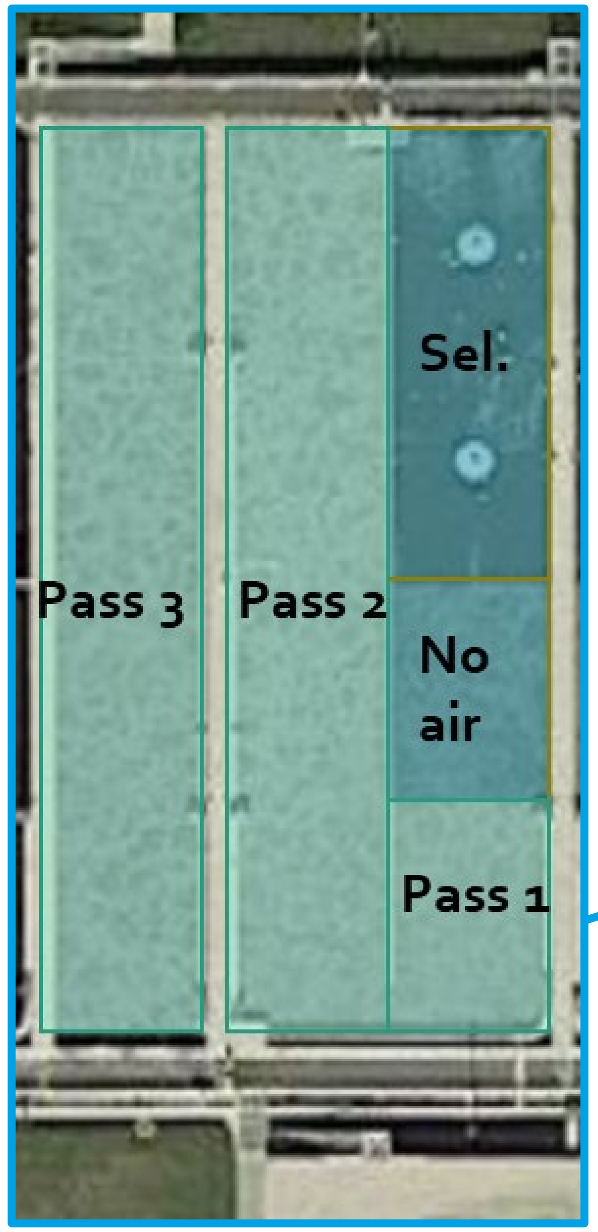
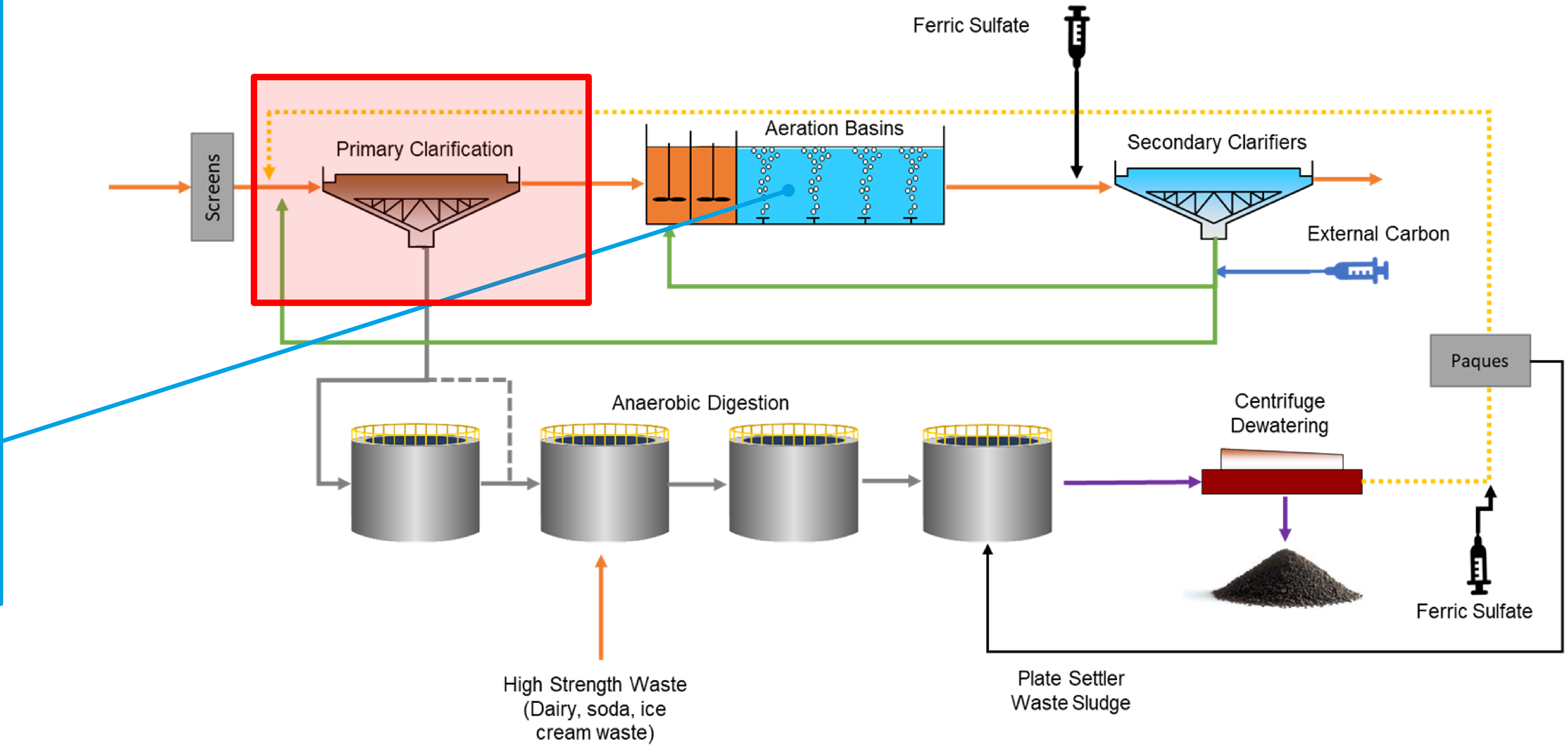
Overview of the Fond du Lac Treatment Process

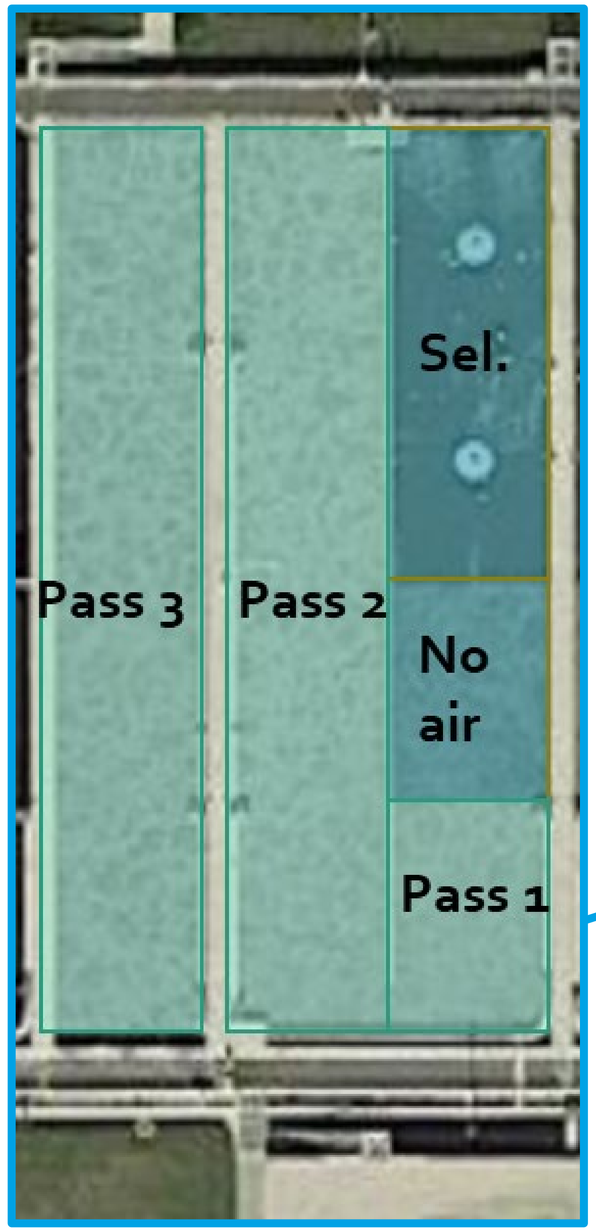
- **Use ML to predict future concentration/load using weather and plant data.**

