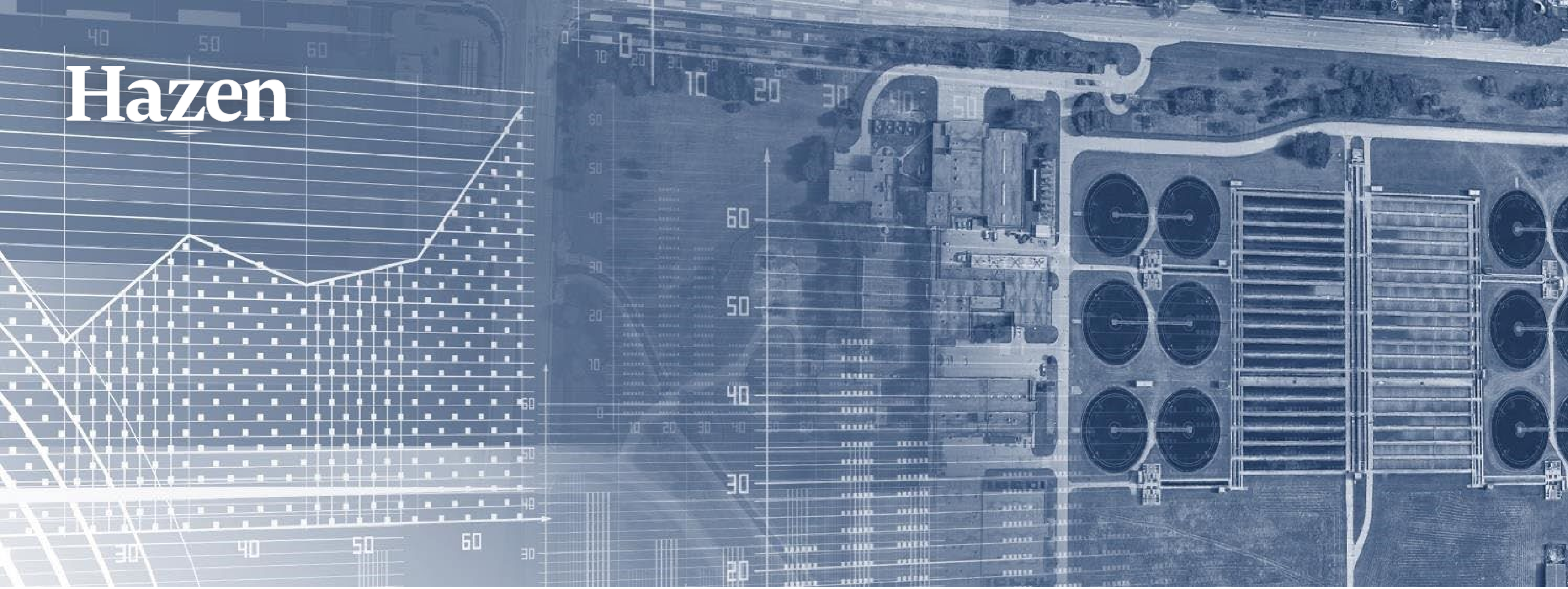
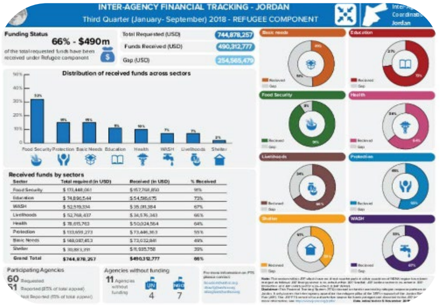


Advanced Operational Control Strategies and Tools

Will Martin
Hazen and Sawyer

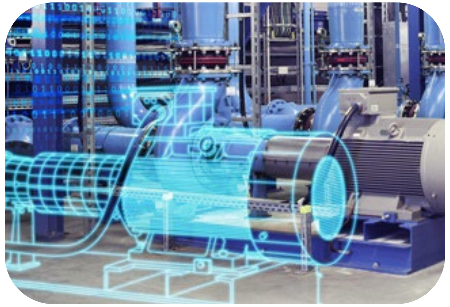
What Kinds of Operational Support Tools Exist For WRFs?

Advanced Controls



Advanced Dashboards

Machine Learning Models



Digital Twins

What Can Operations Support Tools Do?

Control equipment

Make predictions

Give insight

Optimize operations

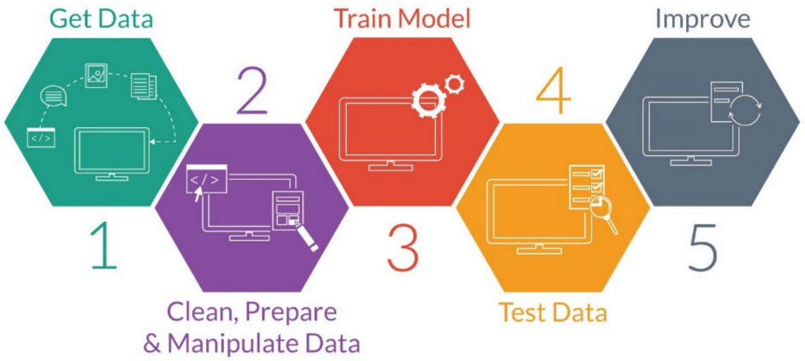
Maintain Assets

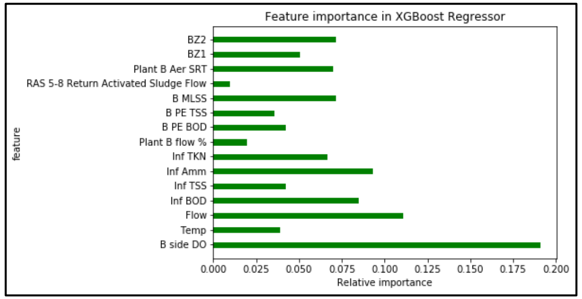
Train Staff

Example: a digital twin and ML model can control the aeration system, optimize operations, and train staff.

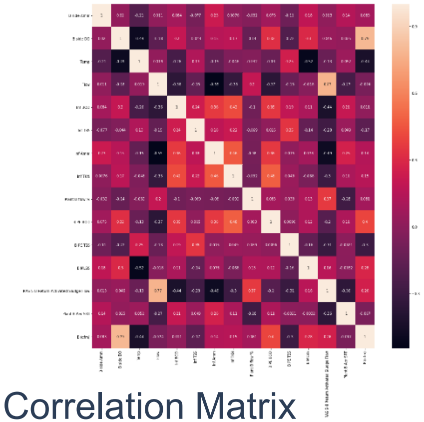
Machine Learning is an Alternative to Traditional Mechanistic Models

- ML uses algorithms, assign weights to independent variables, then seeks to minimize error in predicting a dependent variable
- Uses open-source computer programming languages like Python

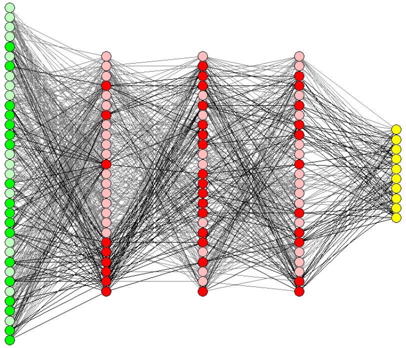




Feature Importance

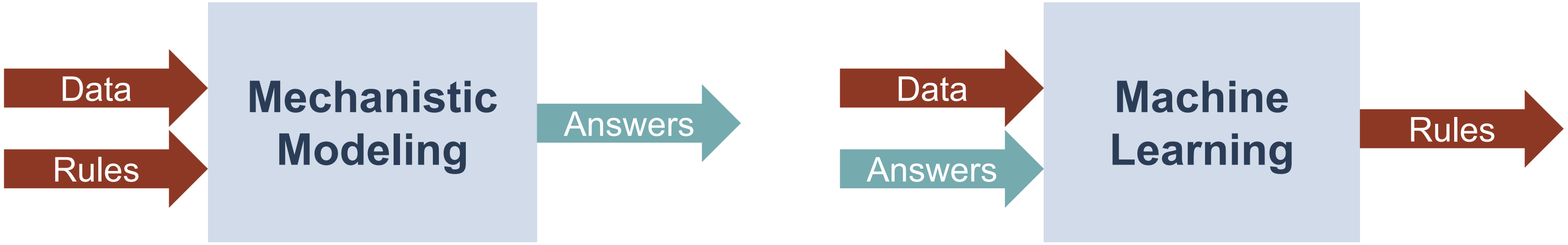


Correlation Matrix



Deep Learning Network

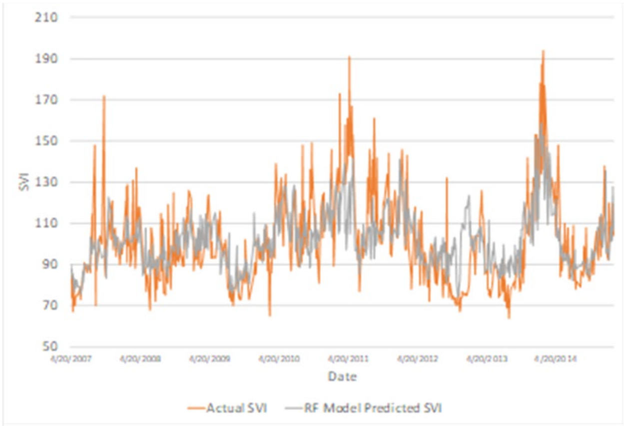
The Difference Between ML and Mechanistic Modeling



ML can make accurate predictions without explicitly being programmed to do so.

