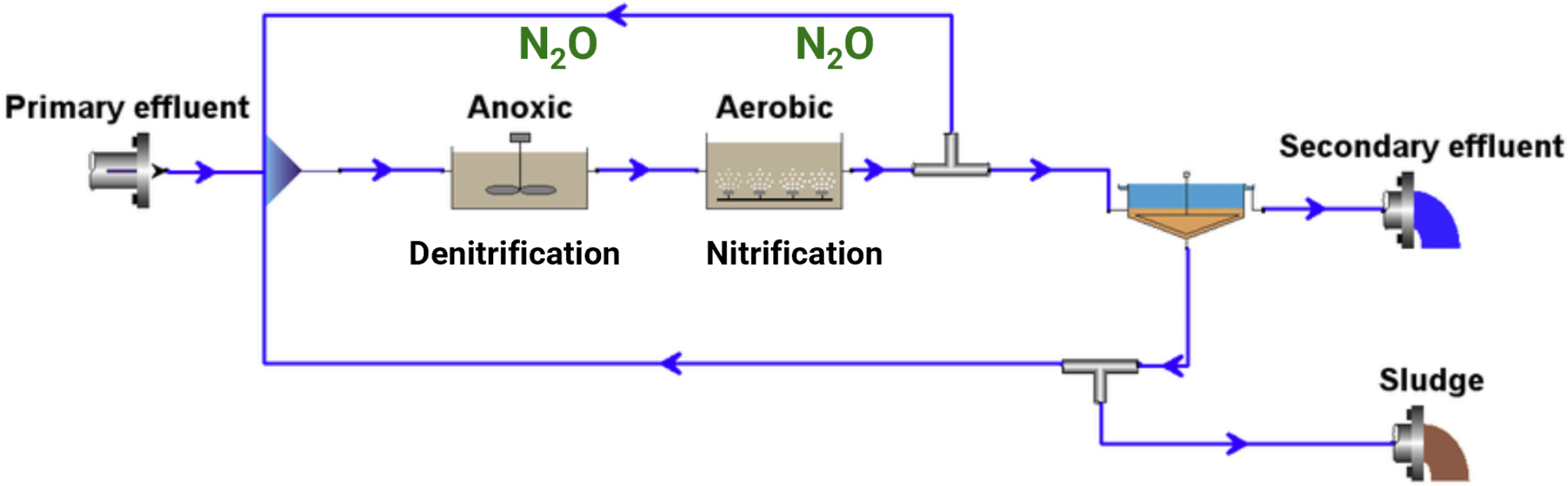
An AI/ML approach for assessing, reducing, and monitoring N2O emissions from WRRFs

U.S. DOE Industrial Efficiency Decarbonization Office
Measuring Life-Cycle Greenhouse Gas Emissions from Water Resource Recovery Facilities Workshop – January 23 – 24, 2024

The Approach

KNOWLEDGE OF N_2O PATHWAYS AND INFLUENCING (RISK) FACTORS



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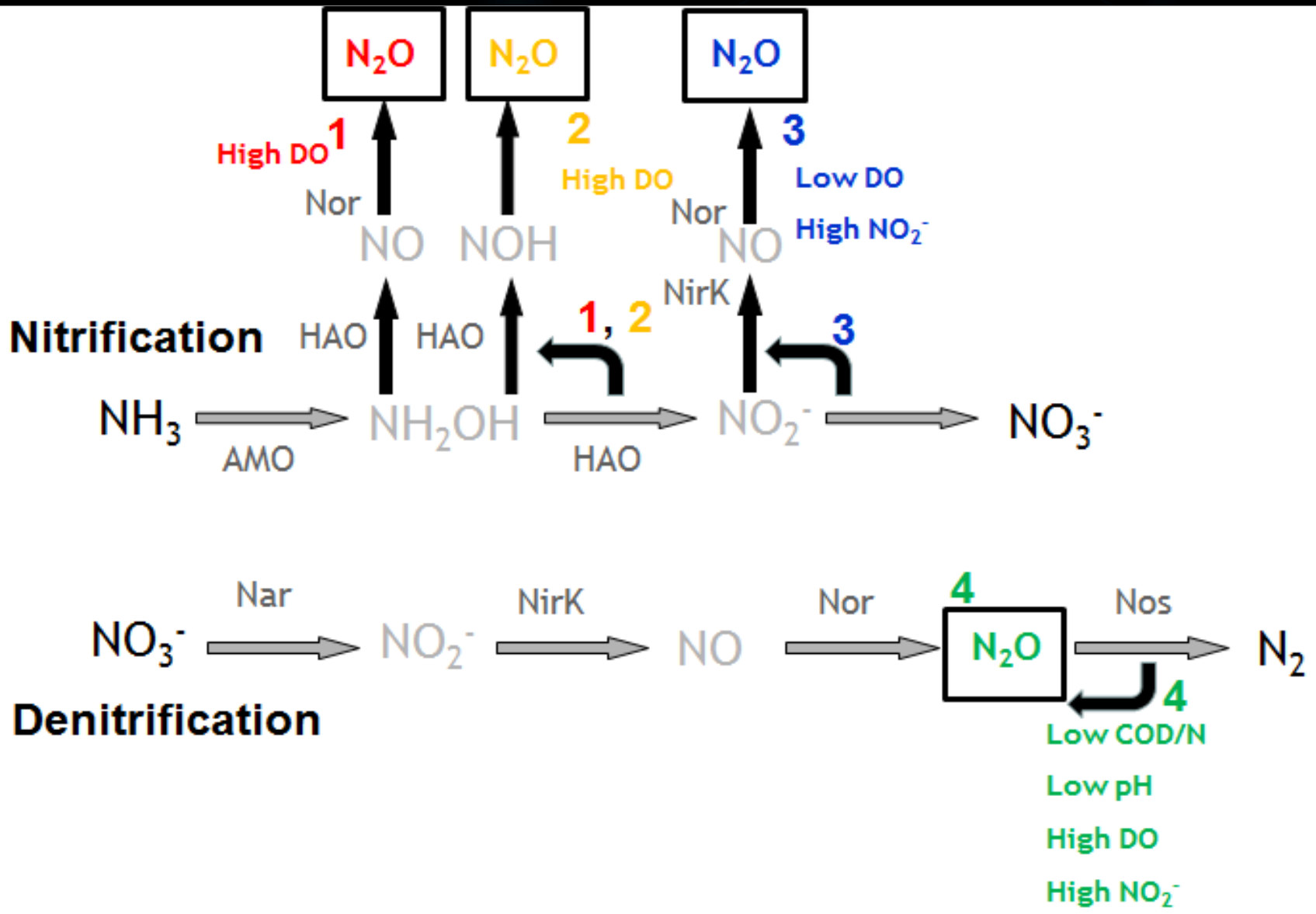

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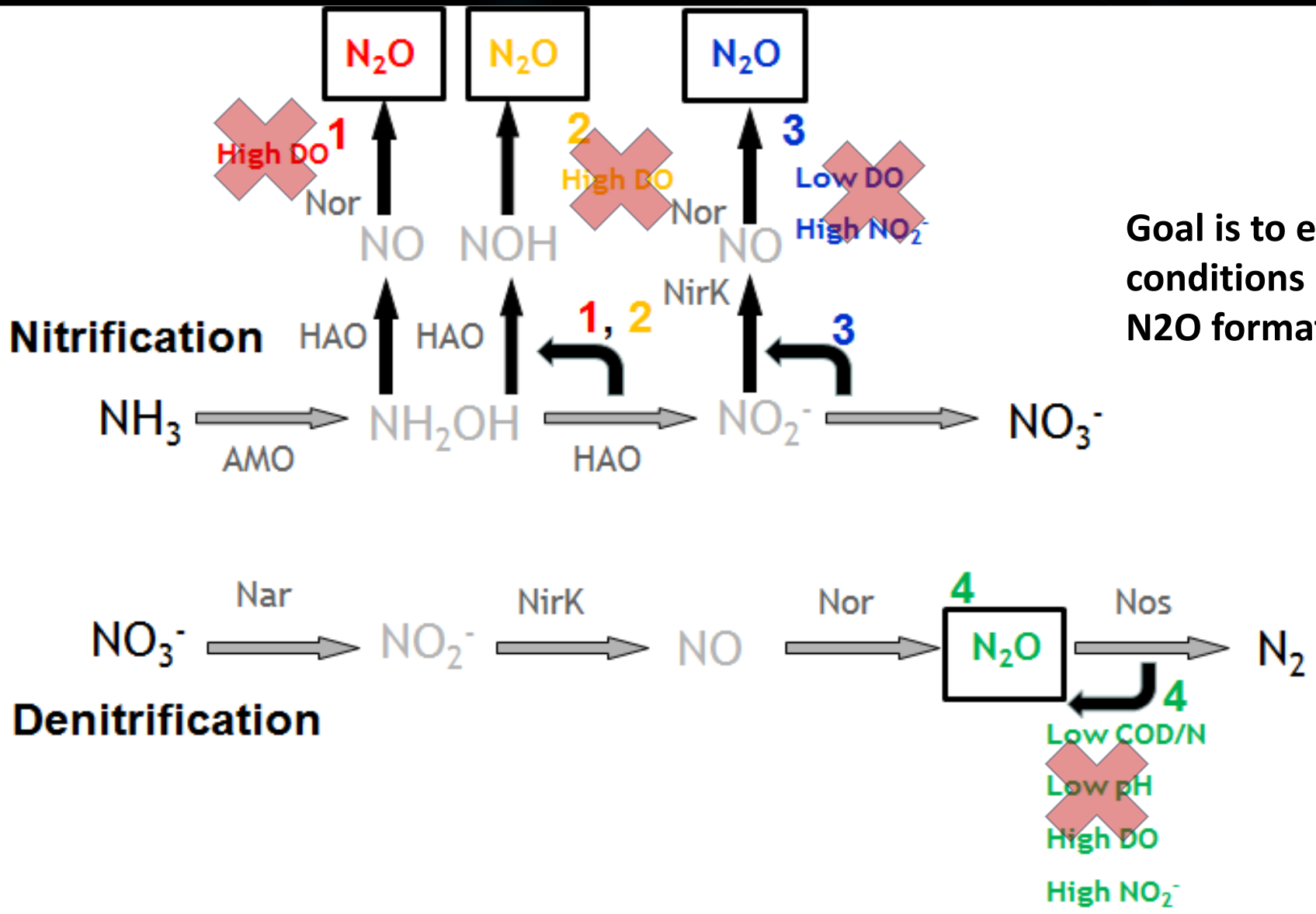


Goal is to eliminate conditions leading to N2O formation risk

AI / MACHINE LEARNING (ML) APPROACH FOR MITIGATING WRRF N_2O EMISSIONS

Knowledge Base (Porro et al., 2014)