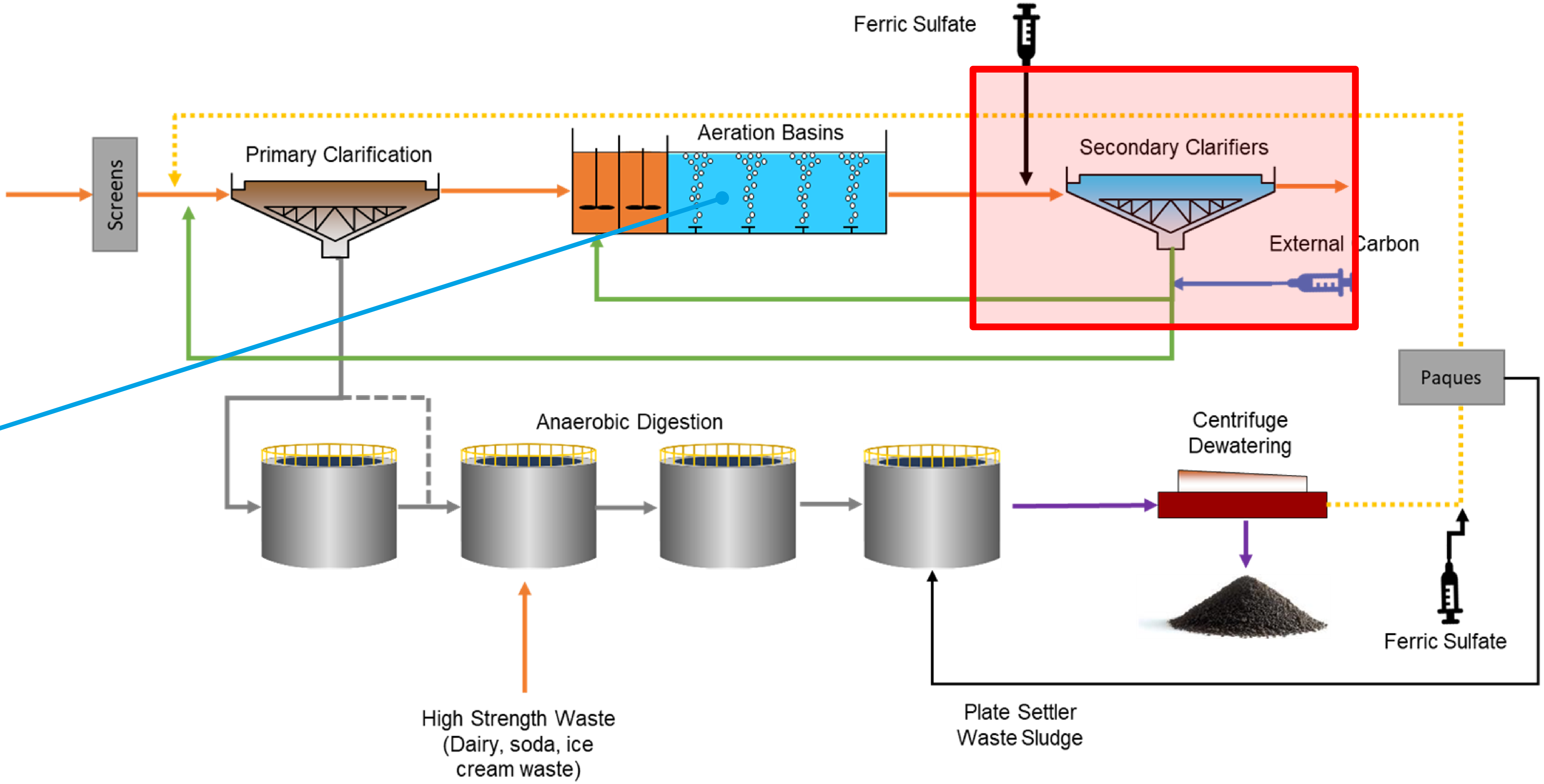




Overview of the Fond du Lac Treatment Process

- **Use a fully calibrated plant-wide mechanistic model to predict effluent quality and conduct scenario analysis.**





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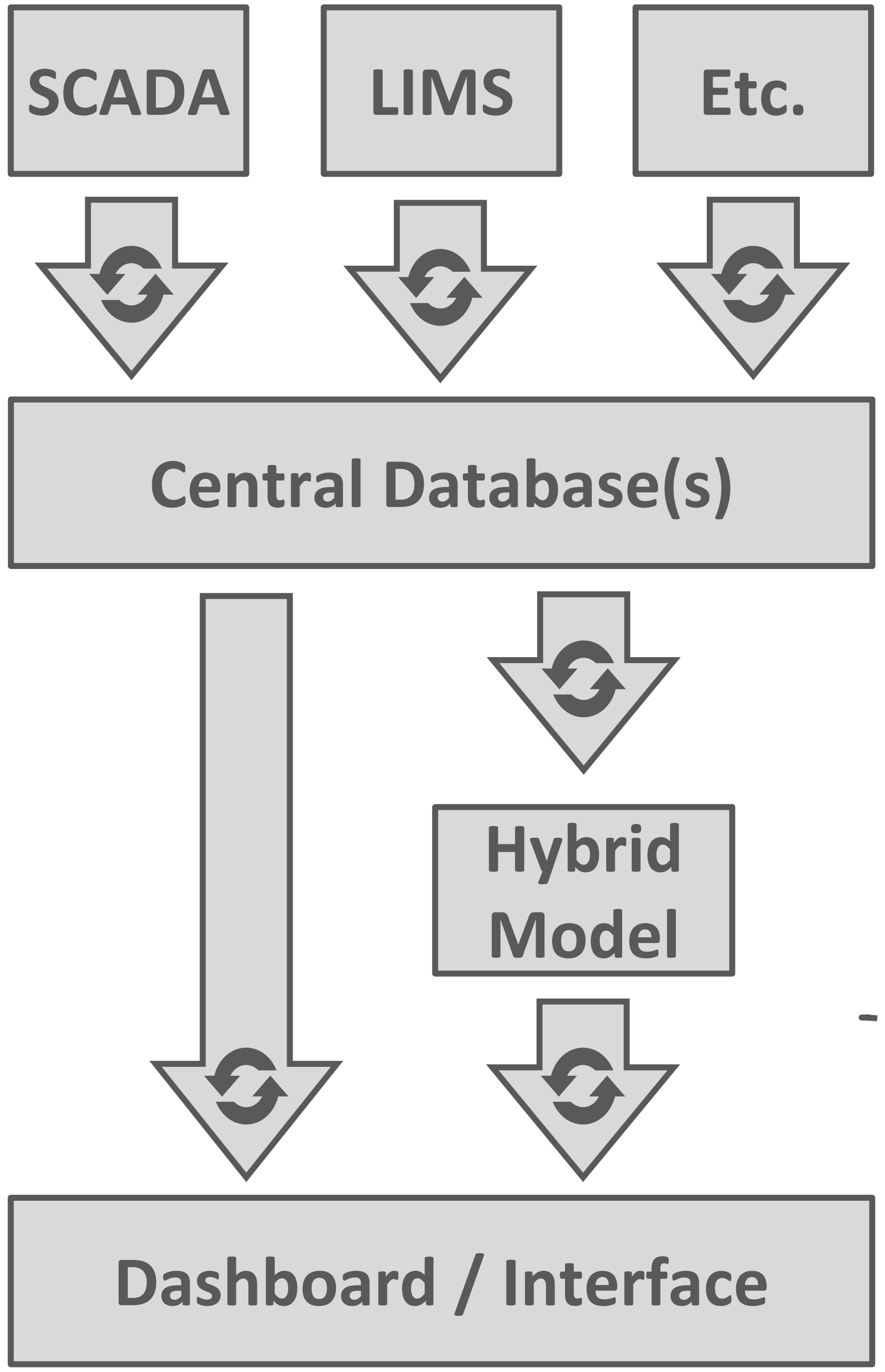
Workflow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LIMS
Etc.
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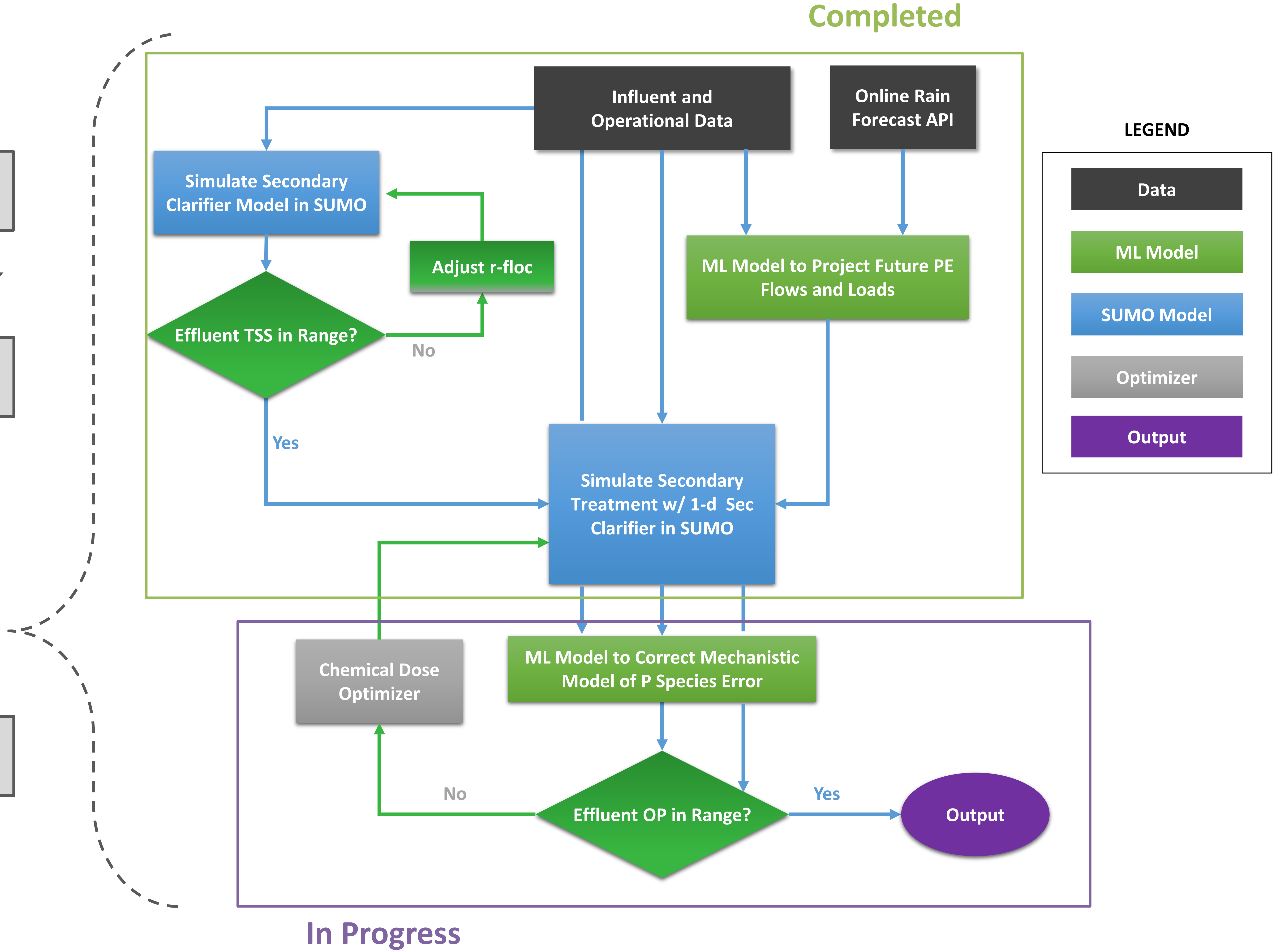
Completed
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Online Rain Forecast API
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Adjust r-floc
Effluent TSS in Range?
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ML Model to Project Future PE Flows and Loads
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Output
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LEGEND
Data
ML Model
SUMO Model
Optimizer
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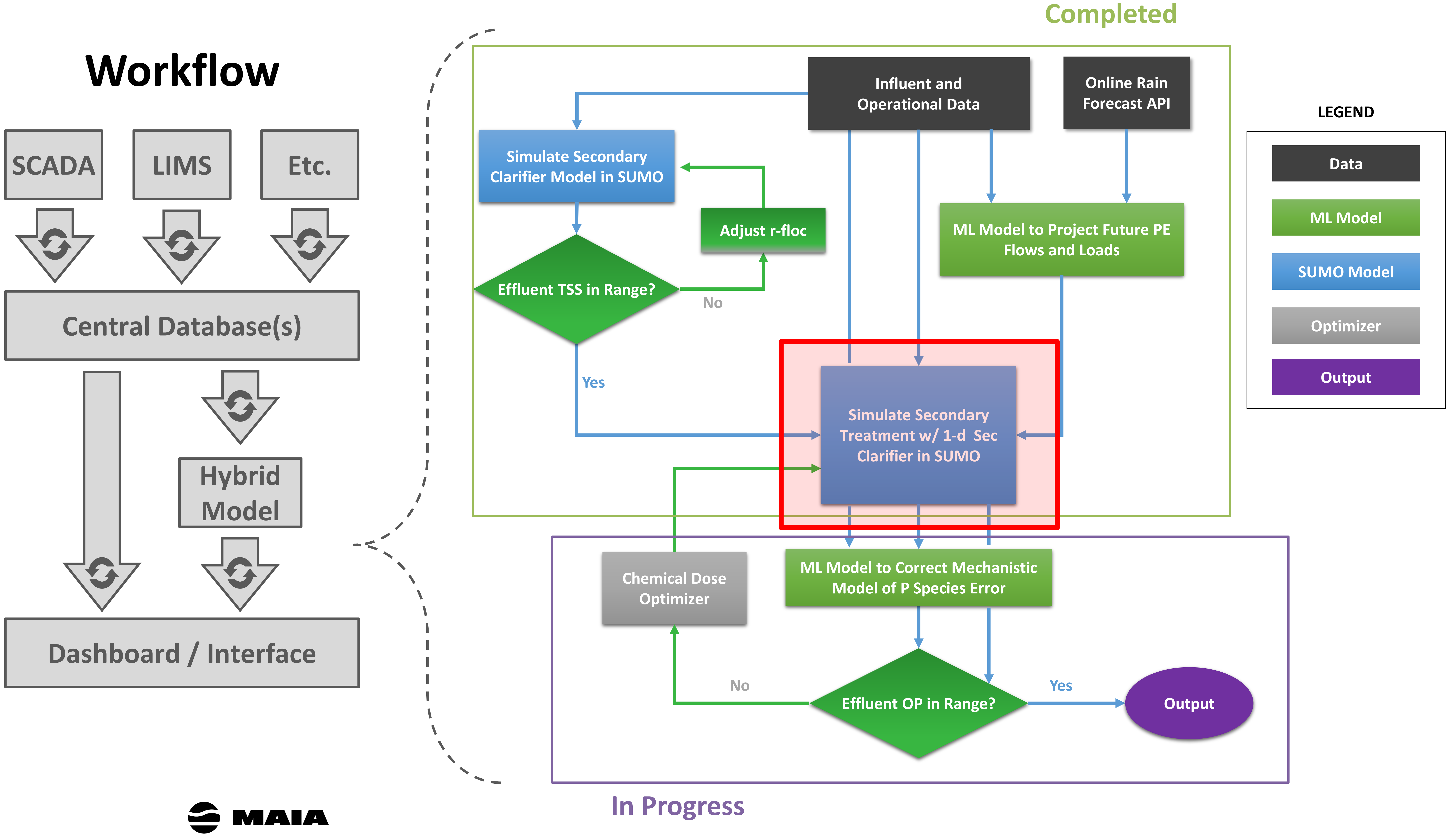