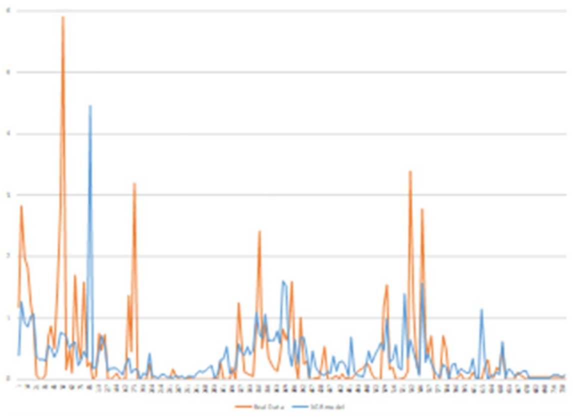
Early Endeavors with ML at WRFs

Predicting SVI



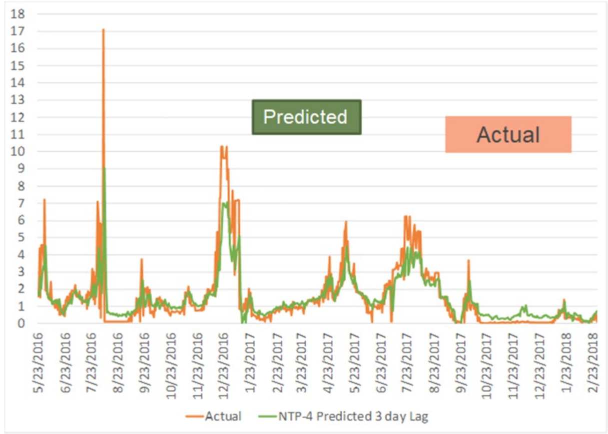
Explanatory variables: DO, PE TSS load, F:M, aSRT, Temp, MLSS, # Tanks in Service

Predicting Effluent Ammonia from an IFAS Plant



Explanatory variables: Airflow to each IFAS grid; aSRT; RAS flow; MLSS; PE TSS and BOD; flow; influent TKN, amm, TSS, BOD; temp, DO

Predicting Effluent Ammonia from a Plant with Intermittent Inhibited Nitrification

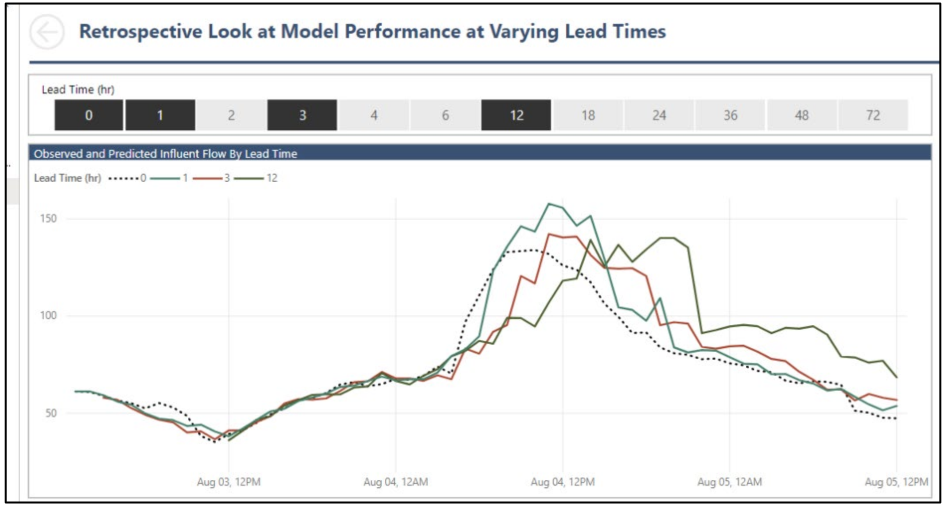


Explanatory variables: influent temp, pH, alkalinity; PE COD, TSS, TKN, ammonia, TP, OP; % RAS; aSRT; total SRT; HRT in AN, AX, and AE zones

Those Early Experiences Led to More Challenging Projects

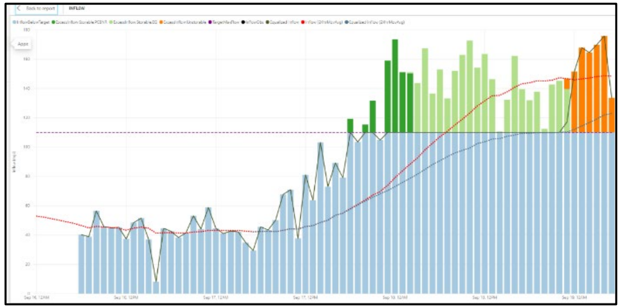
Predict Hourly Flow for the Next 72-hours for Wet Weather Planning

Predict %TS in Cake

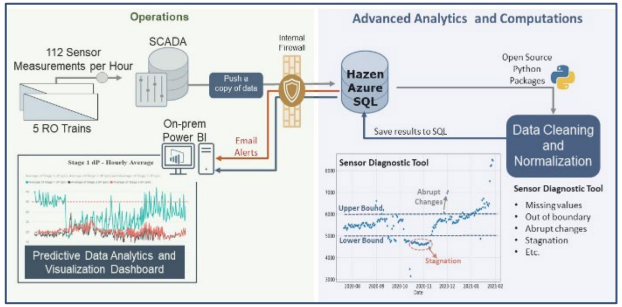


Variety of Applications From Various Sectors of the Water Industry

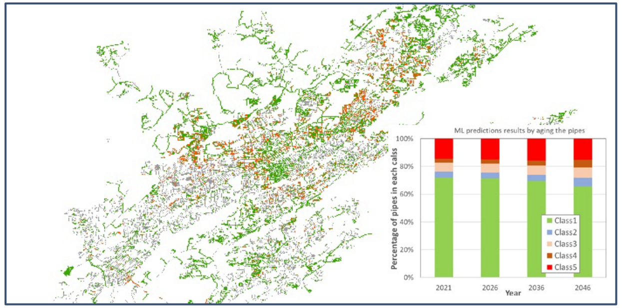
Wet Weather Wastewater Treatment Plant Optimization



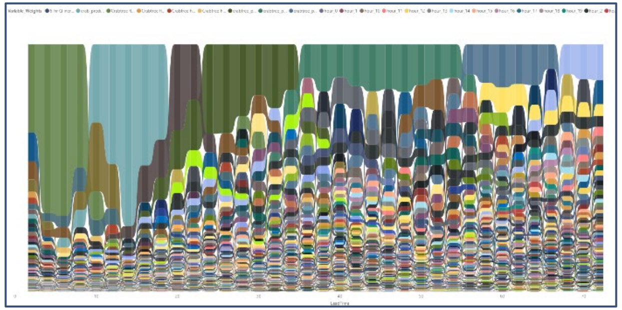
Predicting Collection System Pipe Condition Of Uninspected Pipes



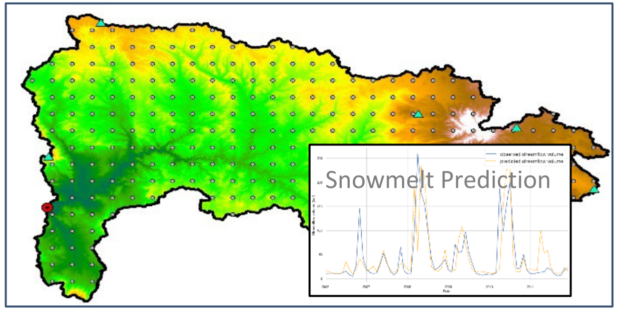
RO Membrane Optimization



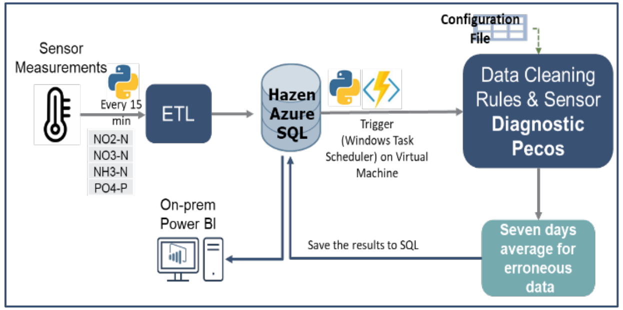
Advanced Data Analytics



Water Supply Planning Using Timeseries Machine Learning



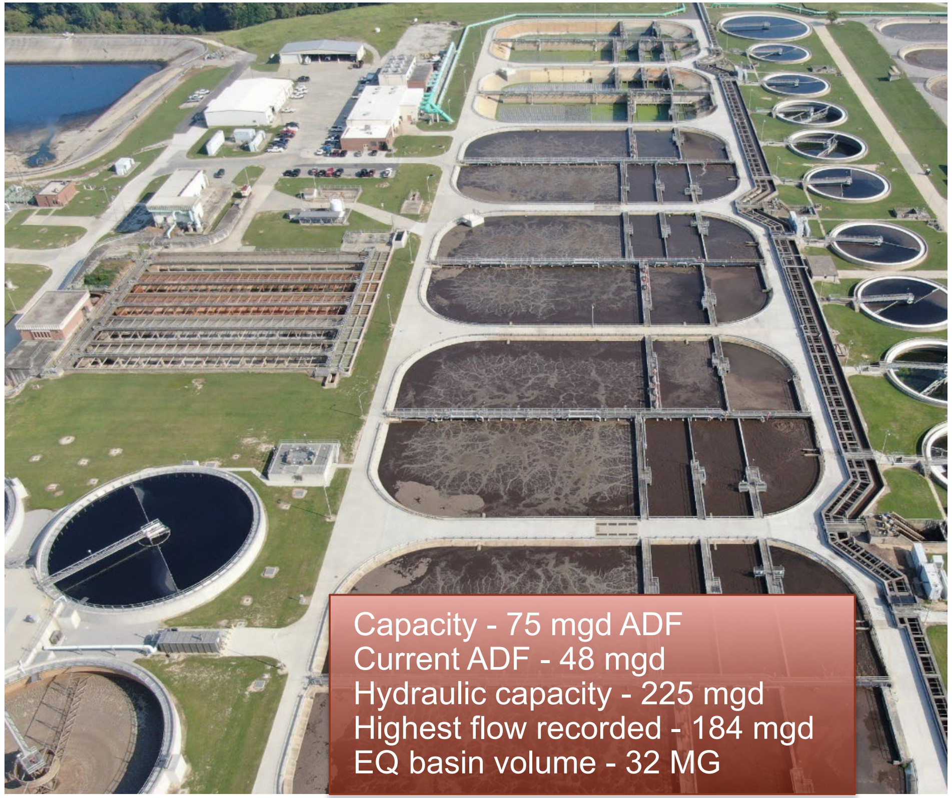
Sensor Fault Detection, Data Storing and Cleansing