Process/ Condition	Operational Parametr/ Condition	Variable	References linking operational conditio to N_2O risk
Nitrification	High No_2	No_2	Kampschreur et al. 2009; Foley et al., 2010; Ahn et al., 2010; GWRC, 2011
	Low DO	DO	Kampschreur et al. 2008; Kampschreur et al. 2009;
	High DO	DO	Ahn et al., 2010, Chandran et al., 2011, Law et al., 2012, Peng et al., 2014

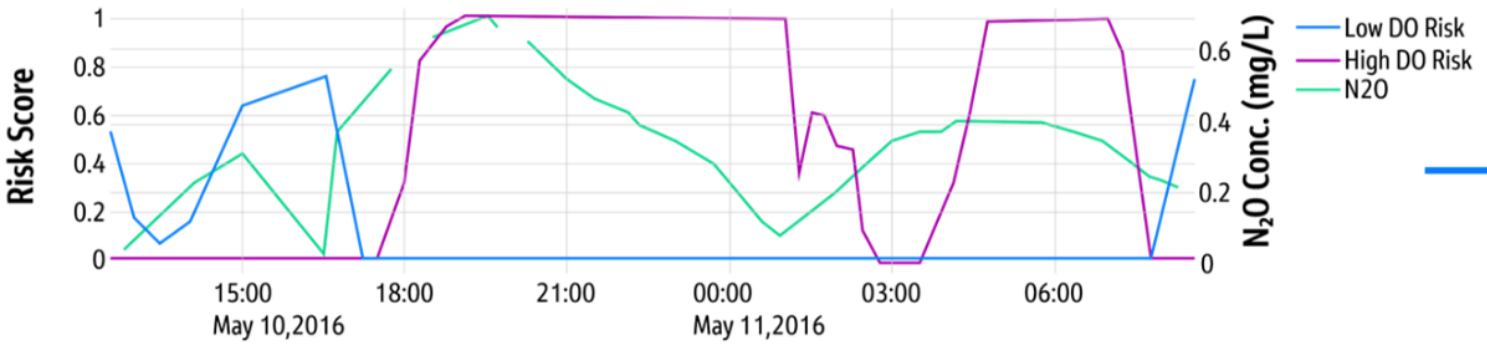
Peer reviewed literature

Can be integrated with:

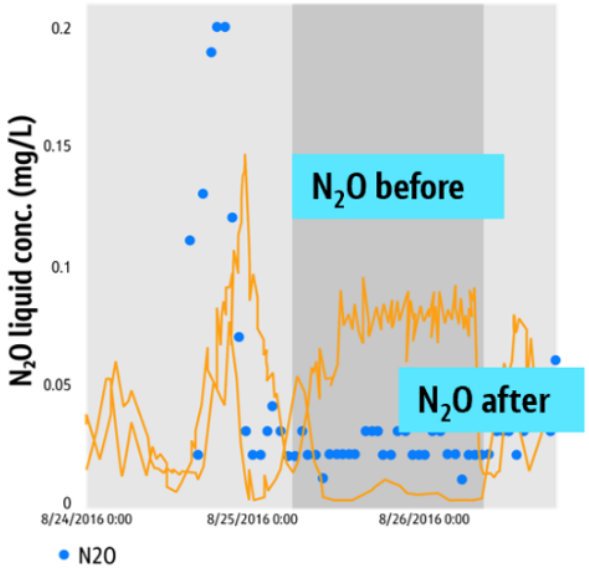
- **Process models**
- **Digital Twins**
- **Advanced Control solutions**

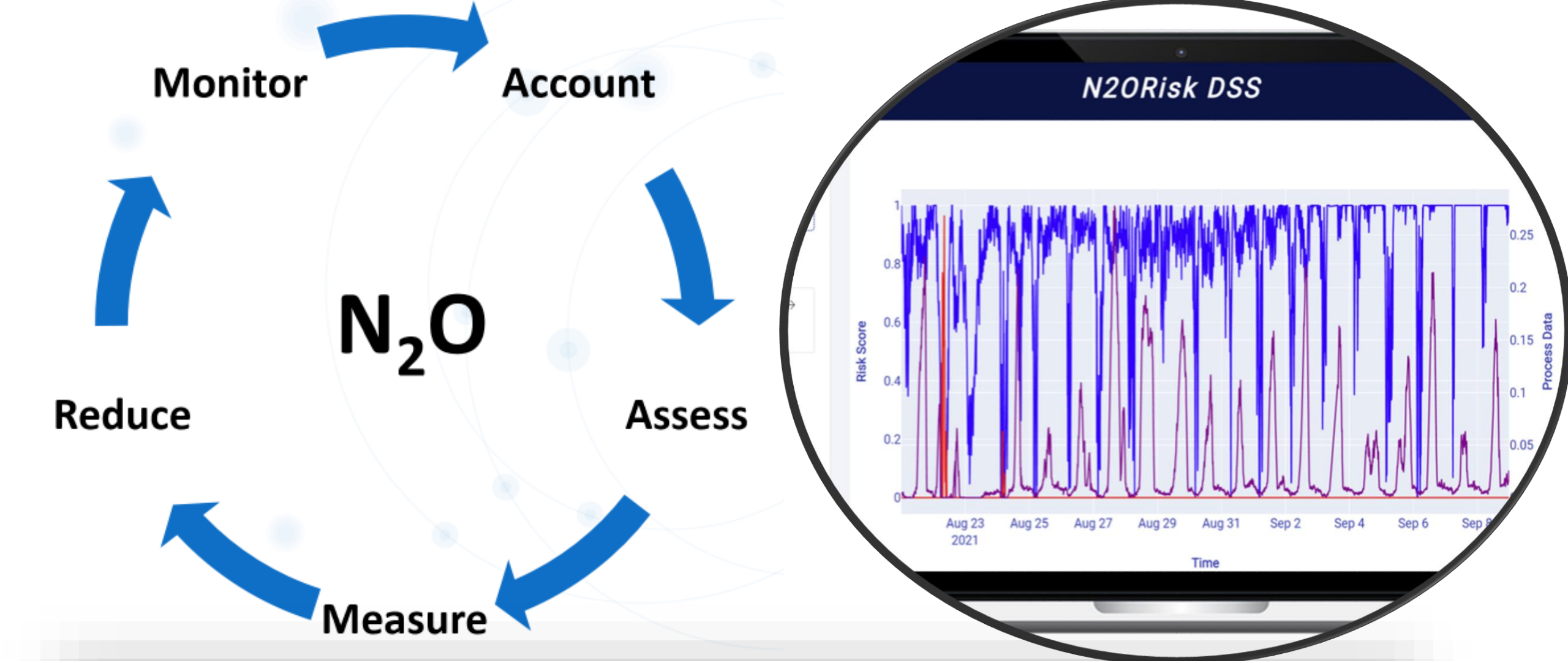
Risk Assessment

ML Predictions



Mitigation



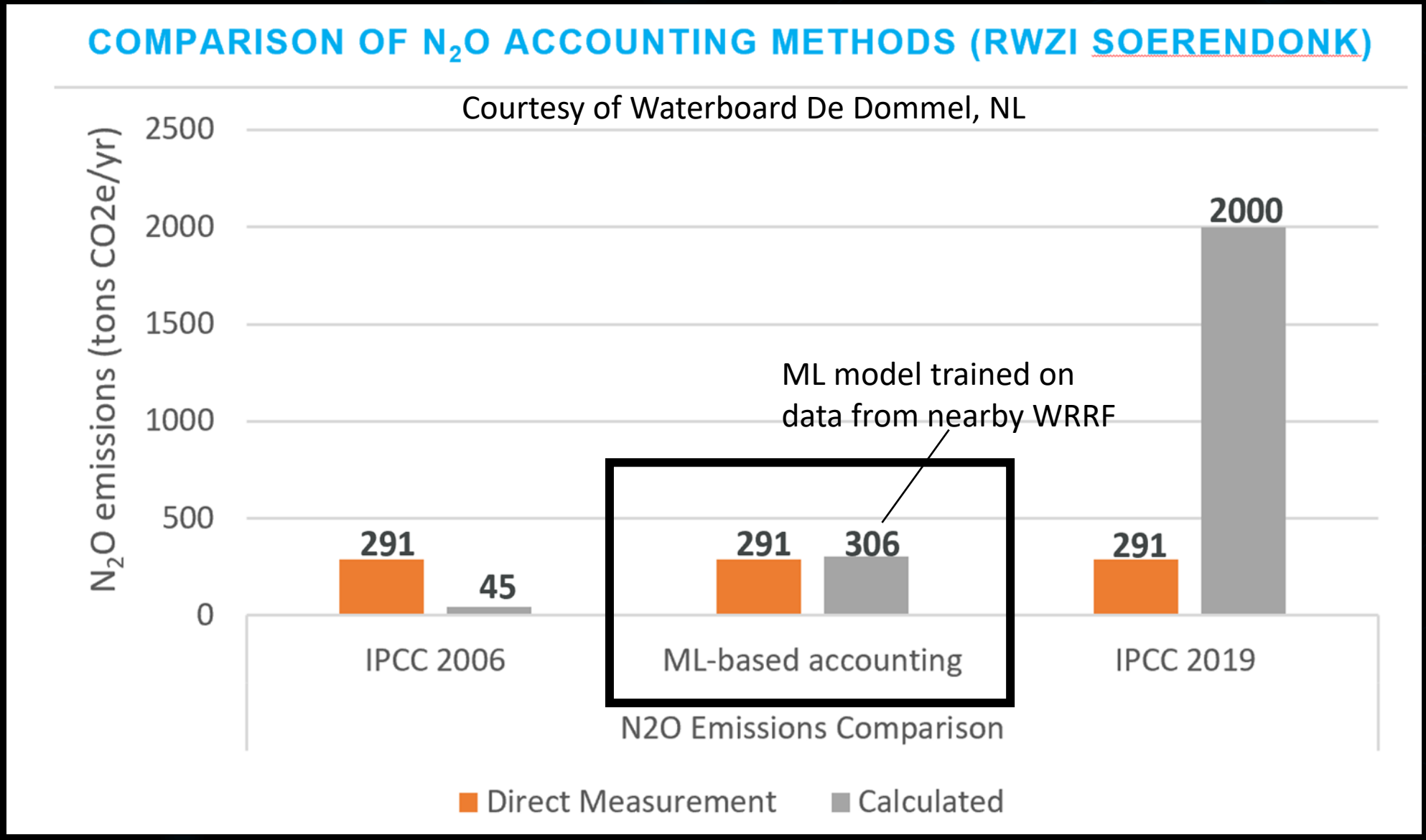

Monitor
Account
Assess
Measure
Reduce
N_2O
N2ORisk DSS
Risk Score
Process Data
Time
Aug 23
2021
Aug 25
Aug 27
Aug 29
Aug 31
Sep 2
Sep 4
Sep 6