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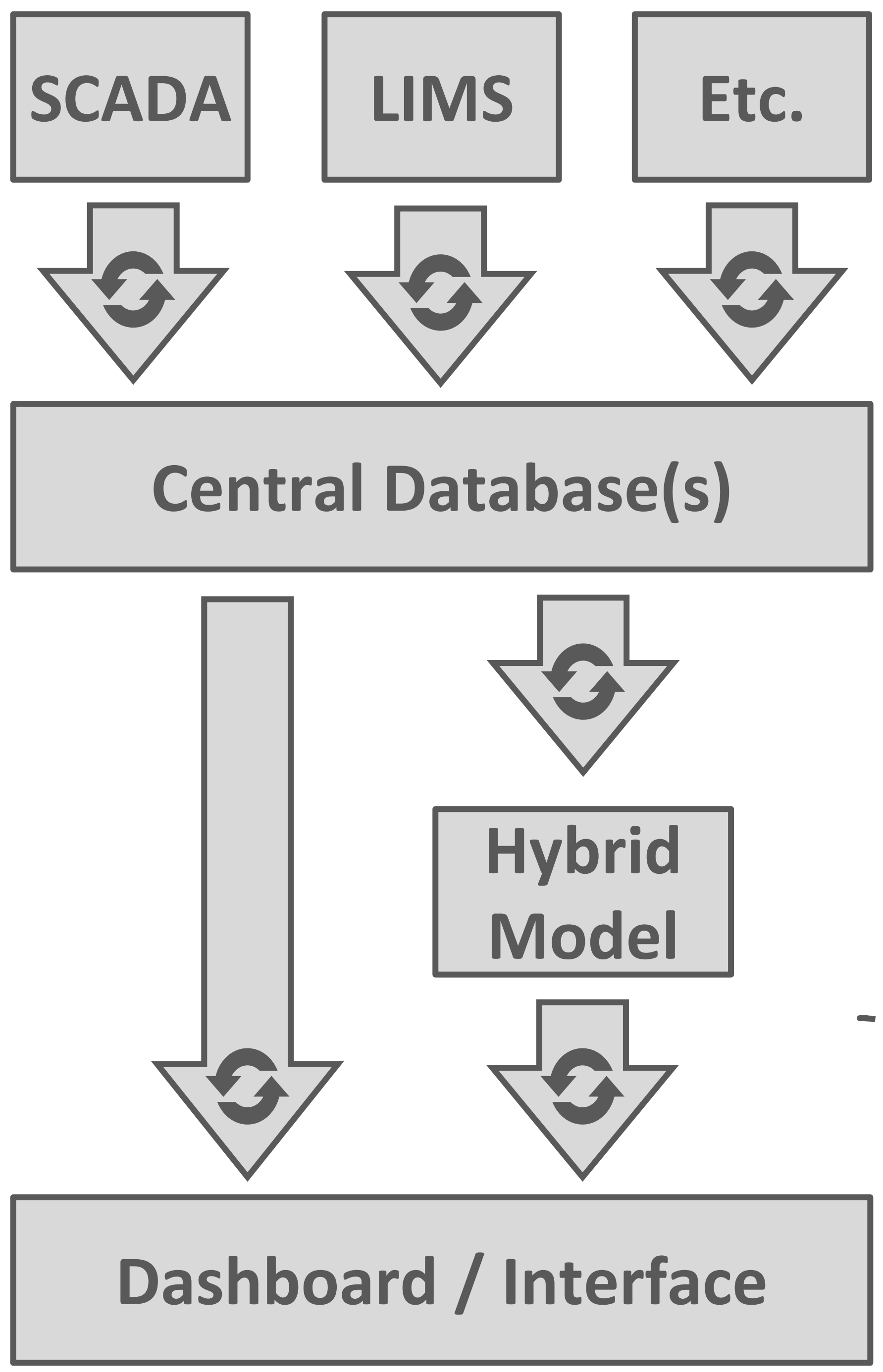

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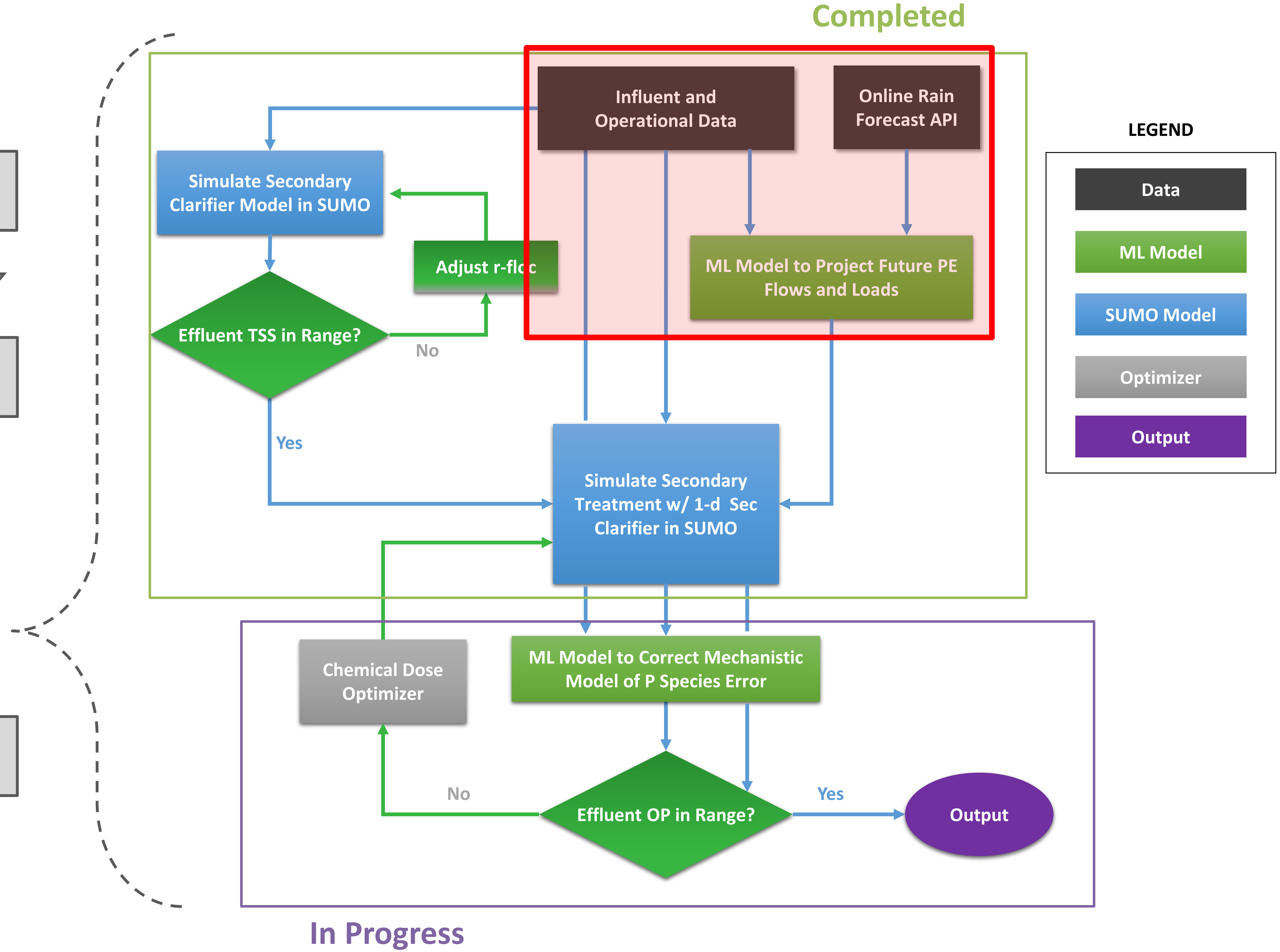