Using Machine Learning to Optimize Wet Weather Treatment at the 75 mgd Neuse River Resource Recovery Facility

The NRRRF is Located in Raleigh, NC, Permitted To Treat 75 mgd, And Must Meet Strict Nutrient Limits

- Annual Average, Load-Based TN Allocation
  - Current TN Allocation: 687,373 lbs/year
  - 3 mg/L TN at 75 mgd
- Quarterly average TP limit
  - 2.0 mg/L
- Monthly average NH3-N limits
  - 1.0 mg/L summer / 2.0 mg/L winter
- Stringent BOD5 limits



Capacity - 75 mgd ADF
Current ADF - 48 mgd
Hydraulic capacity - 225 mgd
Highest flow recorded - 184 mgd
EQ basin volume - 32 MG

NRRRF Realized $500,000/yr in Savings With Advanced Process Controls

- Incorporated ABAC, SC guidance, ammonia-base load EQ, nutrient-paced chemical addition
- Real-time process controls were implemented in 2017
  - Instruments - $124,000
  - Integration - $191,000
  - Engineering - $0
  - Total investment - $315,000
- ROI < 1 year

Electrical savings $300,000/yr

Chemical savings $200,000/yr

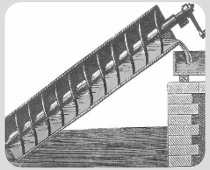
TN reduction from 2.2 to 1.8 mg/L

Nitrogen credits not used valued at $1.3M

Then, Machine Learning Was Used To Develop a Model That Predicts Influent Flow 72-hours in Advance

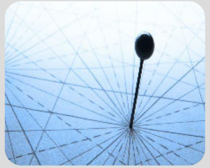
Rainfall

Streamflow



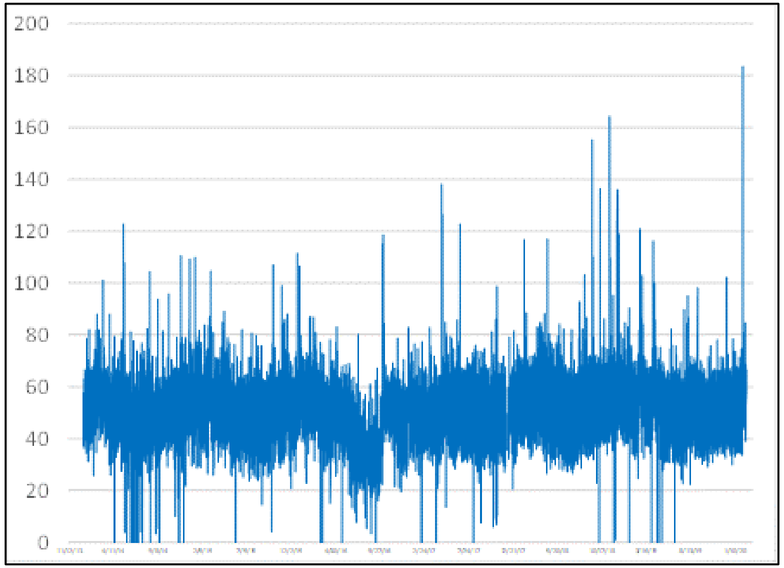
Past Influent Flow to NRRRF

Hour of Day



Collection System Improvements

Used python machine learning algorithms to train a model to 6+ years of influent flow data as a function of explanatory variables.



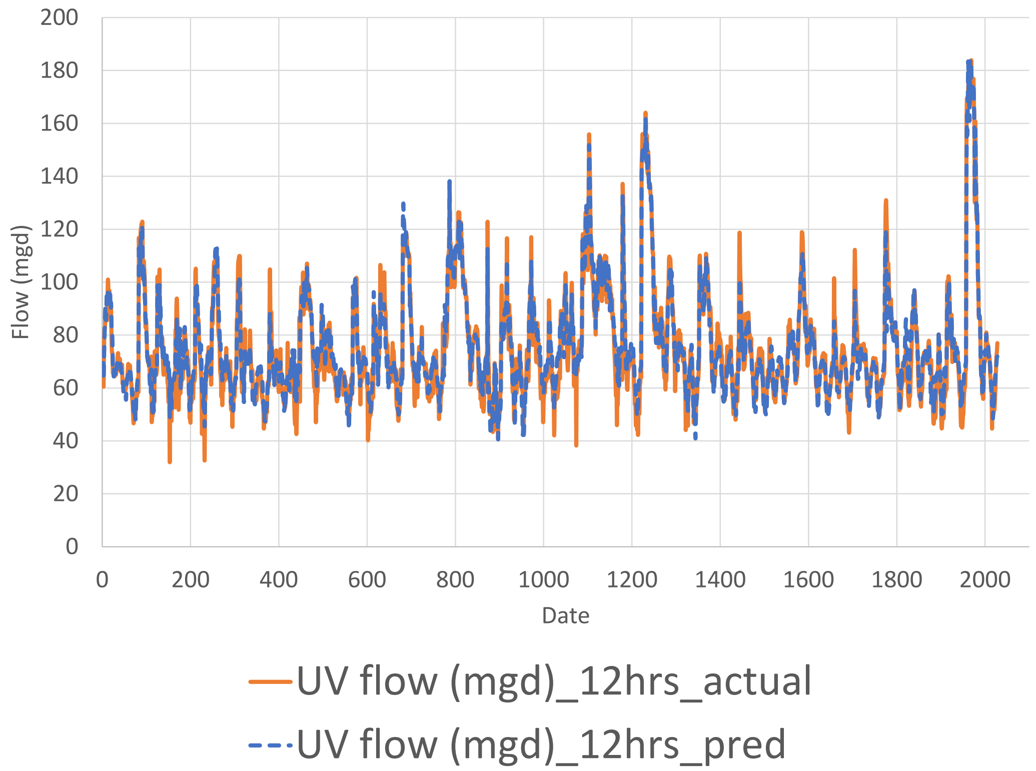
Sustained flows of 184 mgd experienced

Challenge meeting effluent TN and TP during wet weather events

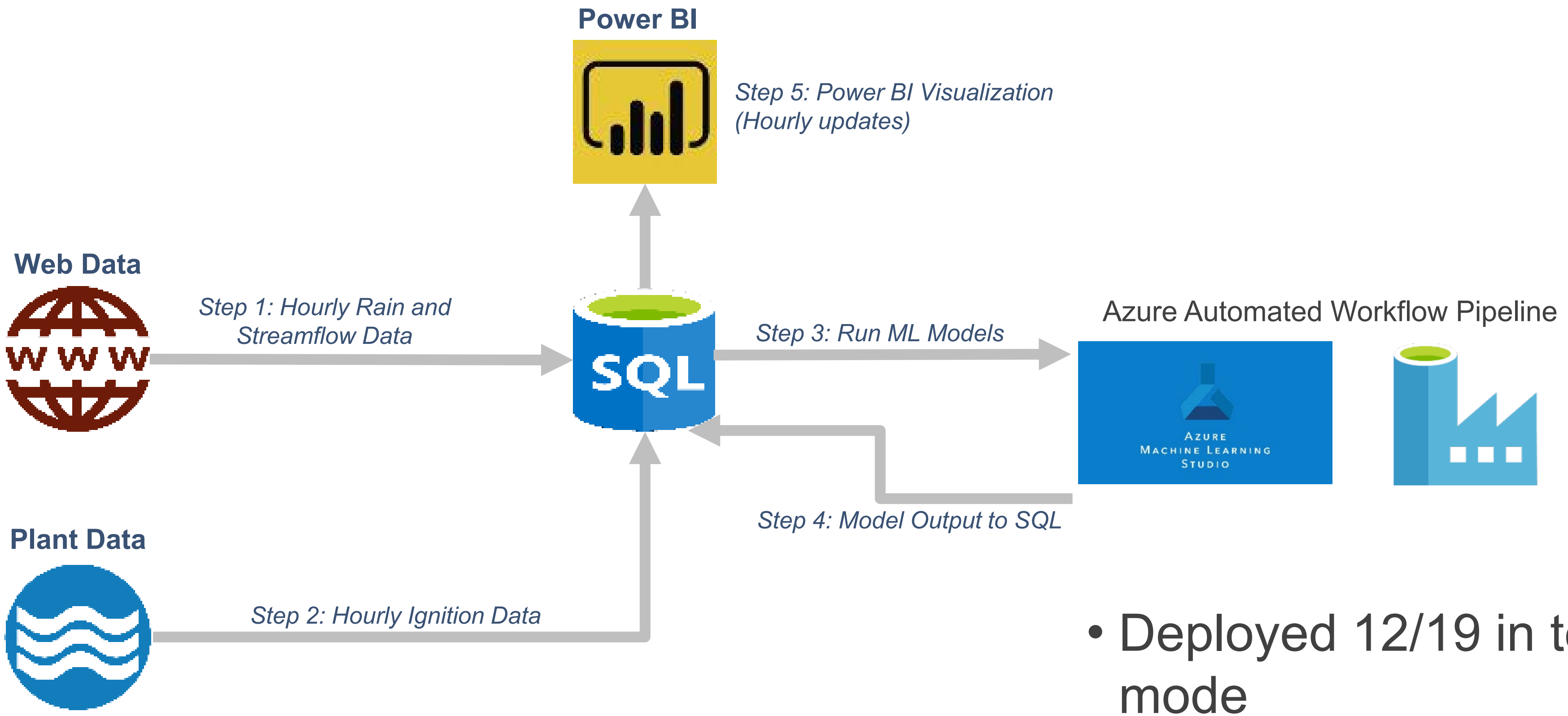
Only 30-60 minutes of advance warning prior to this project