Accounting and Assessing N20

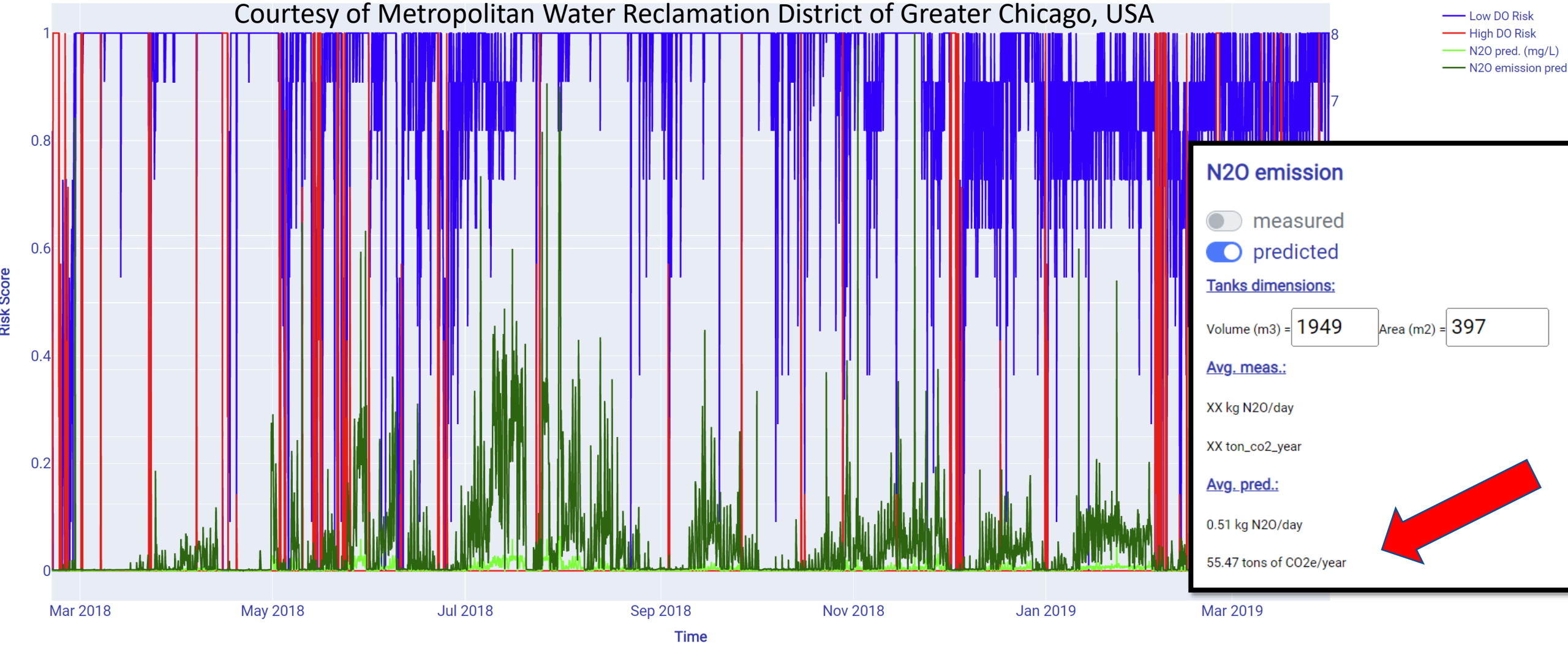
What data do we need?

- SCADA
  - DO, NH_4^+, NO_3^-, MLSS
  - Air flow
- N_2O (if available)

The Emission Factor Problem Exposed



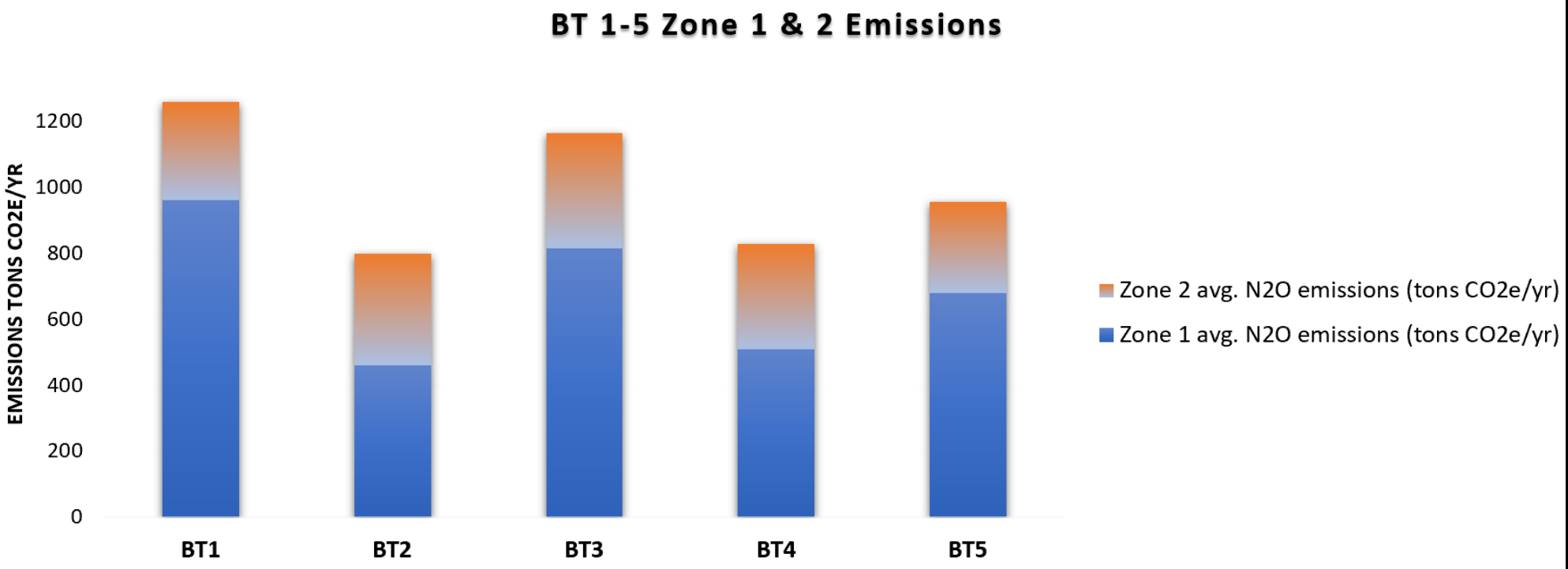
Assessing N_2O Risk (with AI) and Emissions (with ML)



This tells us why we have N2O at different times (and what would generally be needed to reduce risk) and an estimate of N2O emissions based on the site-specific process data. EFs cannot do this.

Summary of N2O emissions (w/ ML), risk (w/ AI), and NH4 per BT

300,000 PE WRRF in NL



	BT1	BT2	BT3	BT4	BT5	Total
Total N2O emissions (tons CO2e/yr)	1261	800	1165	828	956	5010
Average risk	0.40	0.46	0.42	0.40	0.38	
Zone 1 avg. N2O emissions (tons CO2e/yr)	961	461	816	509	**679**	
Zone 1 avg. risk	0.44	0.55	0.44	0.44	**0.39**	
Zone 1 avg NH4 (mg/L)	2.8	1.5	2.5	1.9	**2.6**	
Zone 2 avg. N2O emissions (tons CO2e/yr)	300	339	349	319	**277**	
Zone 2 avg. risk	0.37	0.37	0.41	0.36	**0.37**	

When NH4 conditions are similar, lower risk means lower emissions

Screening and prioritizing sites for action

1	2	3	4	5	6	7	8	9
Site name / process type	Population Equivalents	Calculated emissions per CAW EF (tons of CO2e/yr)	Calculated emissions per N_2O measurements or estimated with ML (tons of CO2e/yr)	N_2O risk profile (why there is N_2O)	General Mitigation Opportunities	Is site ready to reduce N_2O (Y/N)	Ranking based on column 3 EF	Ranking based on Columns 4 and 7
CAS	221,495	1207	2090	due to low DO	Increase DO	Y	2	2
CAS	296,862	1624	1260	due to both high and low DO	Balance DO (eliminate over and under aeration)	Y	1	3
CAS	163,660	895	610	due to low DO	Increase DO	N	3	4
SBR	141,497	774	2000	Mainly due to anoxic phase	Iincrease anoxic period, decrease DO during aerobic	Y	4	1

Various UK sites

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We cannot use EFs for planning N2O measurements/reduction

Measuring and reducing N2O

Methods for Field measuring N_2O emissions

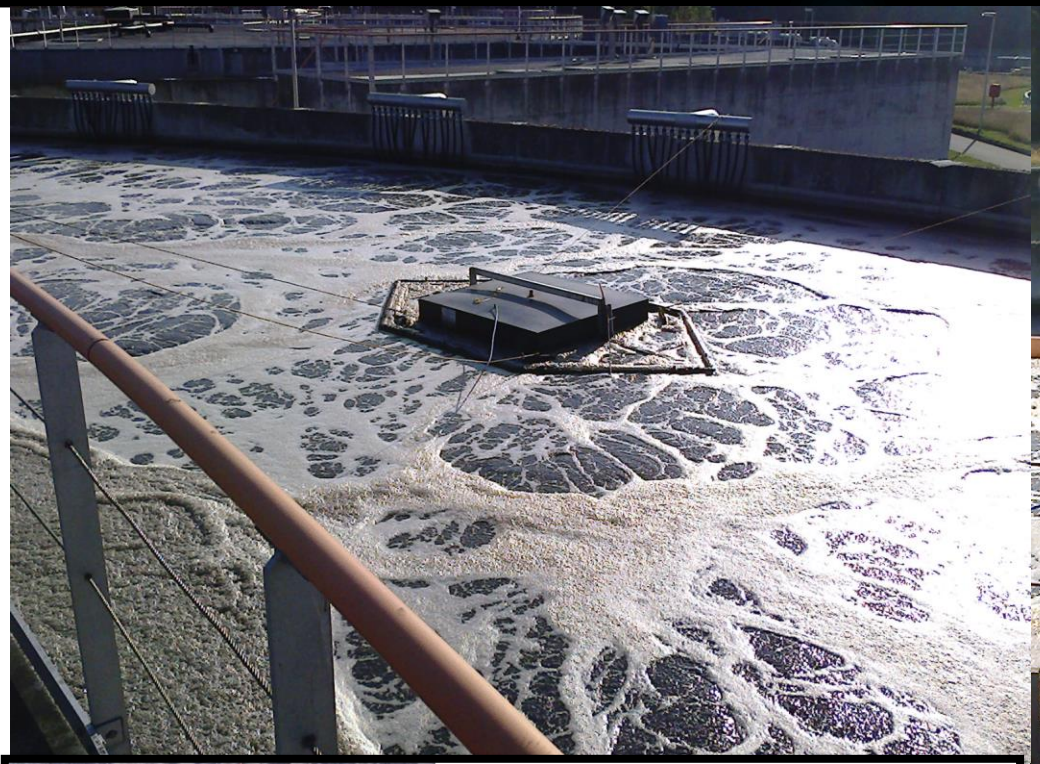
- *Floating hood method*
- *Liquid-phase measurements*
- *Mobile trace dispersion method*
- *Other methods*
- *GC / grab sampling*
- *LessDrone*