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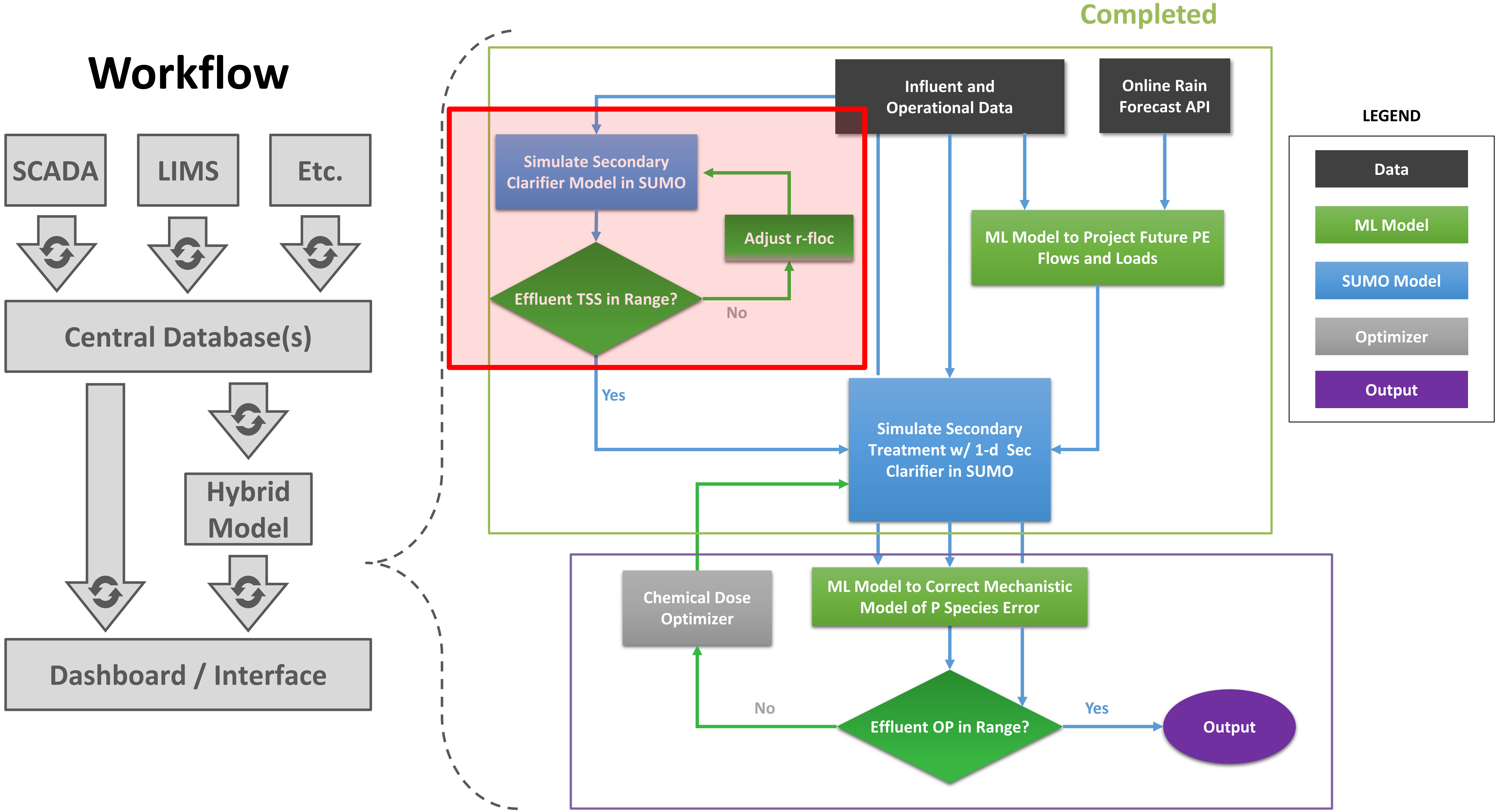

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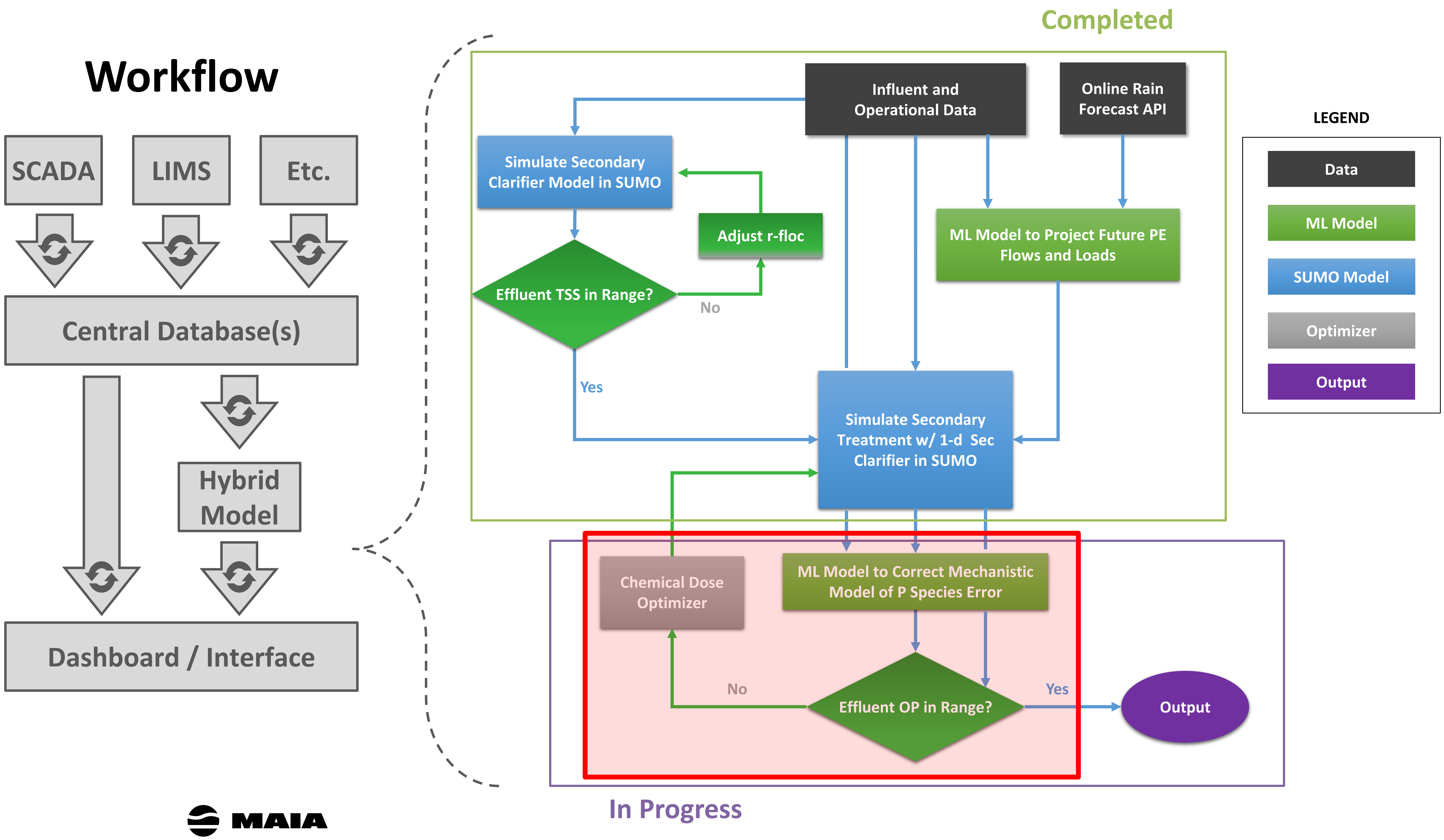
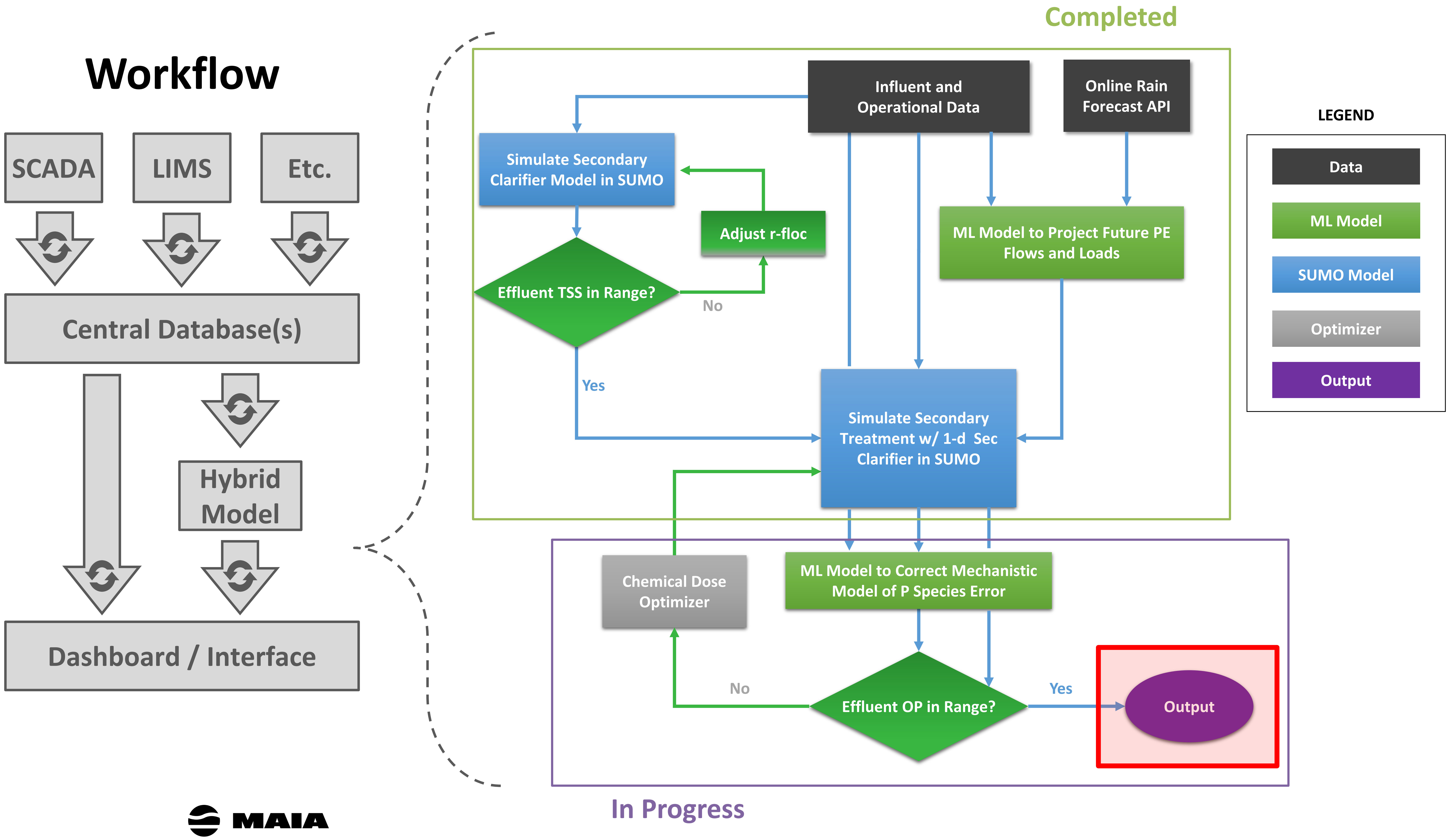