All Storms Predicted with Good Precision by the Model During Training

- 38 storms in 6+ years
- Accuracy is +/- 2.6 mgd 12-hours in advance
- Largest storms are predicted the best, which was the goal



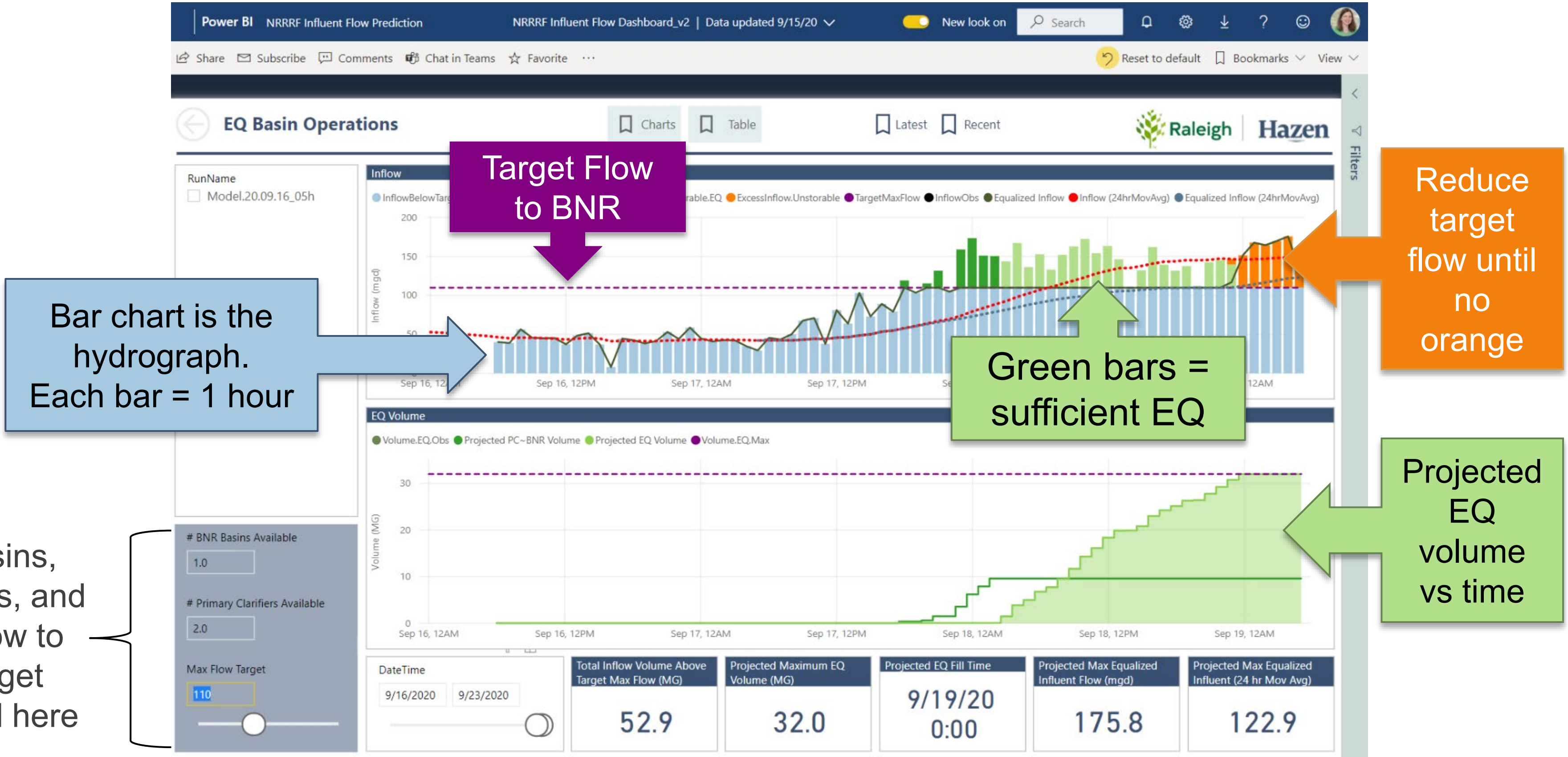
Data Architecture



- Deployed 12/19 in test mode
- Finalized 7/20

Model Prediction Screen – Updated Hourly

Hydrograph Incorporated into Dashboard for Plant Staff to Refine Wet Weather Management Related Operational Decisions



BNR basins, Primaries, and Peak Flow to BNR Target specified here

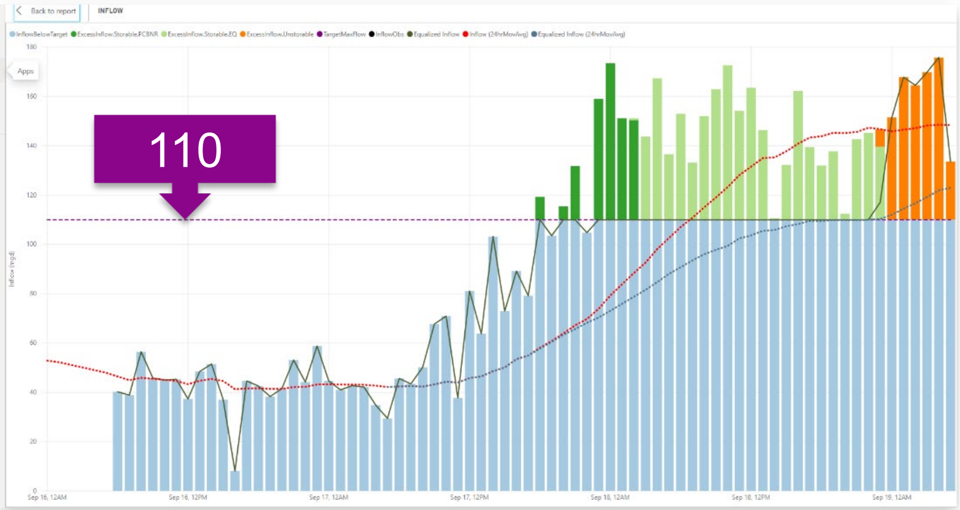
Example of How the EQ Management Tool Works

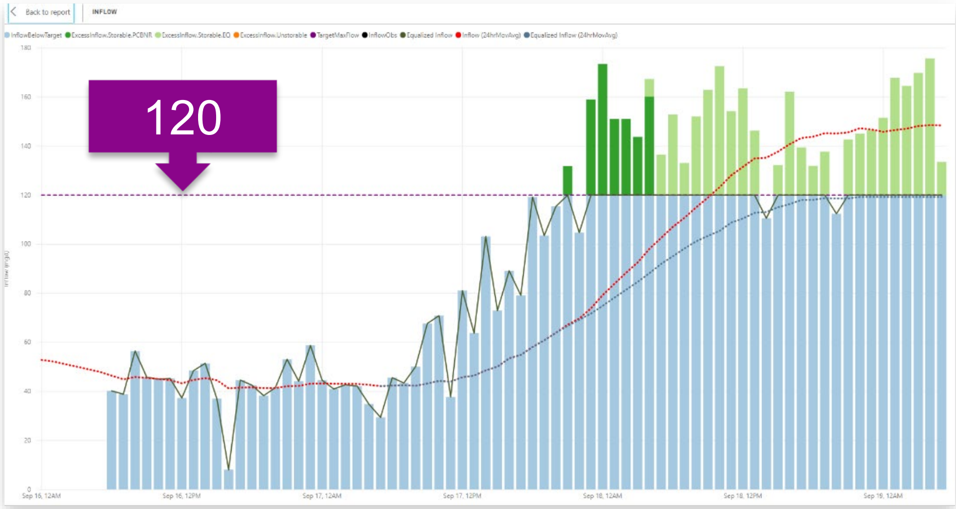
Flow threshold set to 110 mgd.

There is insufficient EQ capacity.

Flow threshold set to 120 mgd.

There is adequate capacity. Strategy is to divert flows when Q > 120 mgd.