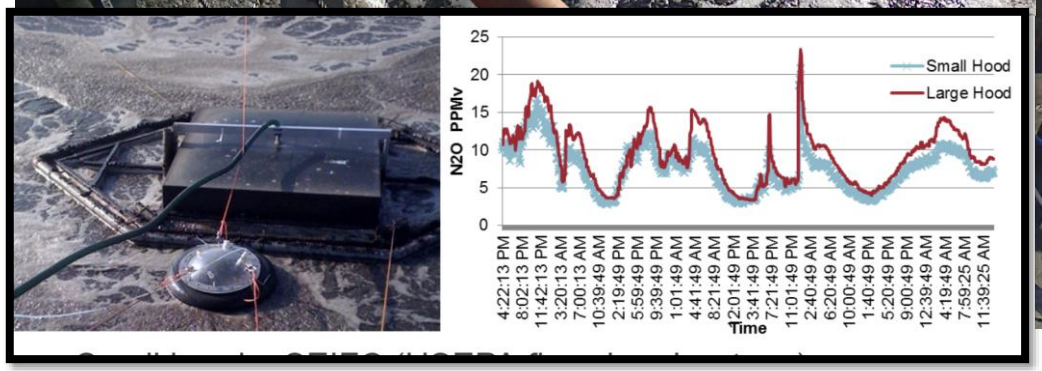
LIQUID-PHASE N2O MEASUREMENTS

Courtesy of Unisense Environment

Courtesy of Welsh Water

FLOATING HOOD METHOD





Online N_2O Gas and Liquid Analysis

SEIFC Flux Chamber
(for online gas – not visible)

Off-gas N2O analyzer
(for online gas and liquid)

Unisense
Microsensors
(liquid)

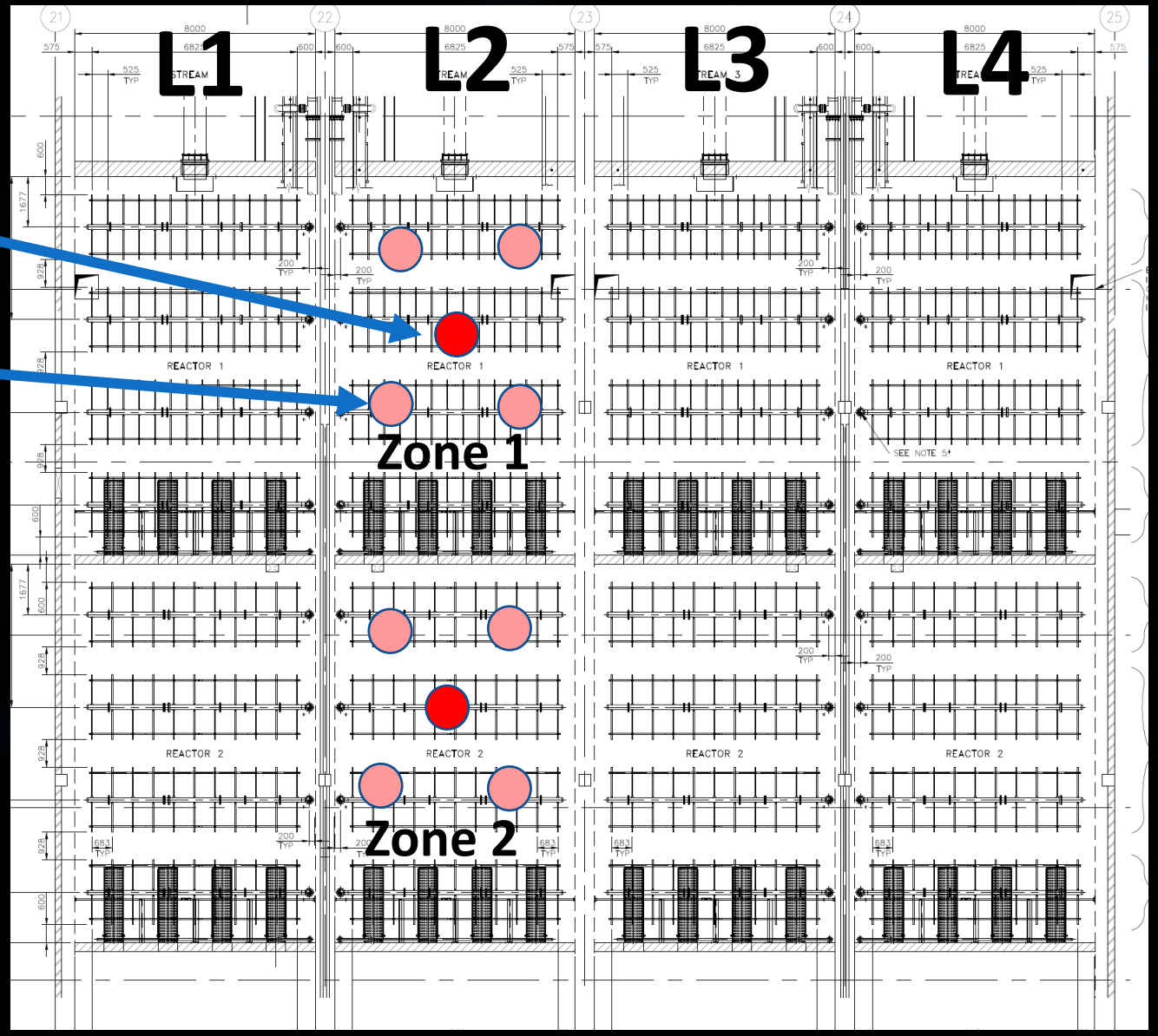
Gas stripping
column for
determining liquid
N2O conc.

Eindhoven RWZI, 2014

Checking spatial variability with physical measurements

Reference location (typical)

Spot check location (typical)

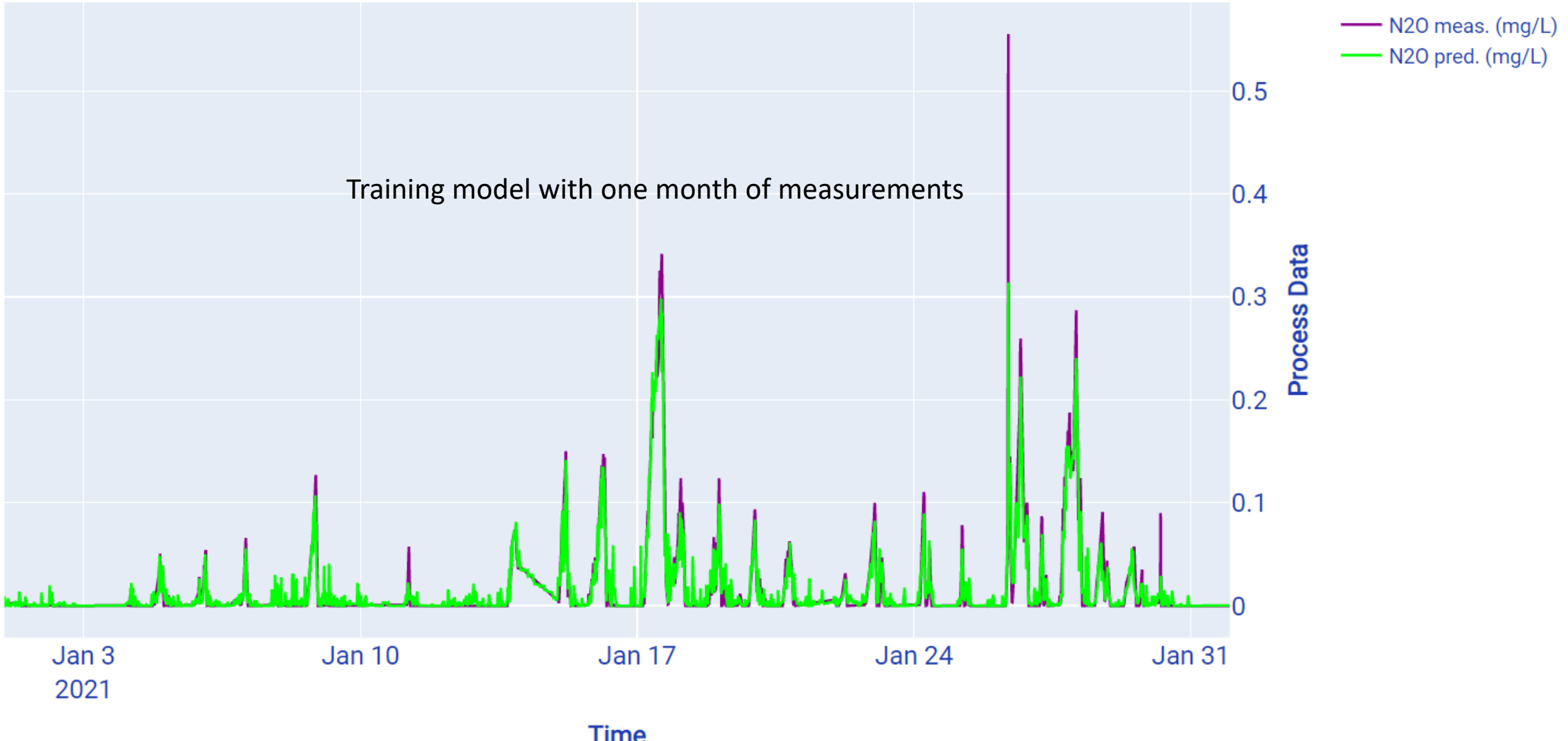


If any of the spot check locations have significantly different N2O conc. than the reference location, then a ML model can be trained so that N2O emissions can be predicted in the spot check locations with the plant data and N2O from the reference location.