Workflow
SCADA
LIMS
Etc.
Central Database(s)
Hybrid Model
Dashboard / Interface
Completed
Influent and Operational Data
Online Rain Forecast API
Simulate Secondary Clarifier Model in SUMO
Adjust r-floc
Effluent TSS in Range?
No
Yes
ML Model to Project Future PE Flows and Loads
Simulate Secondary Treatment w/ 1-d Sec Clarifier in SUMO
Chemical Dose Optimizer
ML Model to Correct Mechanistic Model of P Species Error
No
Effluent OP in Range?
Yes
Output
In Progress
LEGEND
Data
ML Model
SUMO Model
Optimizer
Output
MAIA


Workflow
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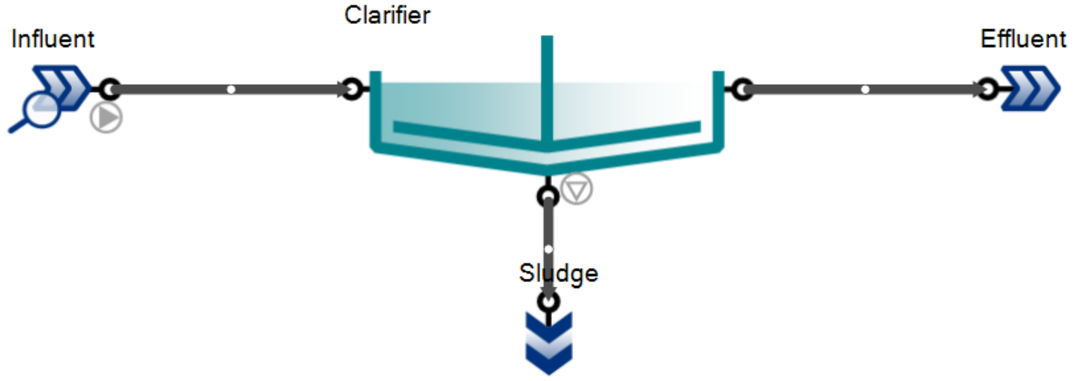
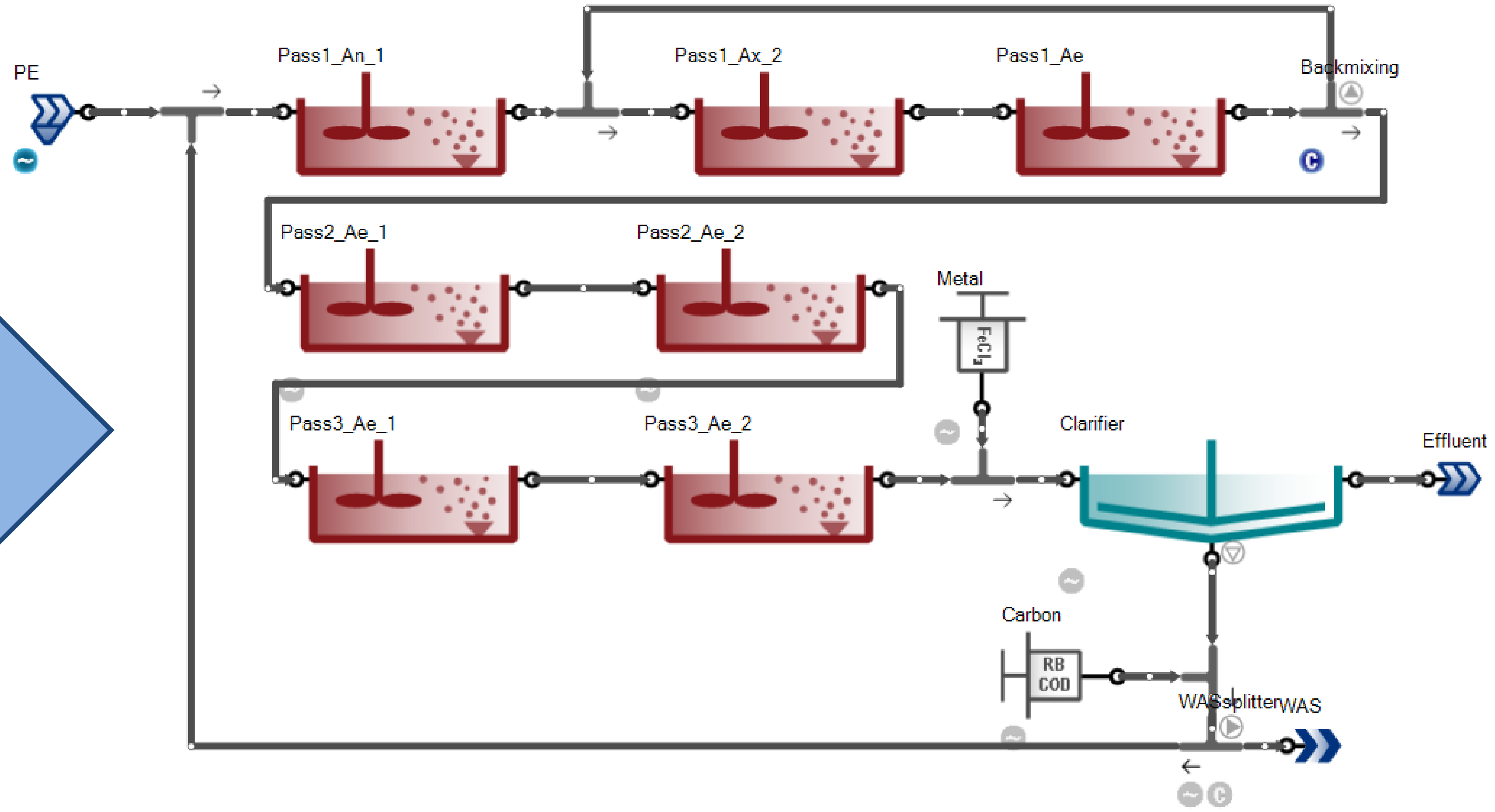
Output
In Progress
LEGEND
Data
ML Model
SUMO Model
Optimizer
Output