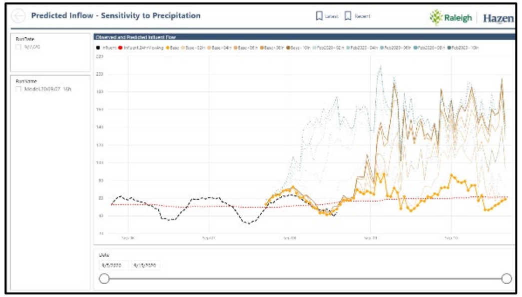




Final Deliverable Has 16 Screens

1. Cover
2. Inventory
3. Model prediction
4. Model sensitivity
5. EqOps
6. Secondary clarifier guidance
7. Model performance
8. Model QC
9. Plant Ops
10. USGS
11. Precip
12. XY
13. Timeseries
14. Map
15. InputWeights
16. Inputs

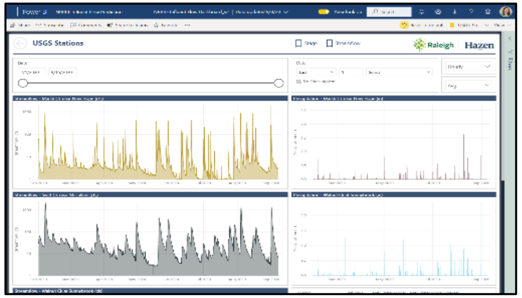
Model prediction



Sensitivity to Rainfall Amount

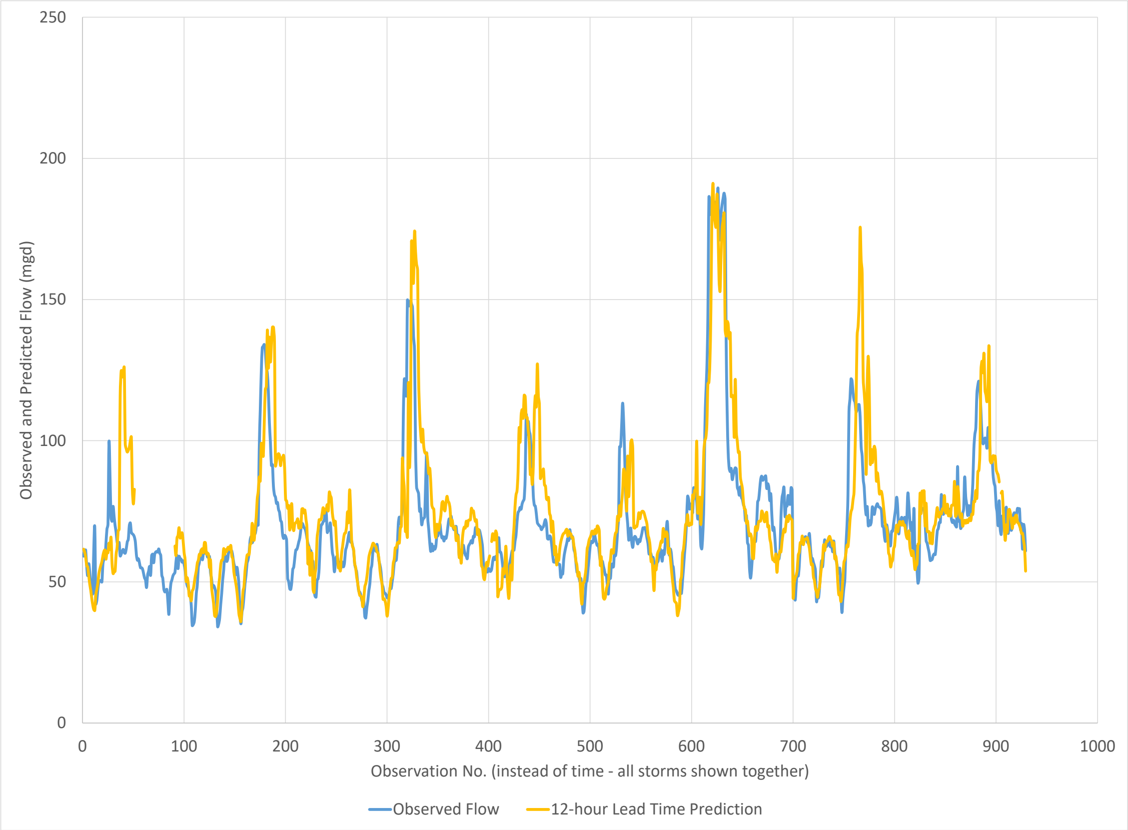
Select flow above which to utilize EQ

Secondary Clarifier Guidance Program to estimate # SCs needed



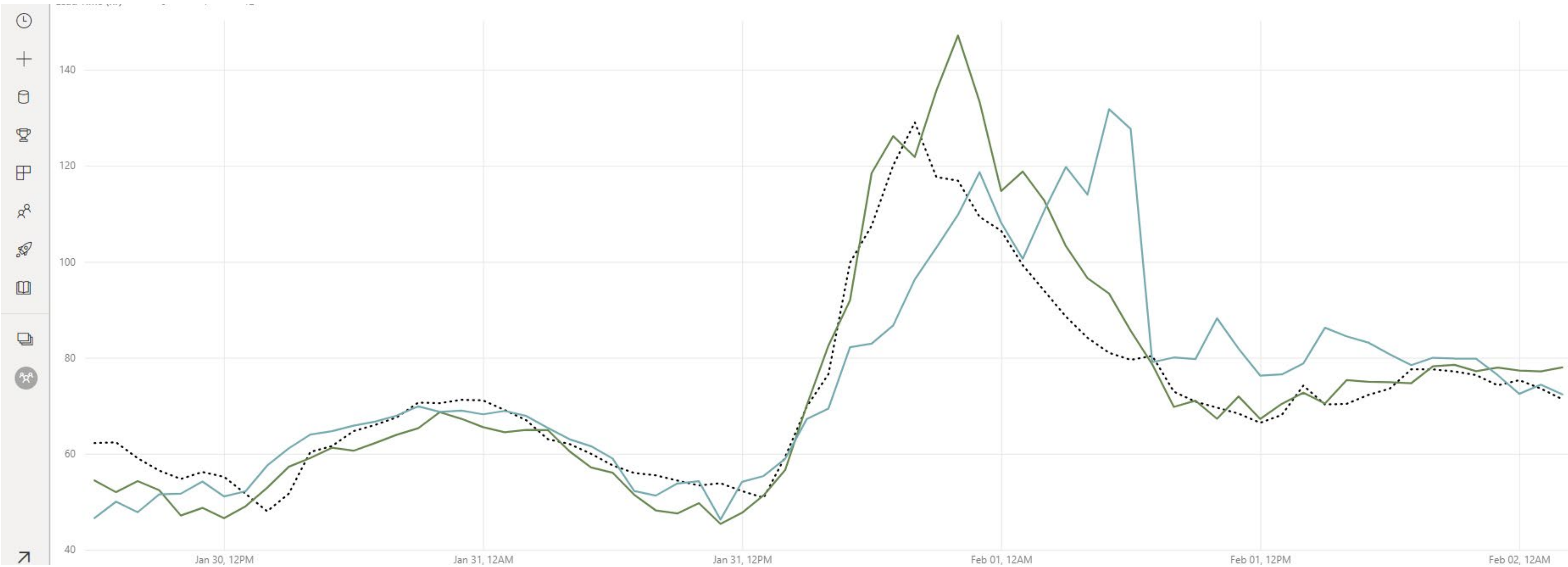
Monitor USGS Streamflow

Model Makes Great Predictions

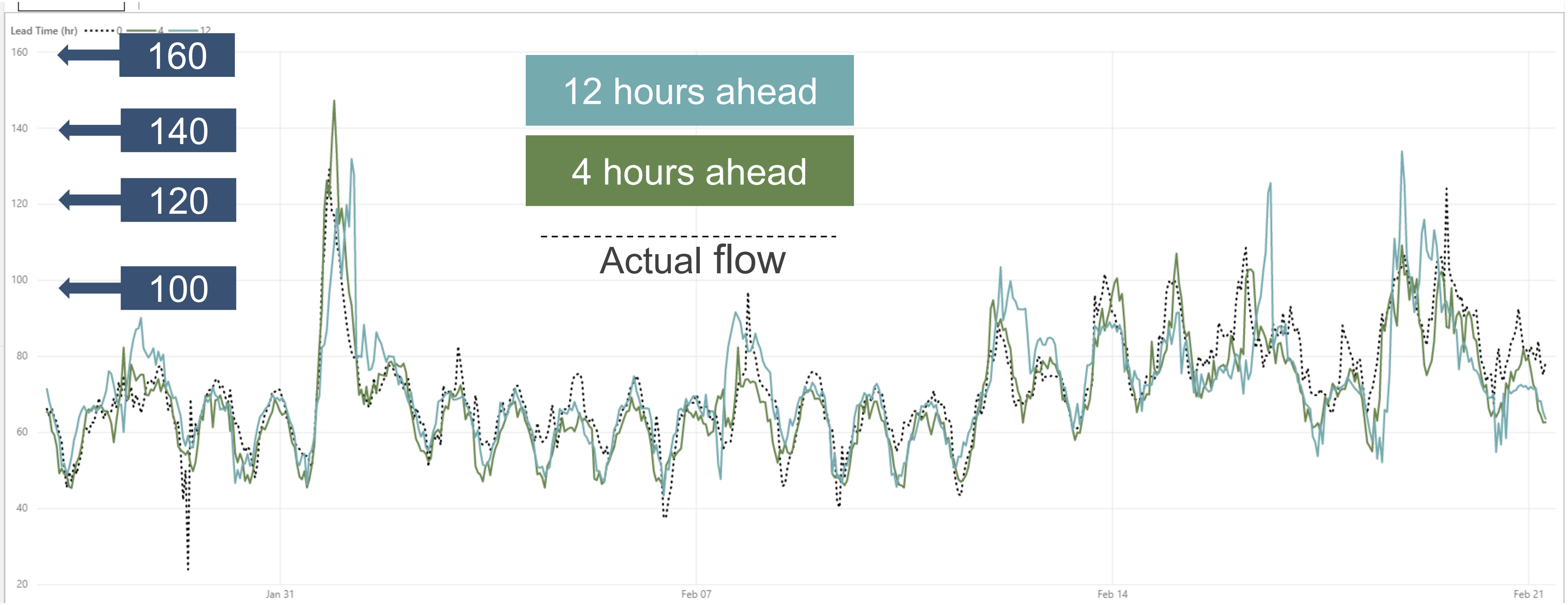


- 8 wet weather events in 2020
  - Blue – observed
  - Yellow – predicted 12-hours in advance
  - Wet weather EQ used 5 times
    - Volume ranged 12.6 – 26.8 MG
    - Never exceeded 32 MG
- Models errs on the side of being conservative
- Program operating 18+ months and still accurate