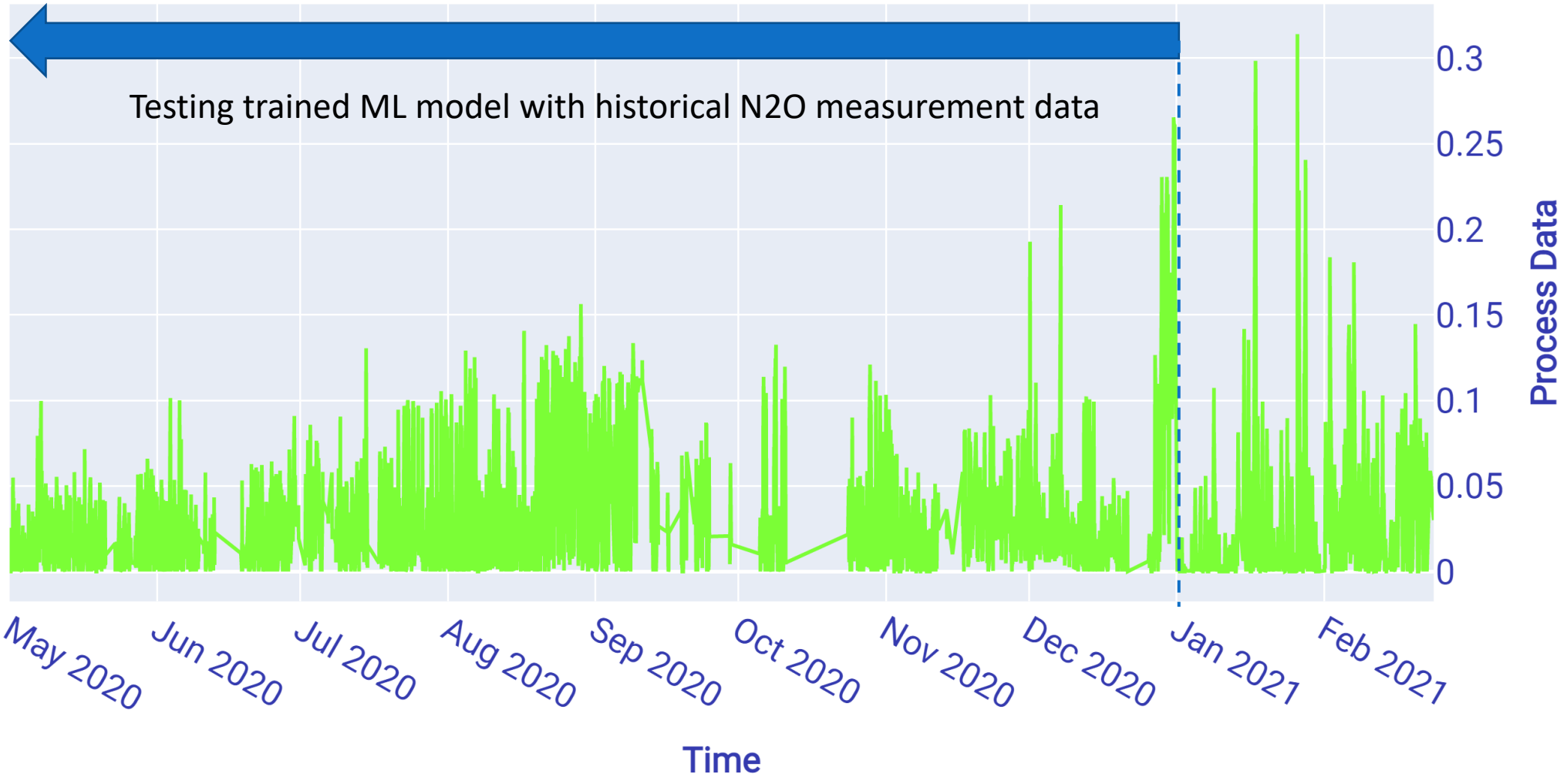
ML models trained with Lane 2 data can be used to account for operating conditions in Lanes 1, 3, and 4 and predict N2O in Lanes 1, 3, and 4

ML Model Training

Courtesy of Hoogheemraadschap De Stichtse Rijnlanden (HDSR), NL



Checking seasonal variability with ML and historical data

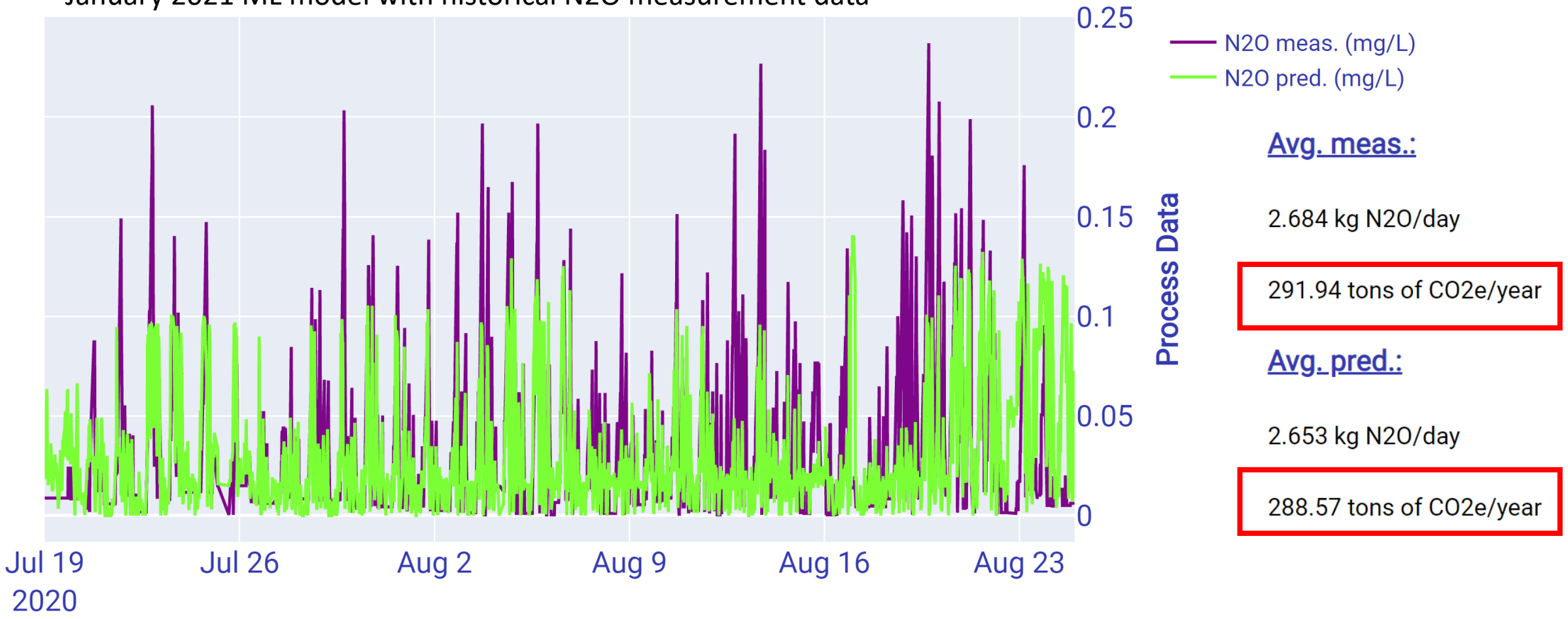


Courtesy of HDSR, NL

How long to measure

Zooming into roughly one-month in July/August 2020 to test trained January 2021 ML model with historical N2O measurement data

Courtesy of HDSR, NL



Avg. meas.:

2.684 kg N2O/day

291.94 tons of CO2e/year

Avg. pred.:

2.653 kg N2O/day

288.57 tons of CO2e/year

Confirms we can use historical data and ML and do not need to measure for a full year to understand season/operational variability without taking action. We can also measure in parallel control and test treatment tanks to baseline and reduce at the same time as opposed to losing a year.

Land van Cuijk RWZI Knowledge-based AI/ML Insights

Cobalt water GLOBAL

N2ORisk DSS

Logout

Data to Visualize:

n2oriskdss_jporro...

n2oriskdss_jporro_LVC3.2

Upload .CSV File

Date Selection

Reset Date Range

02/15/2019 →

02/18/2019

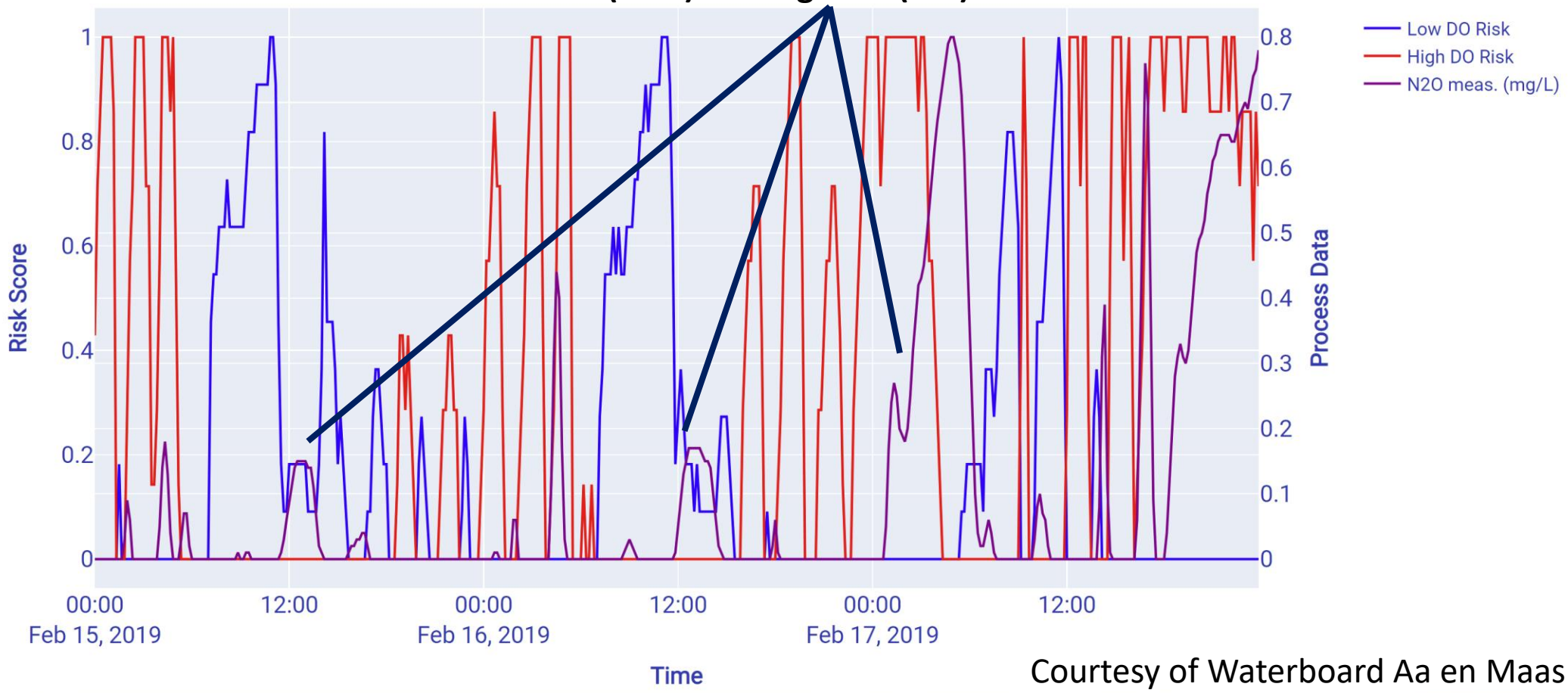
Risk to Display

- Low DO
- High DO
- Overall
- NO2 n/d
- pH
- High DO Denitrif.
- COD/N
- Overall Denitrif.