Mechanistic Model Component



Input MLSS and SVI and optimize r_floc to match effluent TSS

Coefficient of Flocculant Settling



Input dynamic influent and operational data and projected influent loadings

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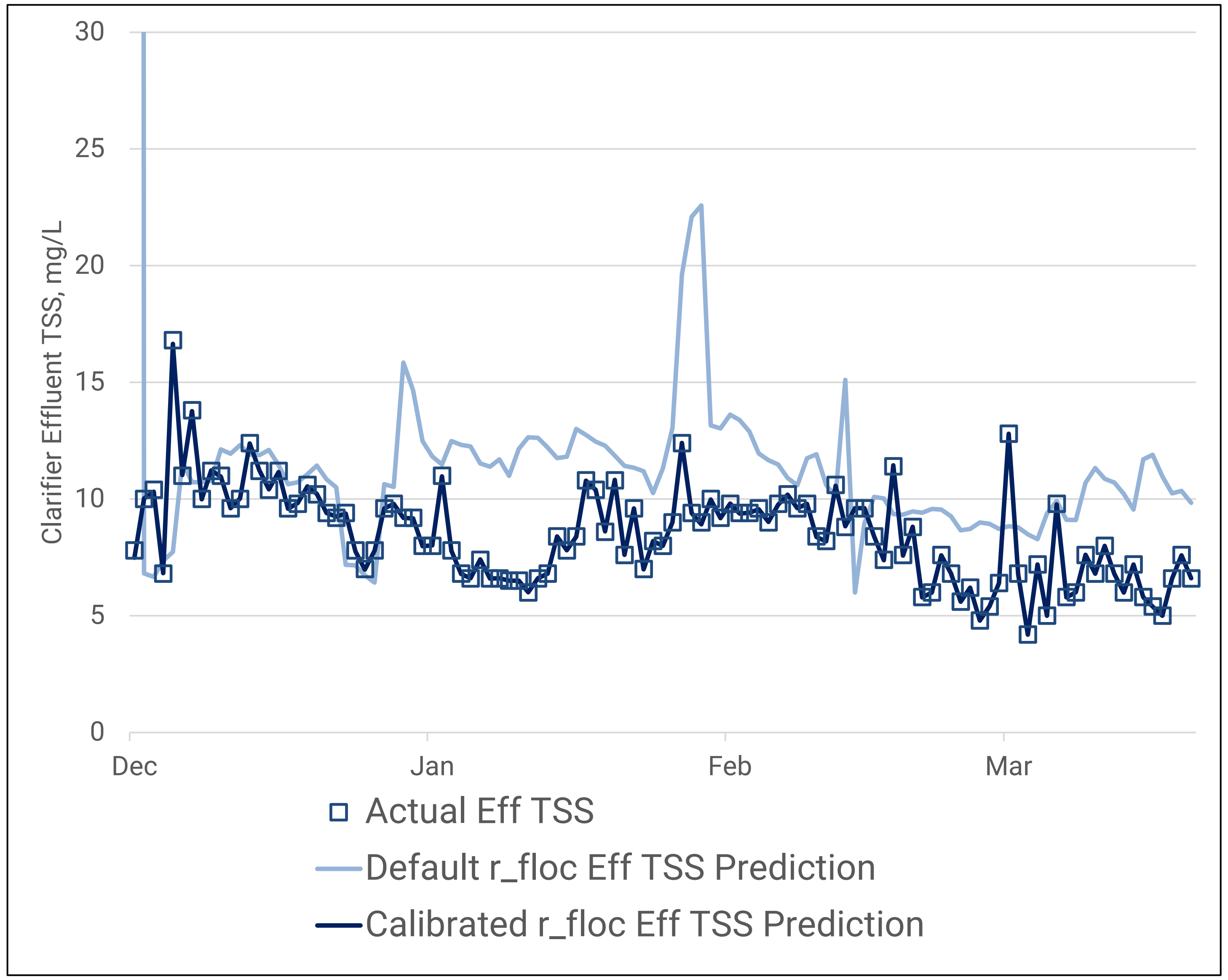
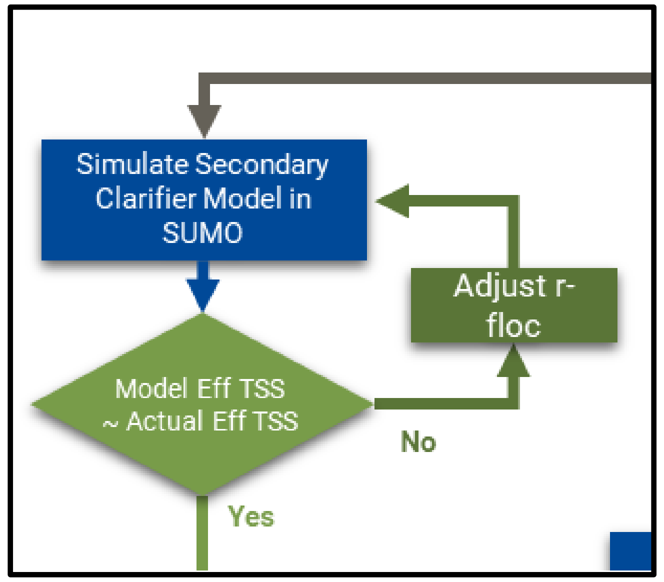
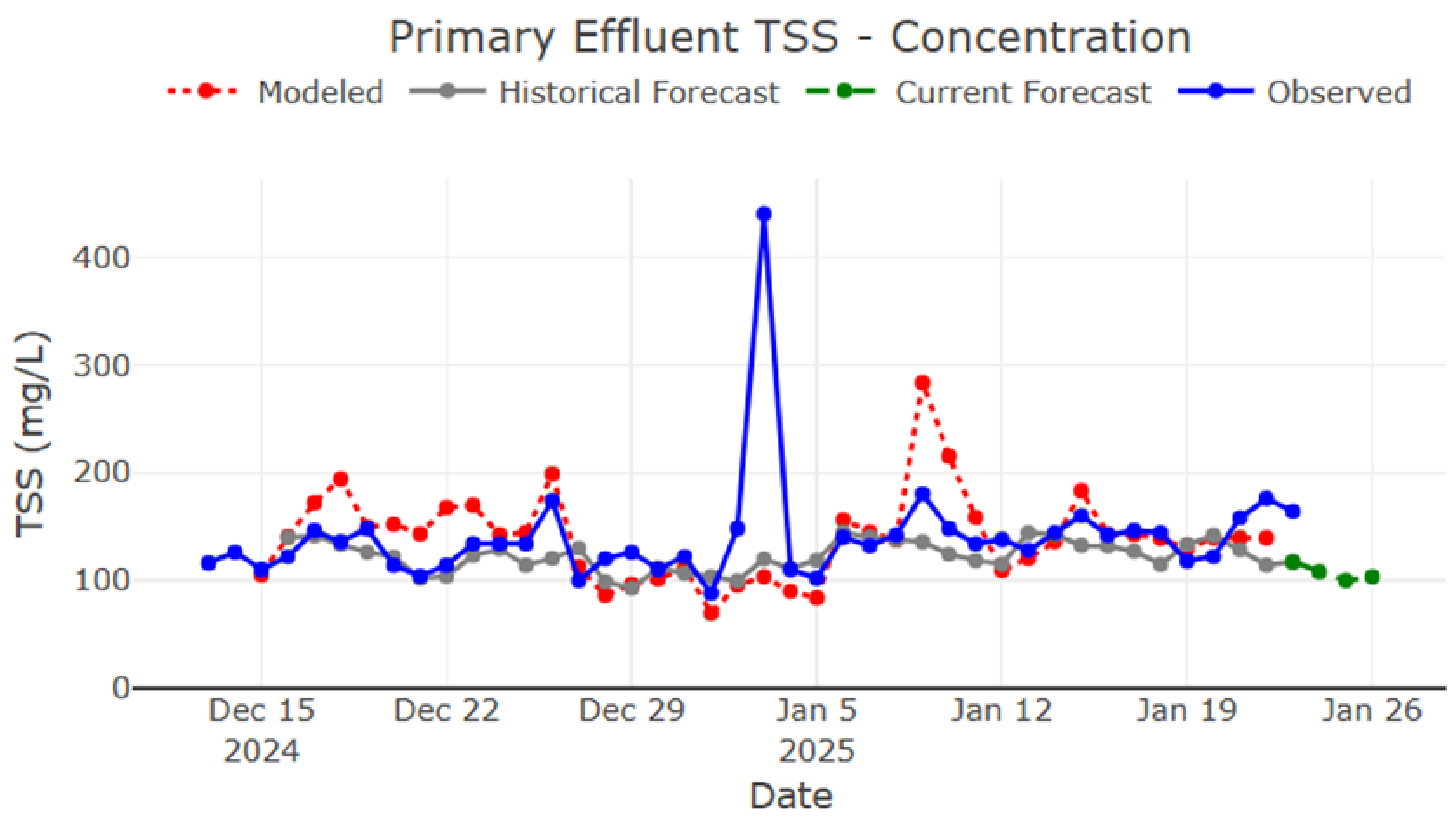
r_floc = Flocculation Coefficient

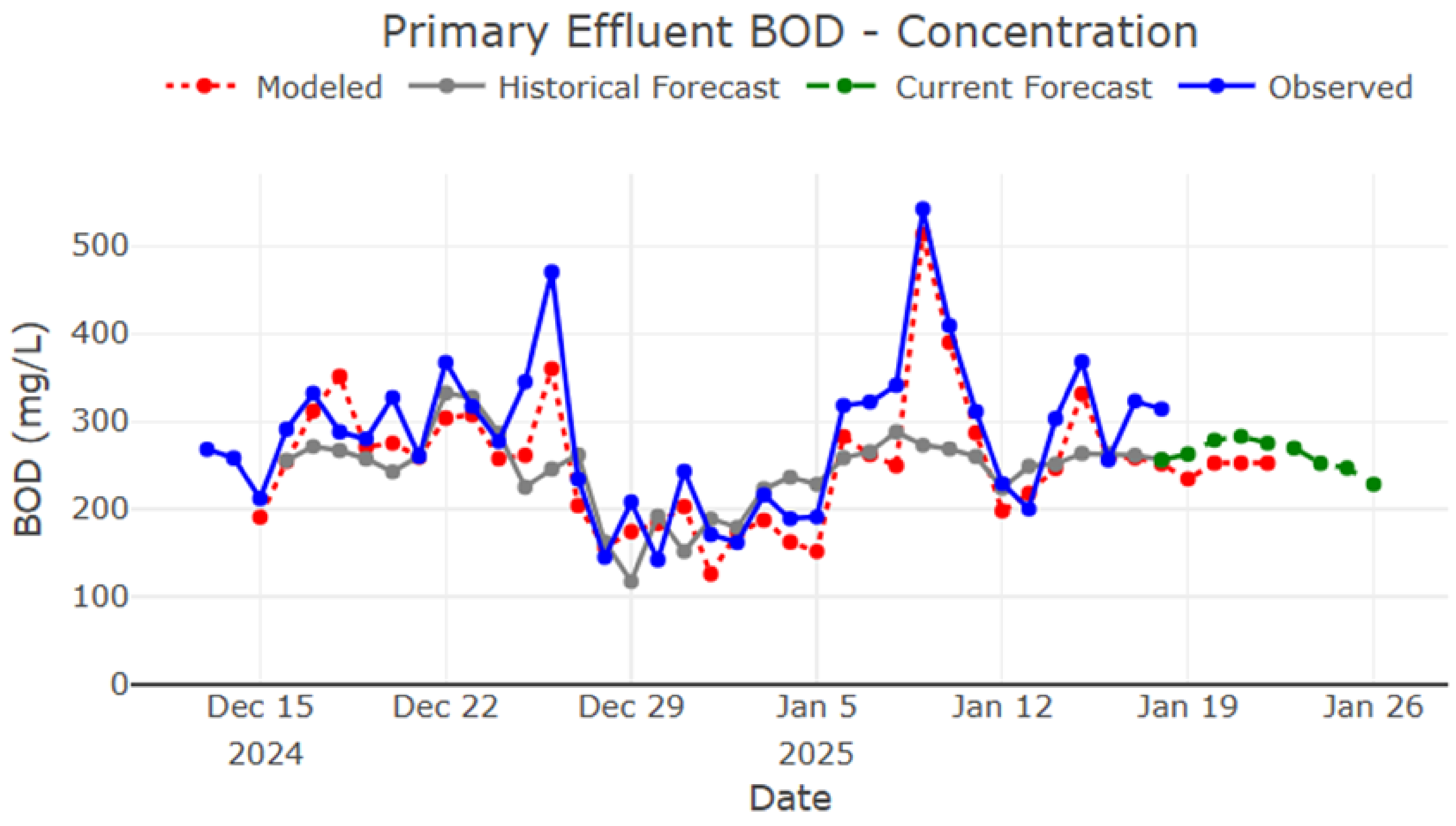
Using Auto Calibration to Improve Predictions