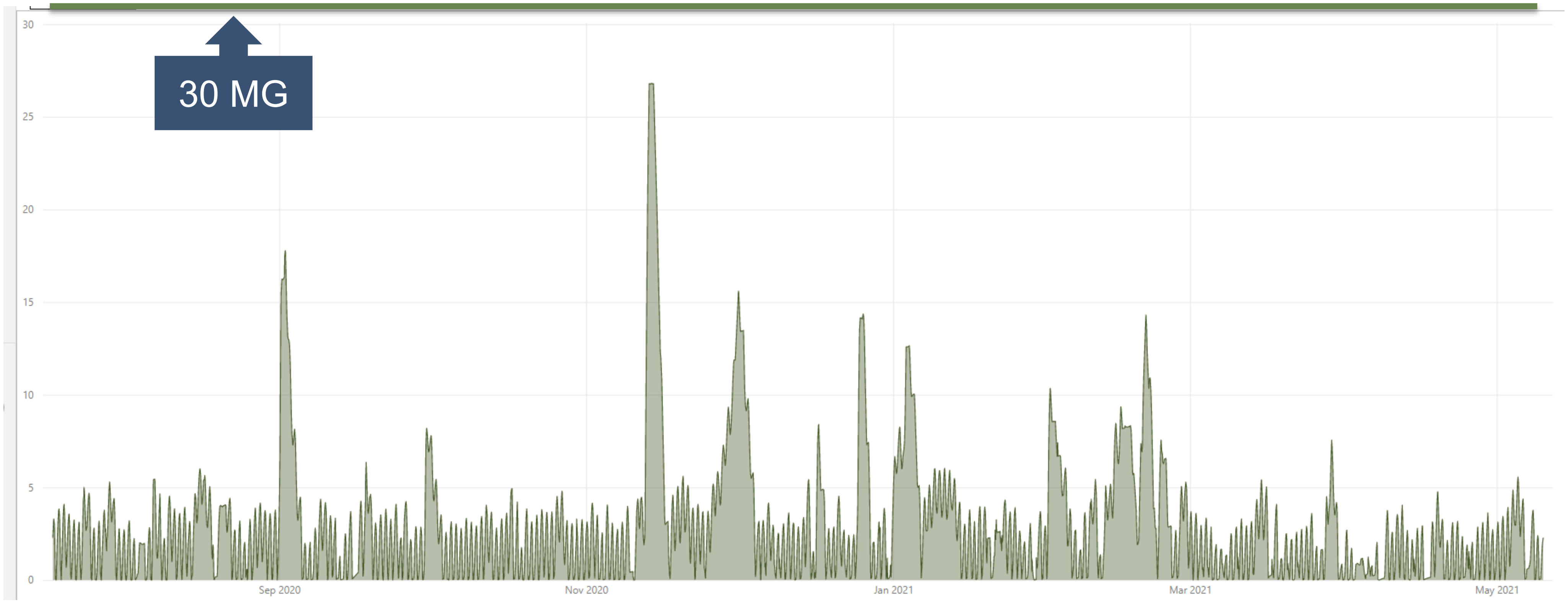
Largest Storm in 2021 Was In February 129 mgd Peak Hour Flow – Well Predicted



Rest of 2021 To Date Shows Good Predictions Continue



EQ Volume Never Exceeded



Dewatering Case Study

Exploratory Questions: Is it possible to predict the cake TS% as a function of past data trends? What variables contribute to this prediction?

Identify Potential Parameters

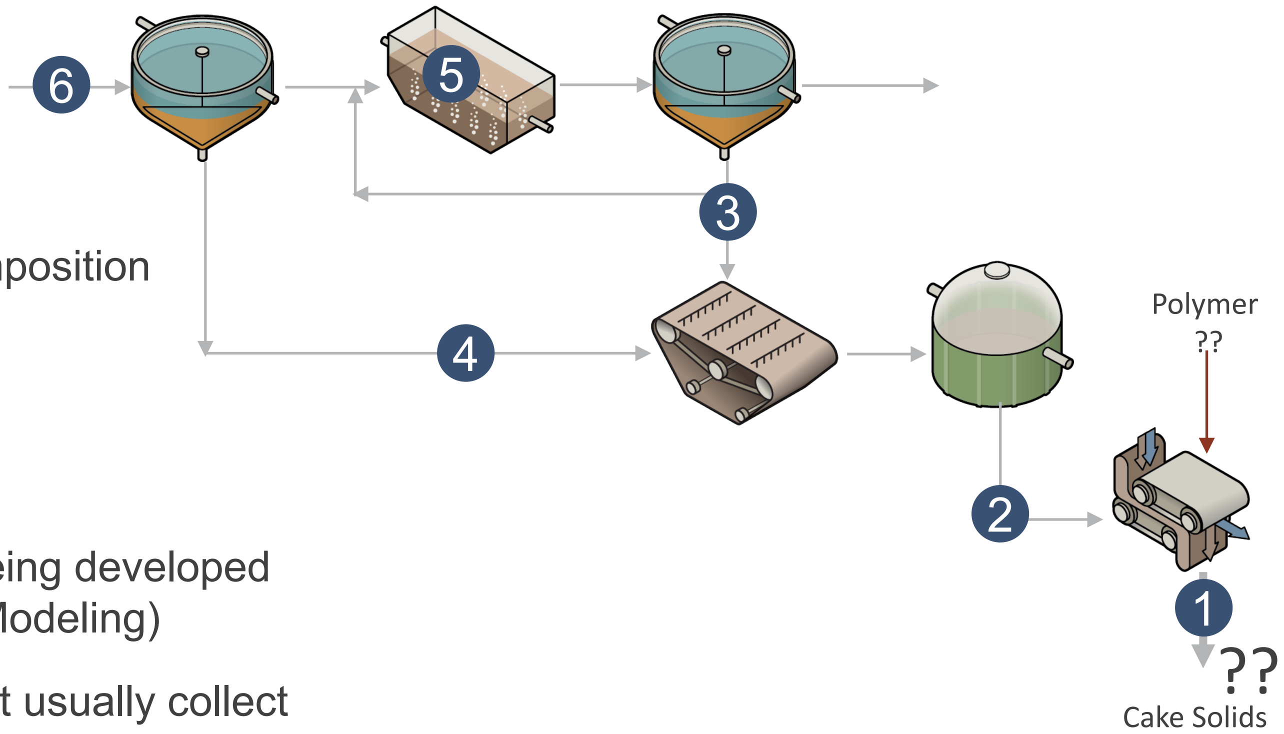
Evaluate/ Analyze Parameters

Develop Predictive Tools

Iterate and Refine Tools

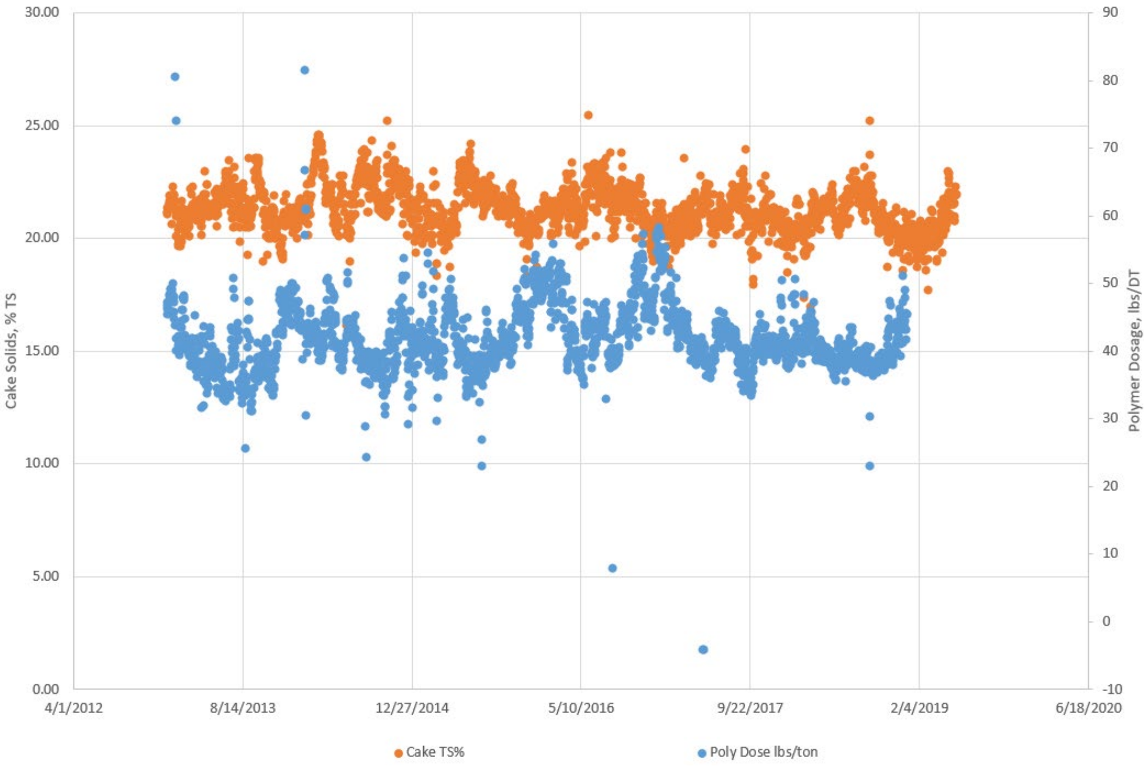
The journey sludge took to reach dewatering is very important