Nitrification Mode

Data to Display

N2O (purple) under N2O risk due to both low DO (blue) and high DO (red) conditions



Courtesy of Waterboard Aa en Maas

Reducing N_2O with Knowledge-based AI/ML Insights

Cobalt Water Global

N2ORisk DSS

Logout

Data to Visualize:

n2oriskdss_jporro...

n2oriskdss_jporro_LVC3.3

Upload .CSV File

Date Selection

Reset Date Range

02/16/2019 →

02/20/2019

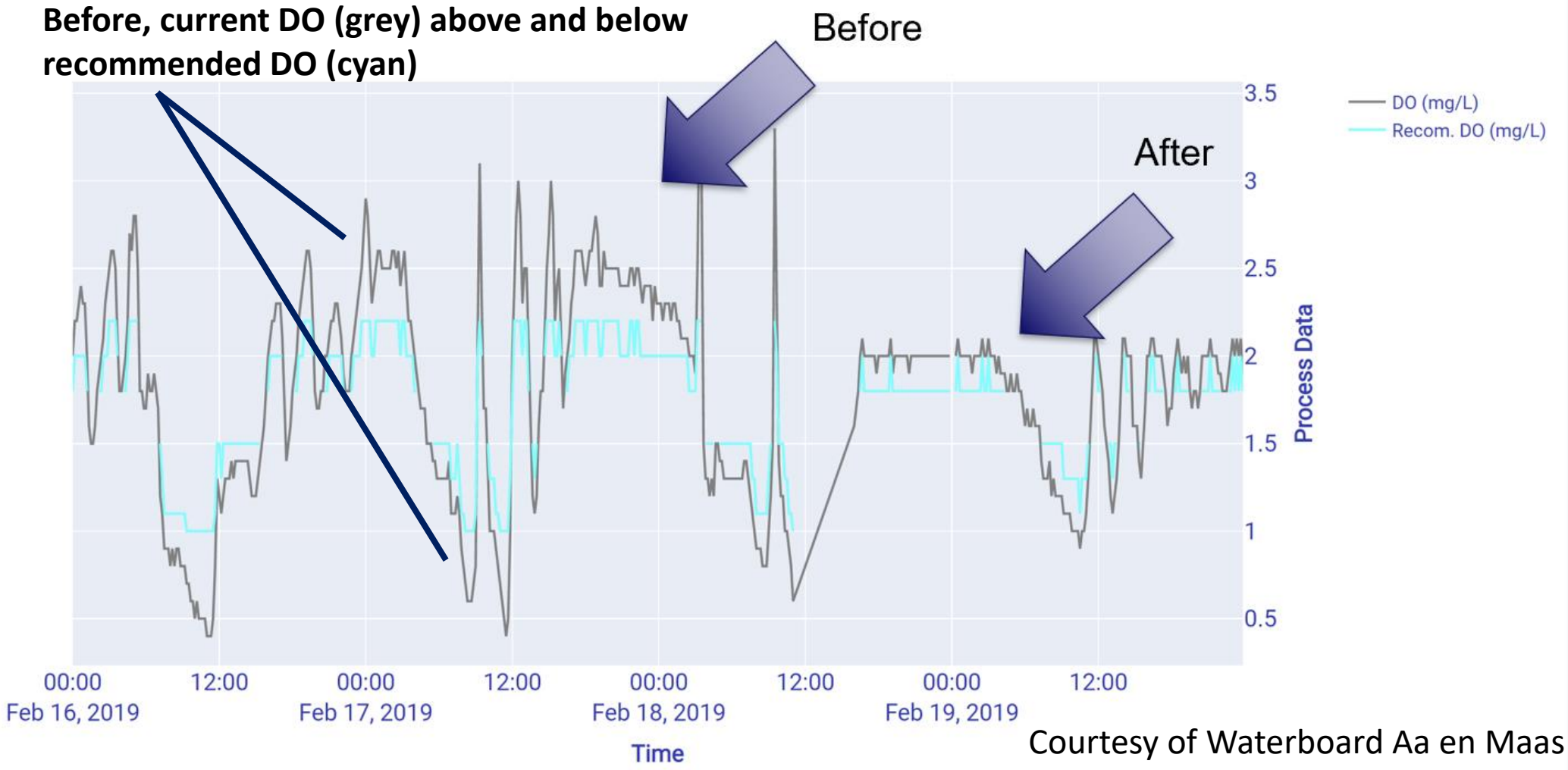
Risk to Display

- Low DO
- High DO
- Overall
- NO2 n/d
- pH
- High DO Denitrif.
- COD/N
- Overall Denitrif.

Nitrification Mode

Data to Display

Before, current DO (grey) above and below recommended DO (cyan)



Courtesy of Waterboard Aa en Maas

Reducing N_2O with Knowledge-based AI/ML Insights

Cobalt water GLOBAL

N2ORisk DSS

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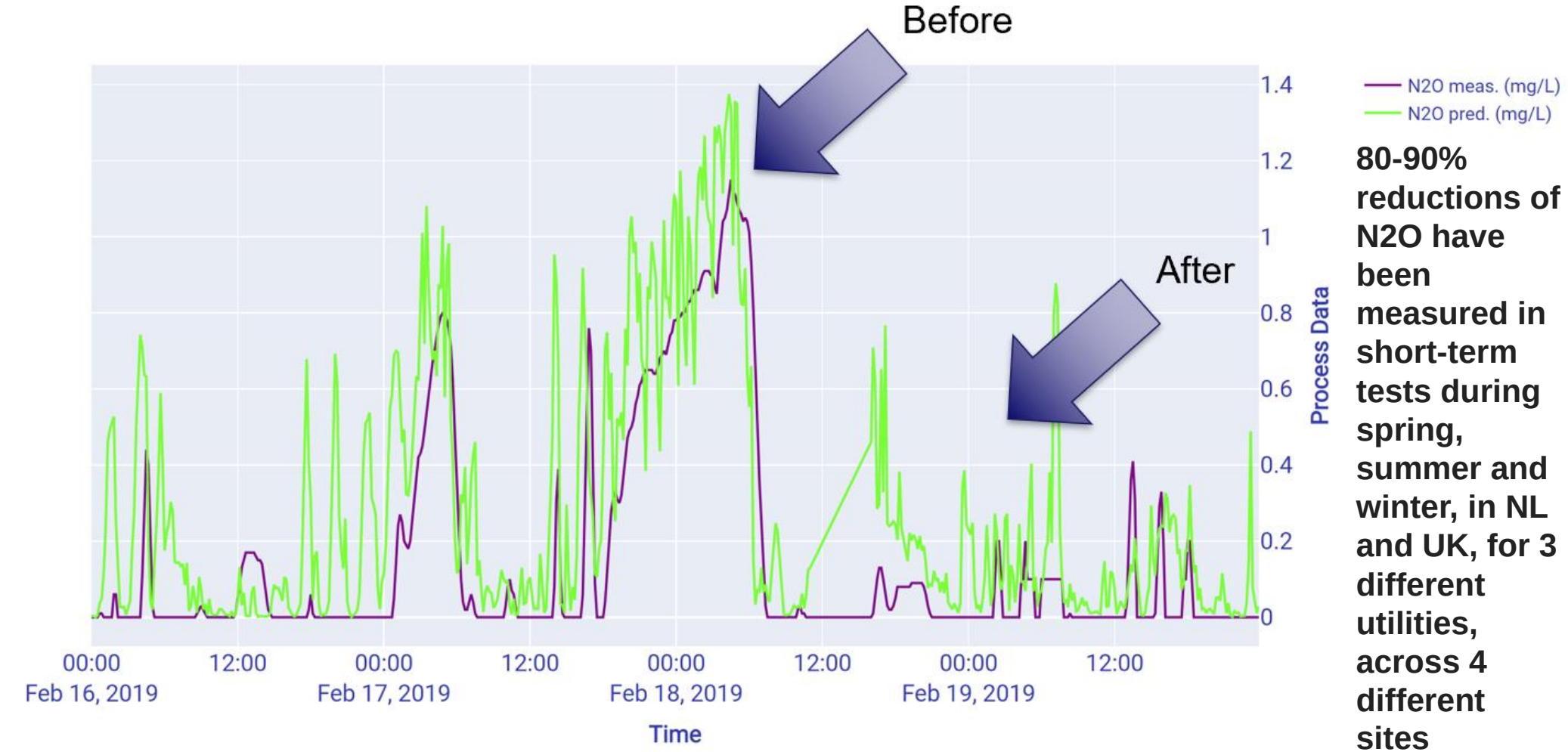