Primary Effluent TSS/COD and Final Effluent TSS





- **Modeled: Sumo Predictions**
- **Historical Forecast & Current Forecast: ML Predictions**
- **Observed: The real data recorded by the plant**

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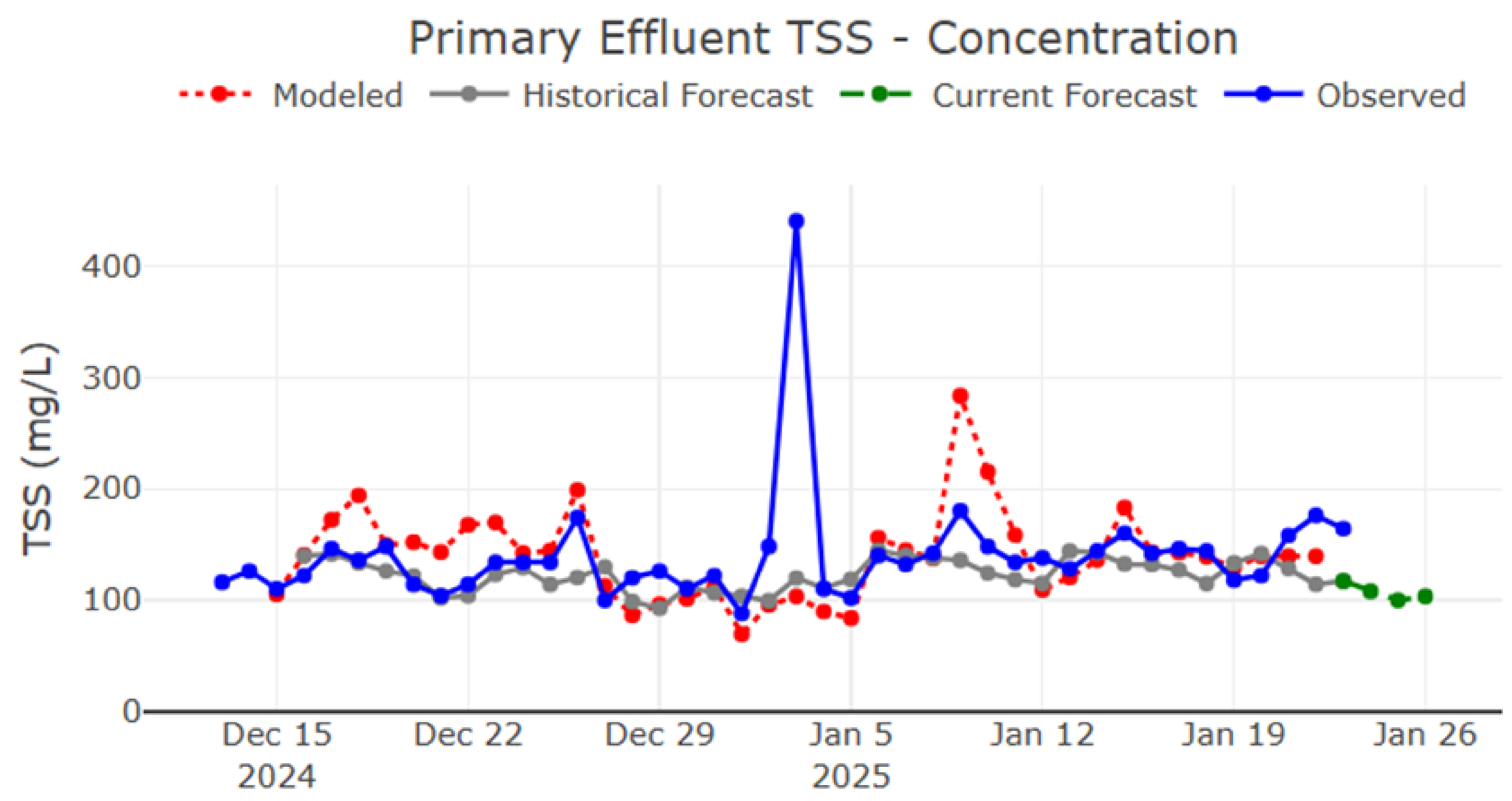
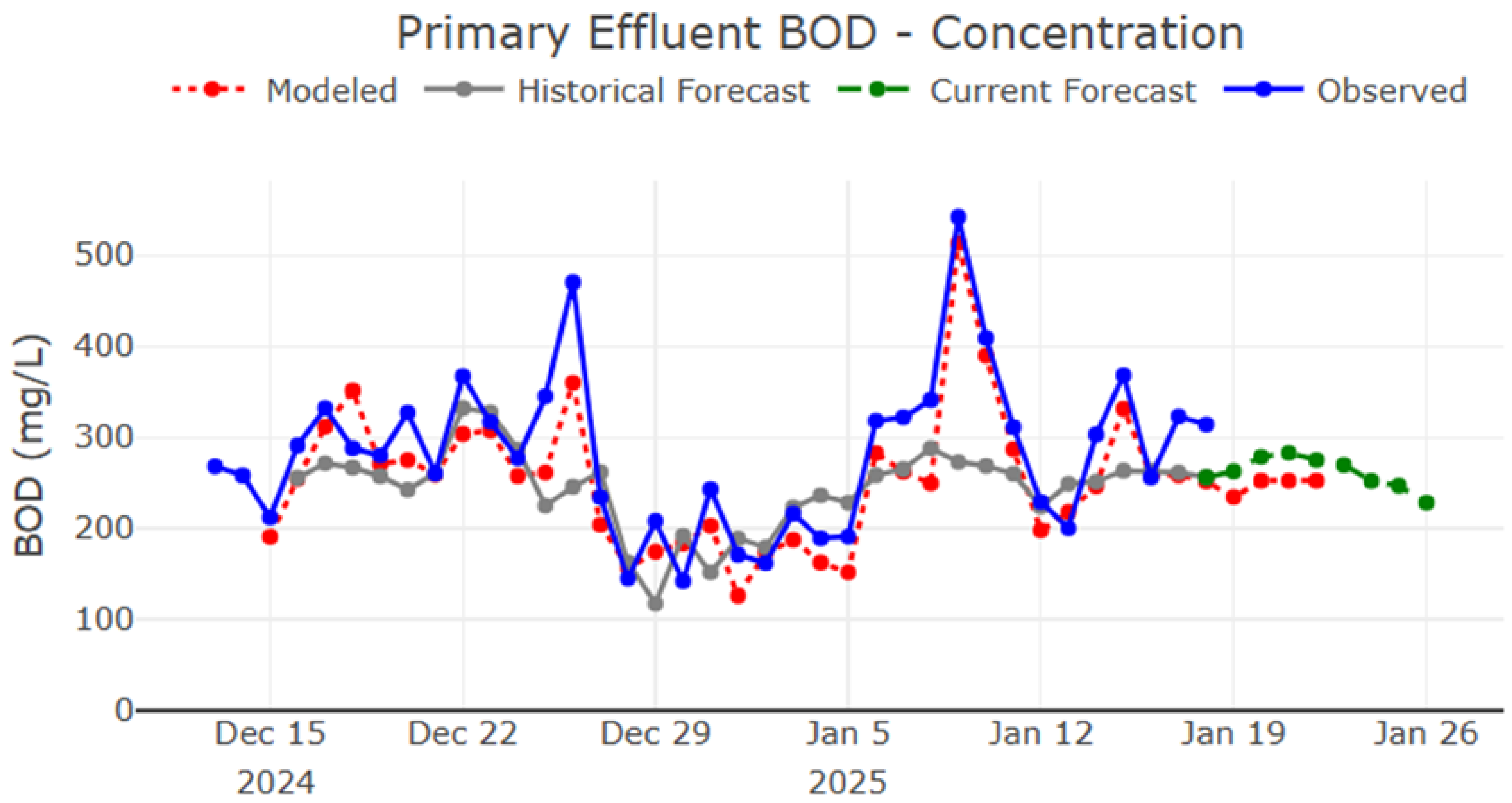
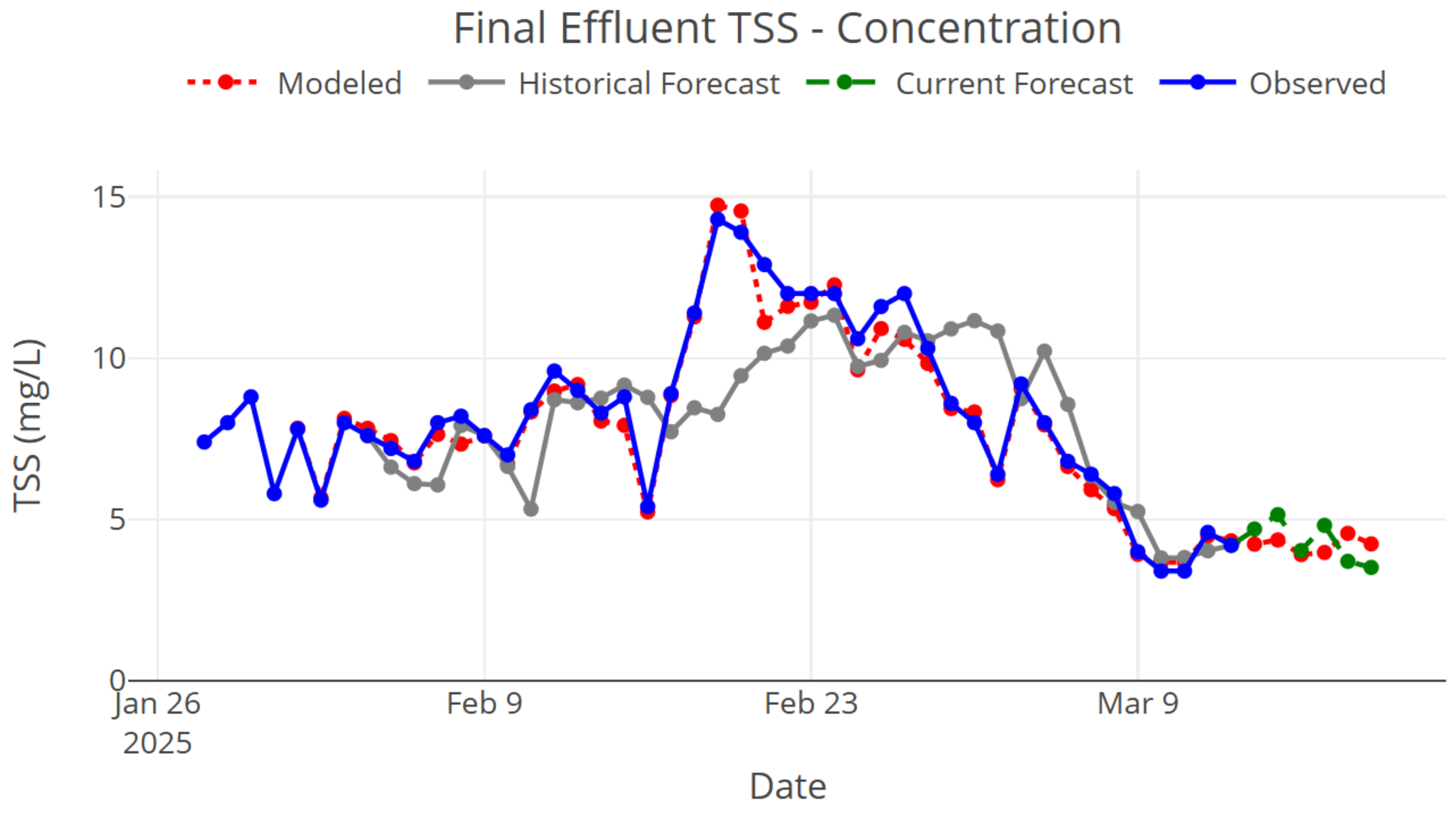
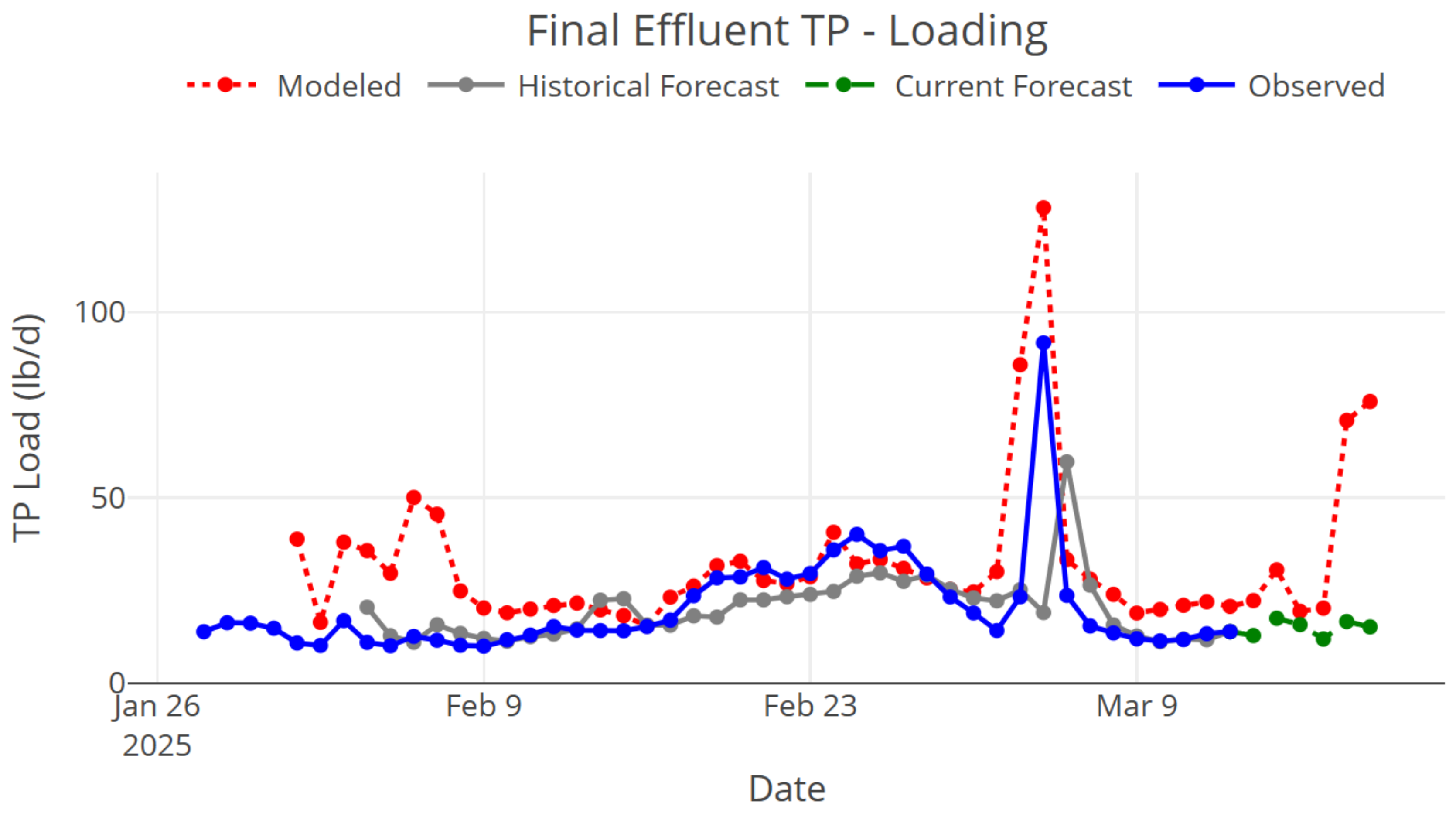
Primary Effluent TSS/COD and Final Effluent TSS