- Types of water associated with floc
- Floc bound water capacity (g Water/g VSS)
  - **Associated with particulates**
  - **Associated with colloidal material**
- Free ion (divalent cations) composition (charge and bonding capacity)
- VS/TS ratio
- Digestion chemistry
- Mechanistic modeling is still being developed (Sumo by Dynamita Process Modeling)
- Some needed data plants don't usually collect



Machine learning can use the history of the sludge to predict dewatering

- We sought a dataset with reliable historical data, spanning many years, with significant variation in % TS
- Explored whether different machine learning models could be used to find an empirical relationship between explanatory variables and dewaterability



Exploration of Explanatory Variables to Predict %TS

Parameters believed to potentially impact dewaterability

Current Values

Polymer Dose

Influent:
- Flow
- TKN
- BOD
- TSS/VSS
- Temperature

Secondary System
- SVI
- MLSS
- RAS Flow/Conc

Solids Processing
- Digester VSR
- HRT/SRT
- Influent Load
- TPS/WAS Ratio
- CNash

Trends also Important as Past Actions Influence Solids Treatment

- 7-day
- 14-day
- 25-day
- 30-day
- 40-day
- Applied to all variables except polymer dose

We Considered Research and Mechanistic Models in our Approach to Variable Selection like C/N*Ash

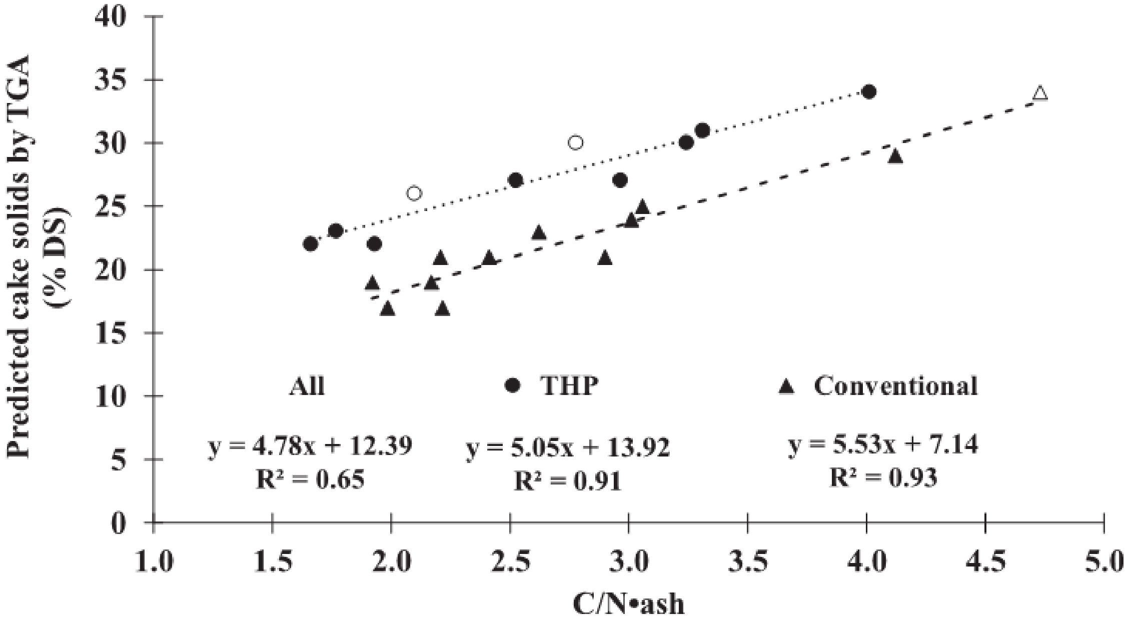
A Novel Parameter Predicting Cake Solids of Dewatered Digestates

Researchers identified a correlation of carbon, nitrogen, and ash content to cake solids.

Formula:

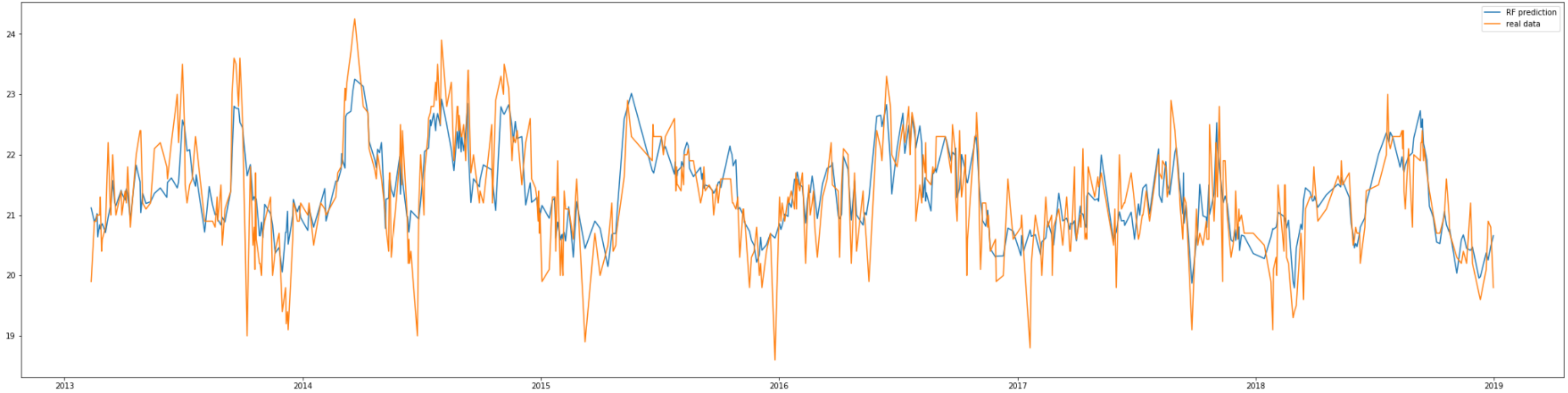
$$\frac{C}{N} * Ash = \frac{Carbon}{Nitrogen} * Ash\ (as\ a\ \%)$$

Does this theory apply to our machine learning model?



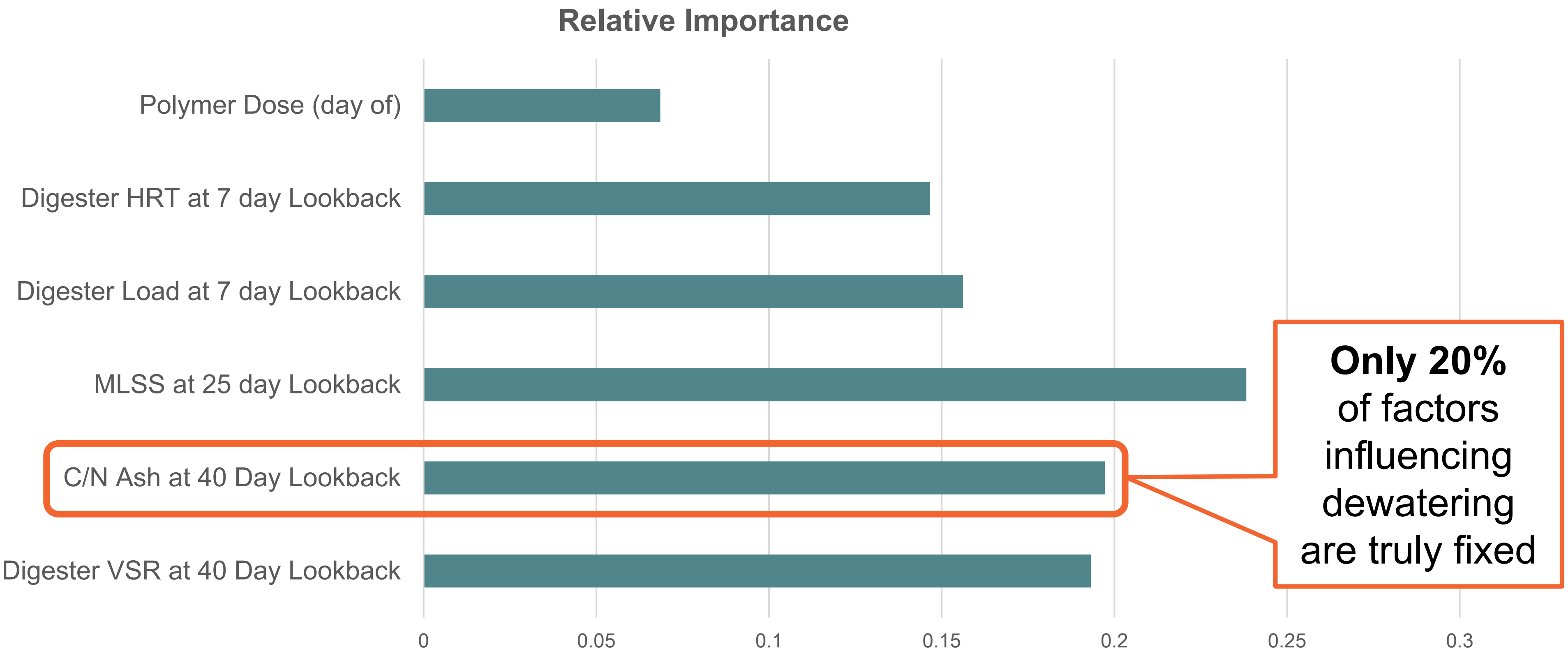
O.K. Svennevik et al. / Water Research 158 (2019) 350-358