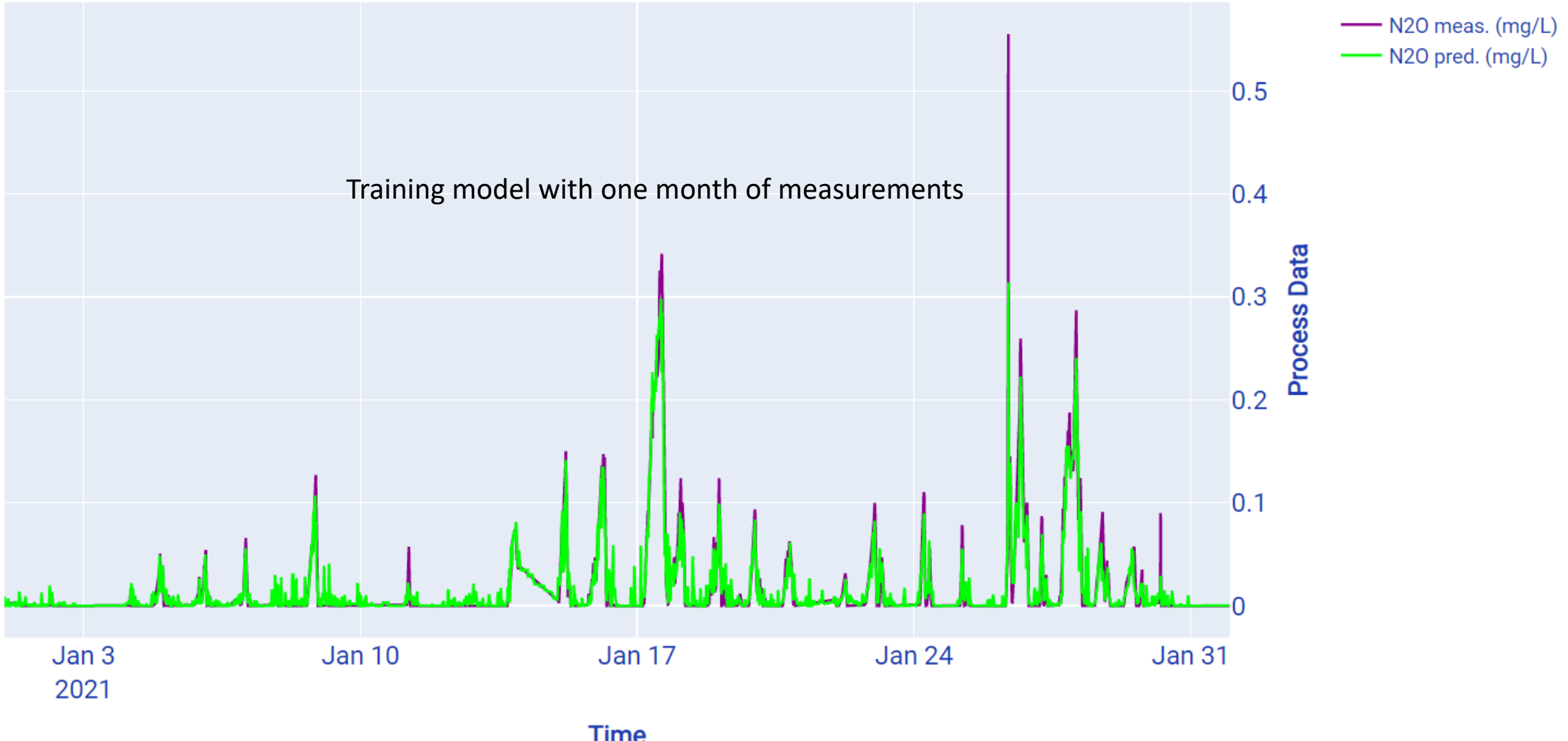
80-90% reductions of N2O have been measured in short-term tests during spring, summer and winter, in NL and UK, for 3 different utilities, across 4 different sites

Monitoring the process and continuously reducing N20

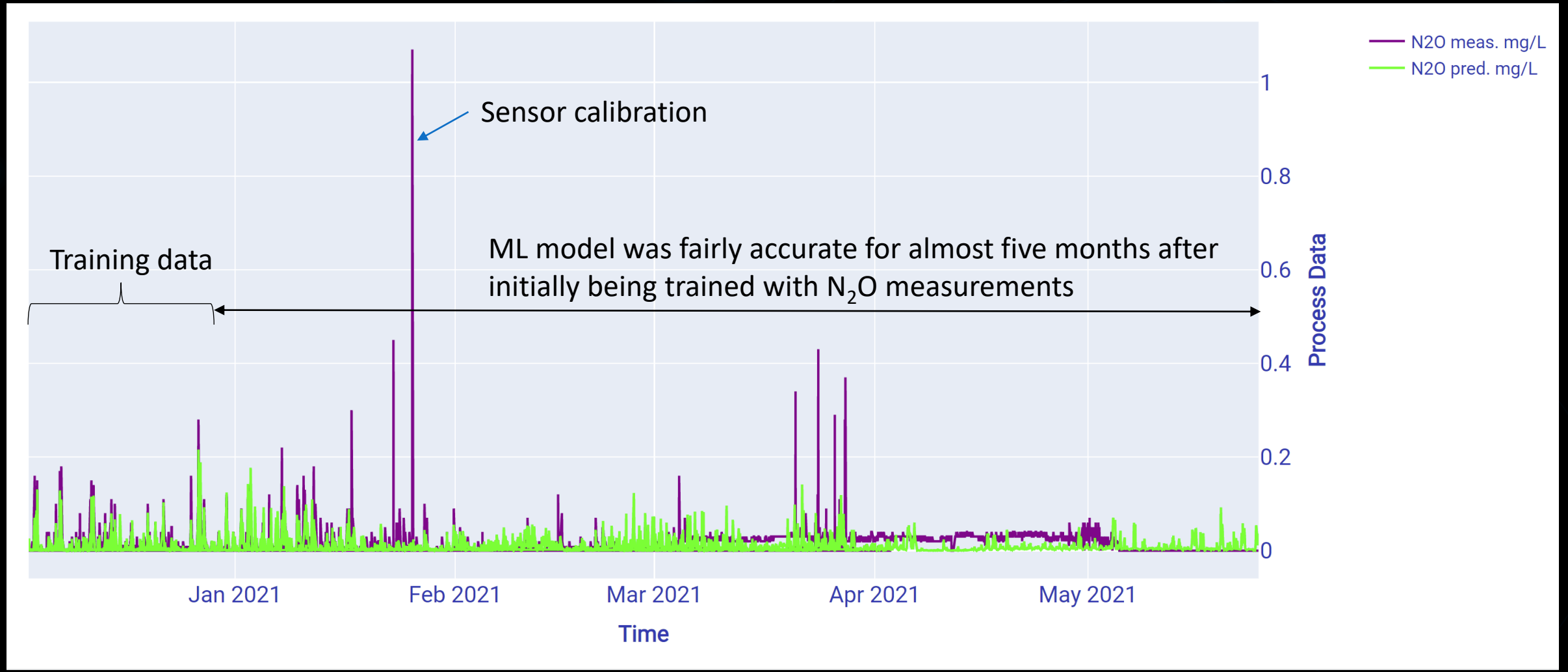
What do we monitor?

- SCADA
  - DO, NH_4^+, NO_3^-, MLSS
- Risk
- N_2O

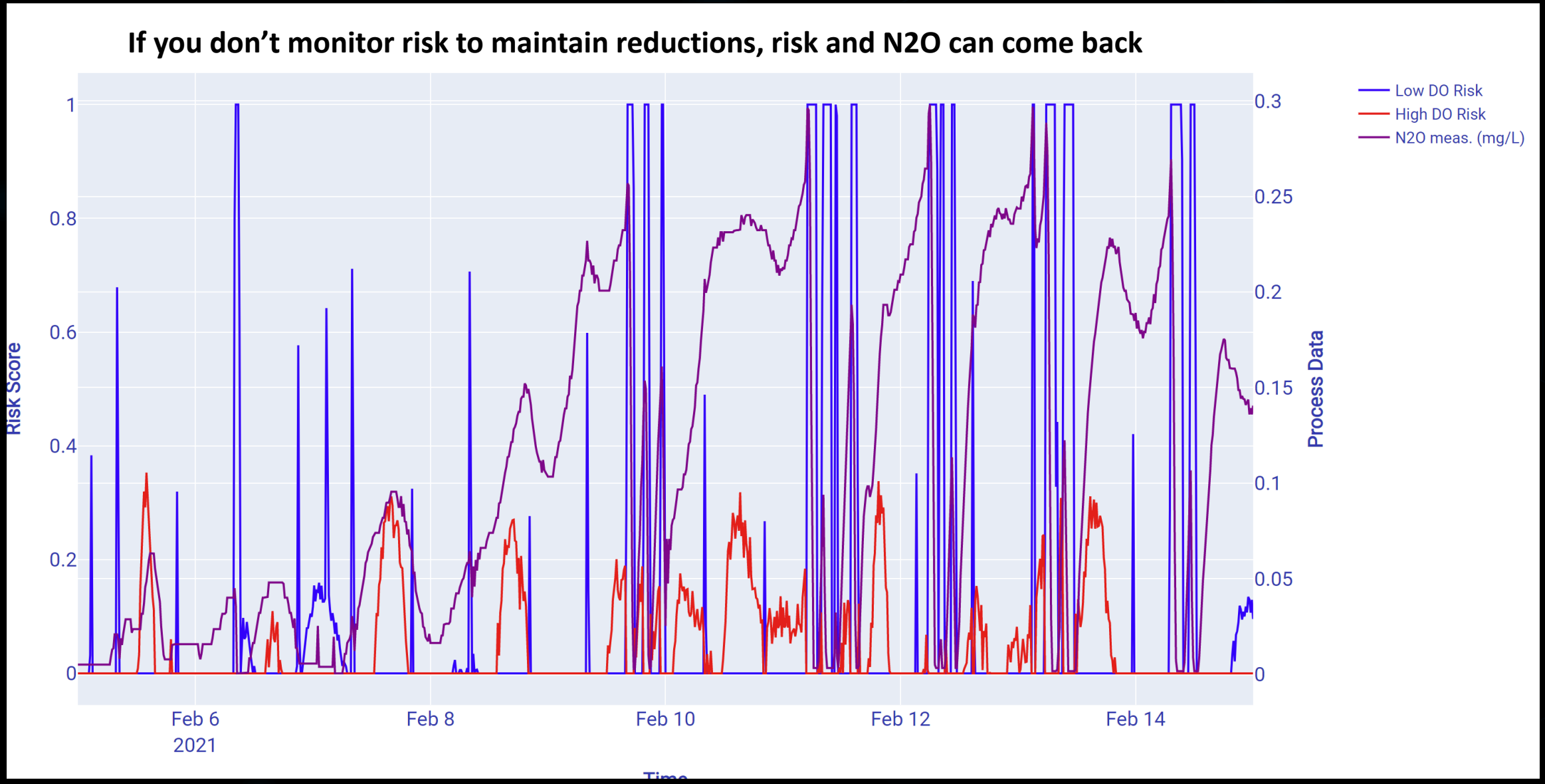
ML Model Training



Testing of ML model based on first month of measurements against measured N_2O for several months after at site in NL