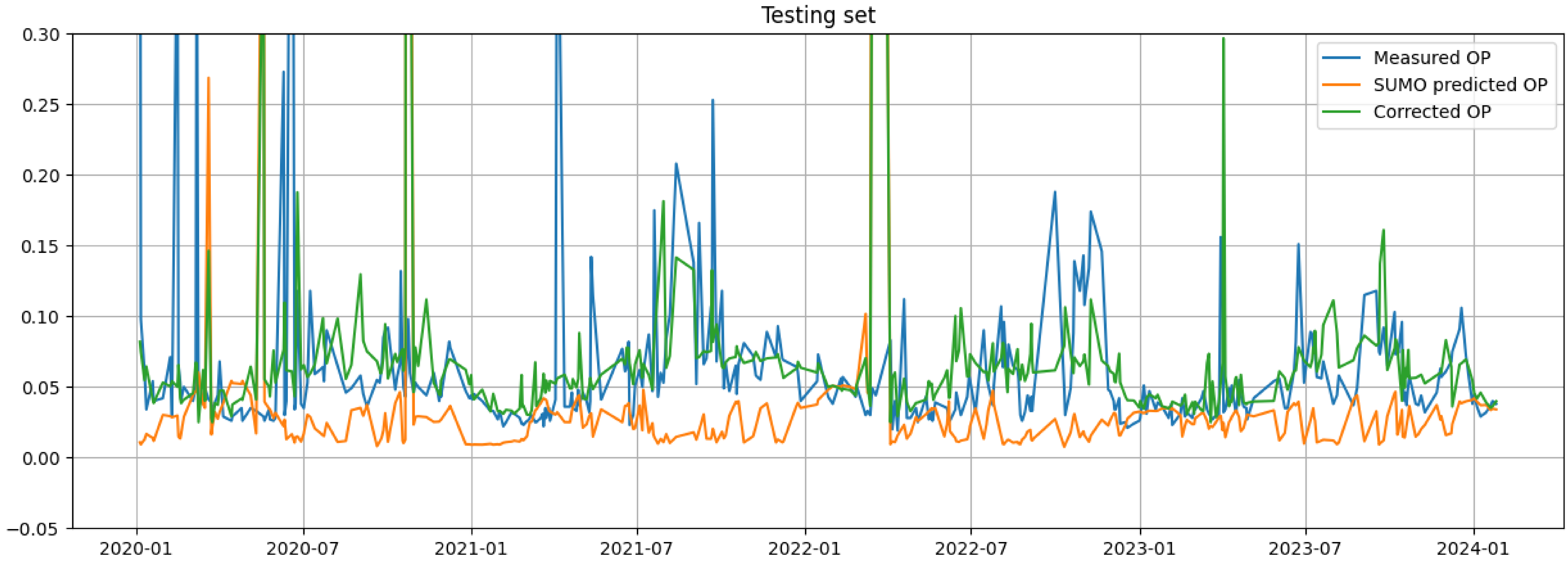








ML Model for Mechanistic Model Effluent OP Error Correction



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Project Outcomes

- Effluent P was **more stable and kept below the target value** after application of the simple (Phase 1) hybrid model.

- The Hybrid model has been a **useful tool to facilitate the Fond du Lac operators** making more informed decisions.

- Phase 2 **work will improve** data management, and ML/mechanistic models and **is ongoing.**

- Leveraging both **process engineering** and **hybrid model integration** expertise lays the groundwork for an effective operational decision-making tool.

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Questions?
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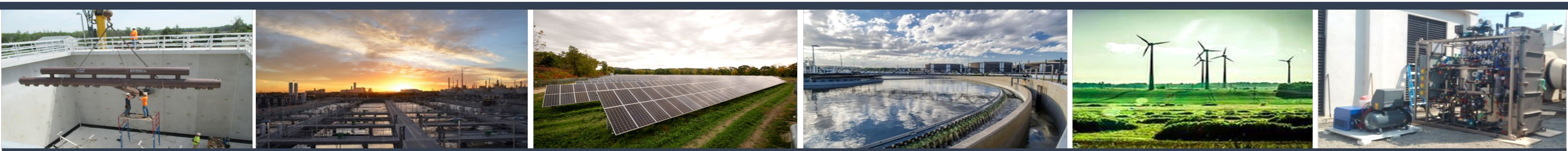

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