Random Forest Prediction was Most Accurate



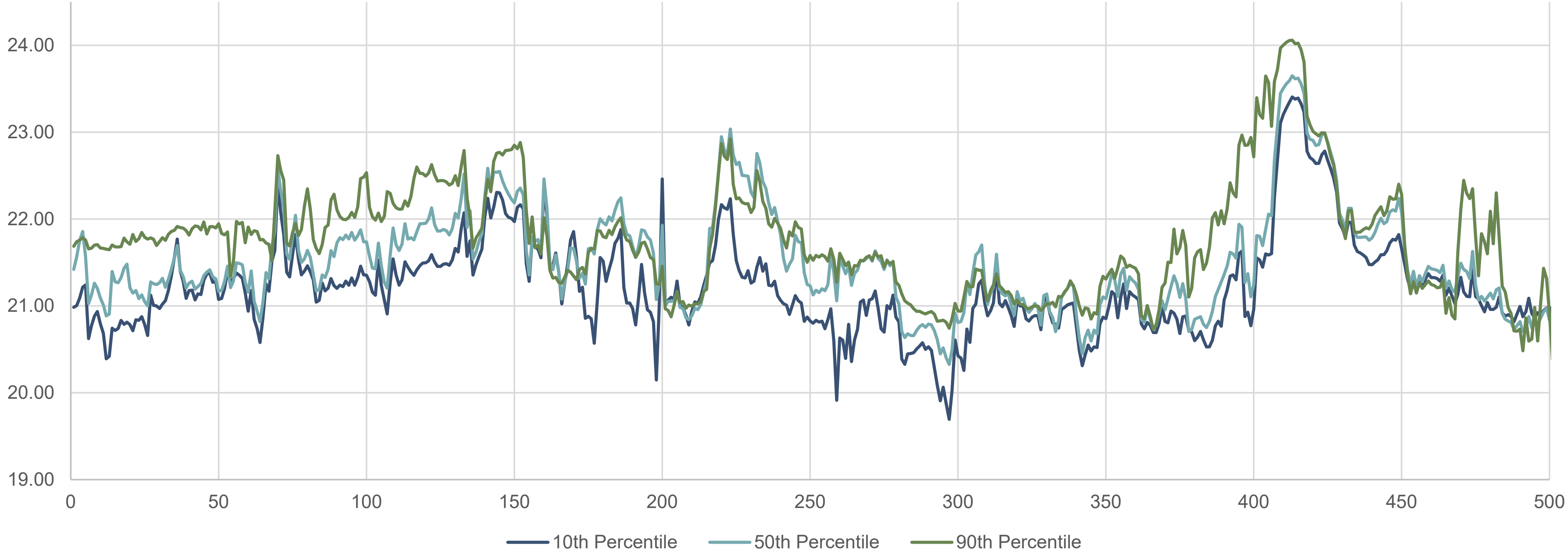
Parameter	Unit
Mean Absolute Error	% TS: +/- 0.4%

Key Variables Predicting Dewaterability and Their Relative Importance



Sensitivity Analysis on C/N*Ash Shows Expected Relationship that a Higher Ratio → Higher %TS

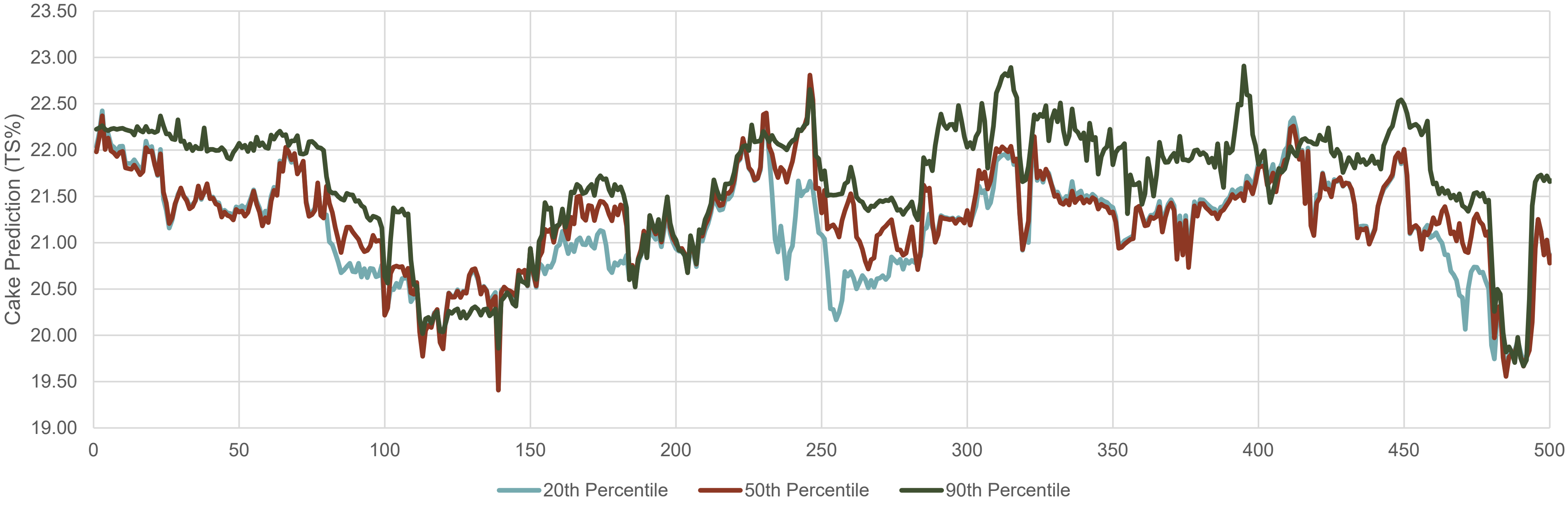
Adjusting C/N*Ash



*The model predicts improved dewaterability with a higher C/N*ash ratio, which is consistent with research*

Model Also Shows that the Longest HRT → Higher %TS

Adjusting Digester HRT



Model developed at this plant suggest that longer HRT (potentially more volatile destruction) leads to better dewaterability

How Would This Tool be Used In Real Life?

Big Picture Insights

- Learn how your plant behaves
- Verify those conclusions are sound
- Iterate and revise model until the conclusions make sense

Planning

- Estimate annual operating costs
- Identify potential efficiency losses*
- Identify seasonal trends

Day-to-Day

- Predict %TS
- Optimize dewatering machine settings
- Increase lb polymer/DT if low %TS expected

*For example, %TS is lower than model predicts, HRT in digester is the same, but perhaps mixing became less efficient, resulting in a change in state (the role/importance of HRT).

Considerations for Deployment

ML Project Lifecycle

Problem definition

- What is the problem we are trying to solve?
- Do we have sufficient and reliable data to develop an ML approach?
- Is ML an improvement over conventional approaches?

Model Development

- Data gathering and visualization
- Data screening
- Variable selection
- Create the model(s)
- Assess accuracy
- Refine/iterate on variable selection

Deployment

- Define data architecture
- Connect all data sources to model
- Build a visualization for model output
- Create the automated workflow

Continuous Retraining

- Create automated workflow to run old + new data through original model training code
- Compare old and new model results
- Human-in-the-loop reviews accuracy
- Deploy best performing model

Benefits of an Open Source Approach

Programming	python	Keras	TensorFlow
Deployment	Azure	Power BI	Microsoft SQL Server

Develop desktop ML models using Python

→

Deploy in test mode on Hazen desktop or Azure space

→

Transfer deployment to Client's Azure production environment or on-site/edge server

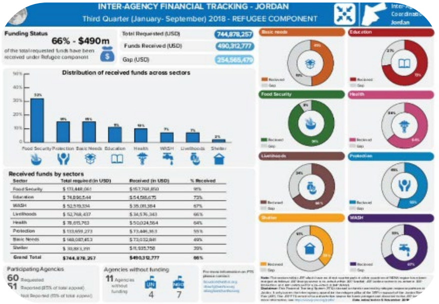
→

Client can hire any data engineer for subsequent projects

Summary

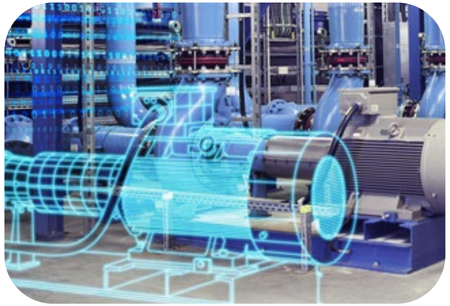
Many New Operational Support Tools Exist For WRFs With Strong Proofs Of Concept

Advanced Controls



Advanced Dashboards

Machine Learning Models



Digital Twins

Questions?

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