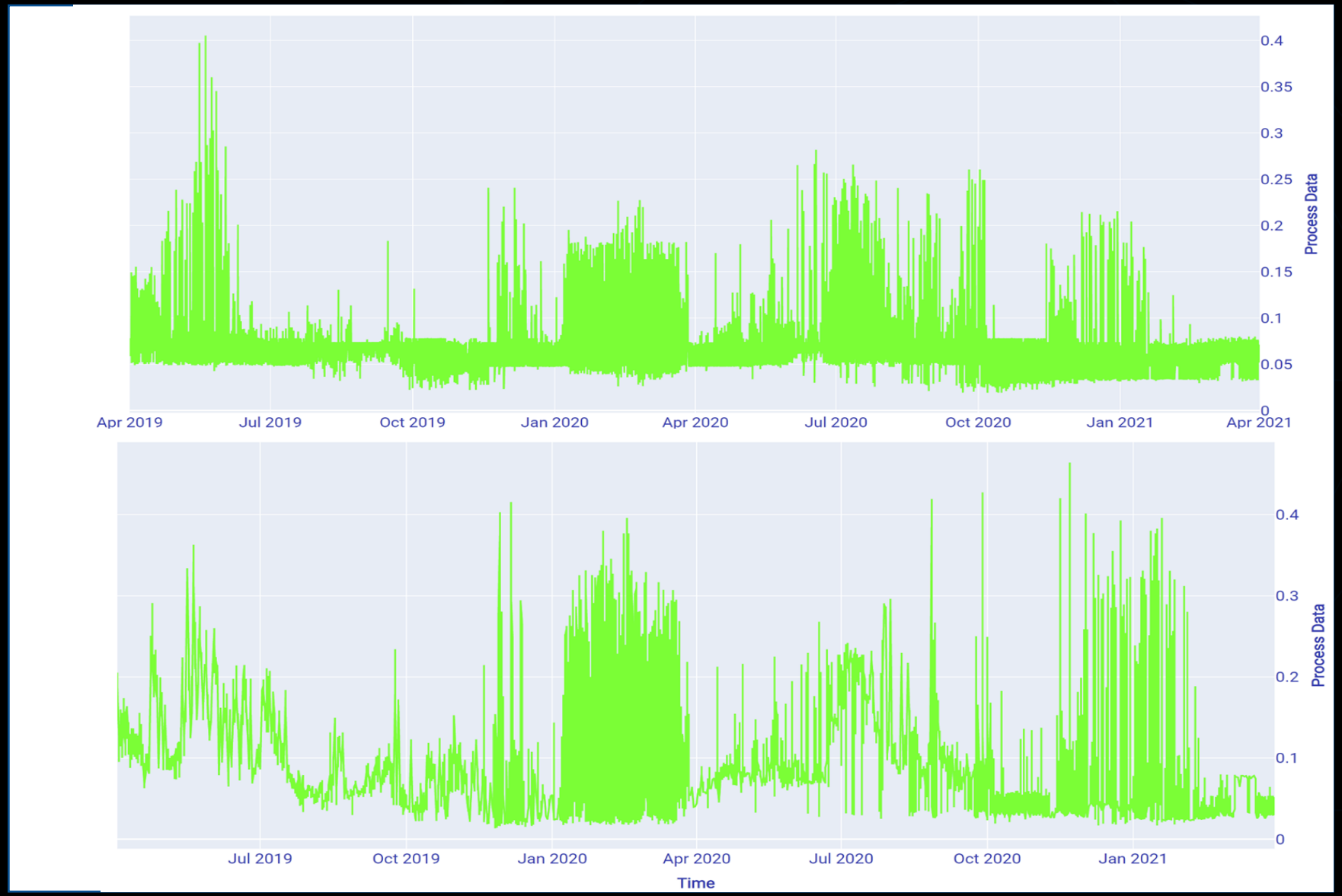
Monitoring after reducing N2O



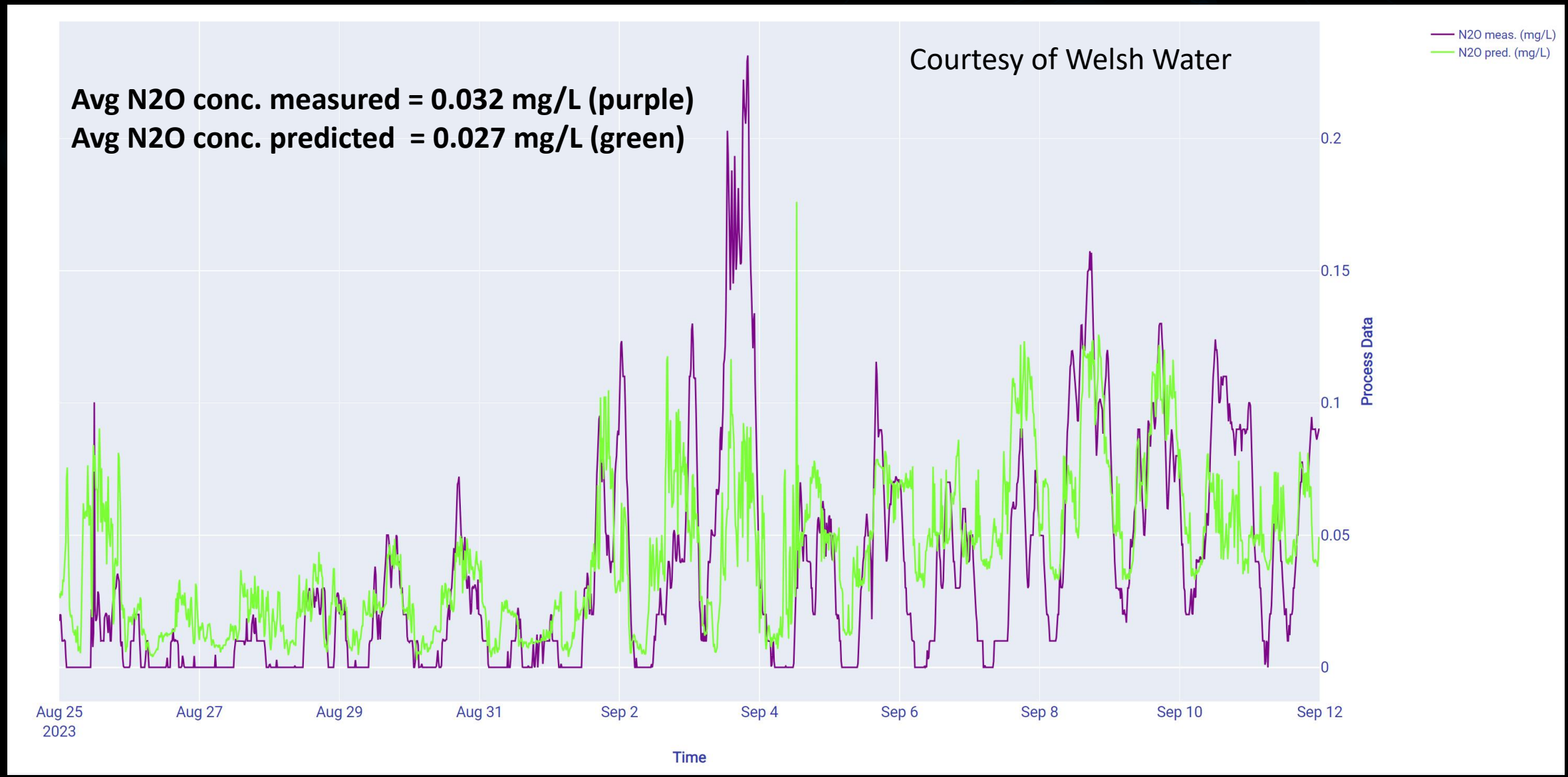
Monitoring N2O in other lanes w/ ML

Lane 1

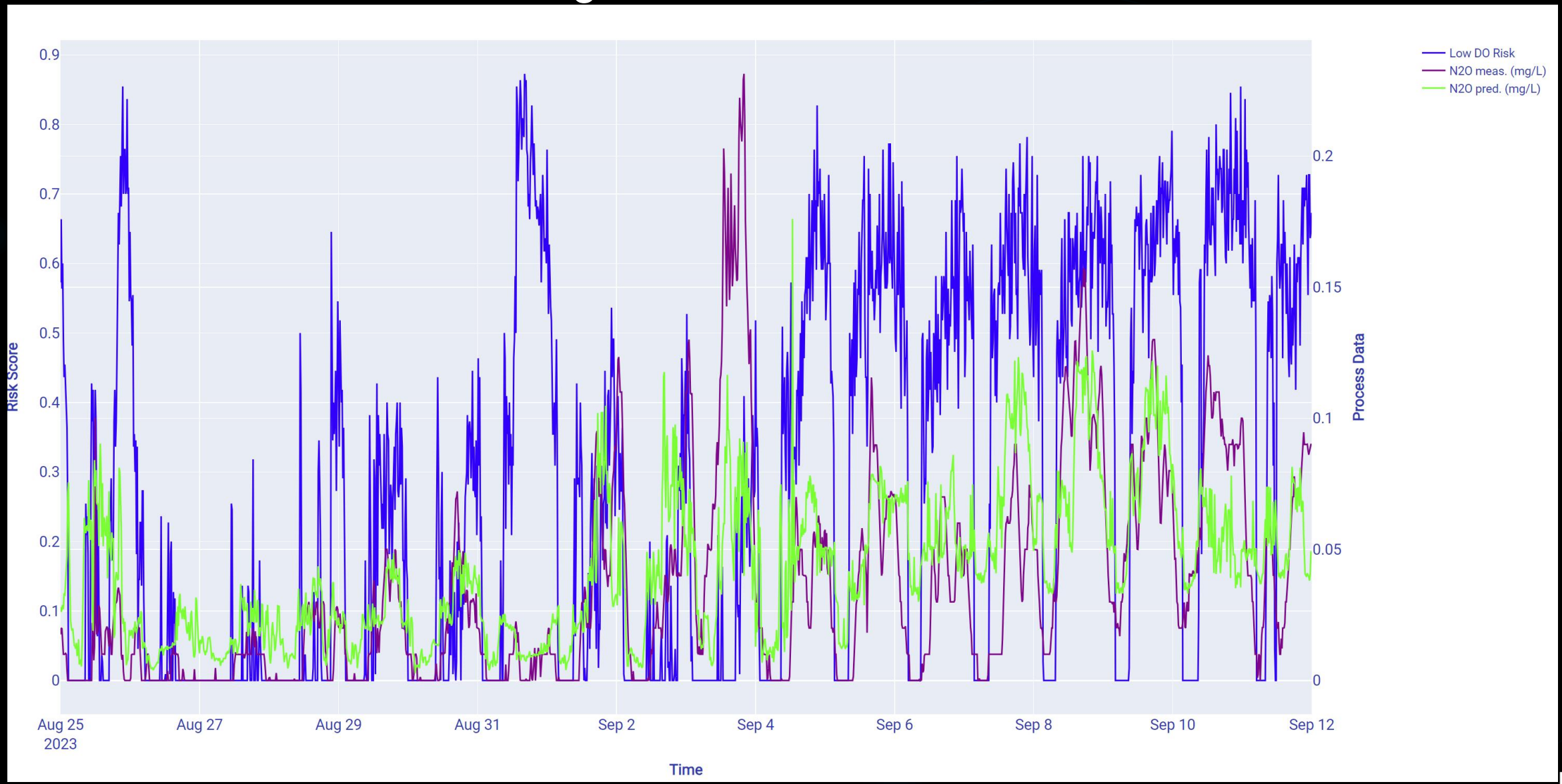
Lane 2



Monitoring N2O in other lanes w/ ML
Cog Moors Lane 1 measured N2O versus Lane 2 model predictions (Model trained on Lane 2 N2O measurements)

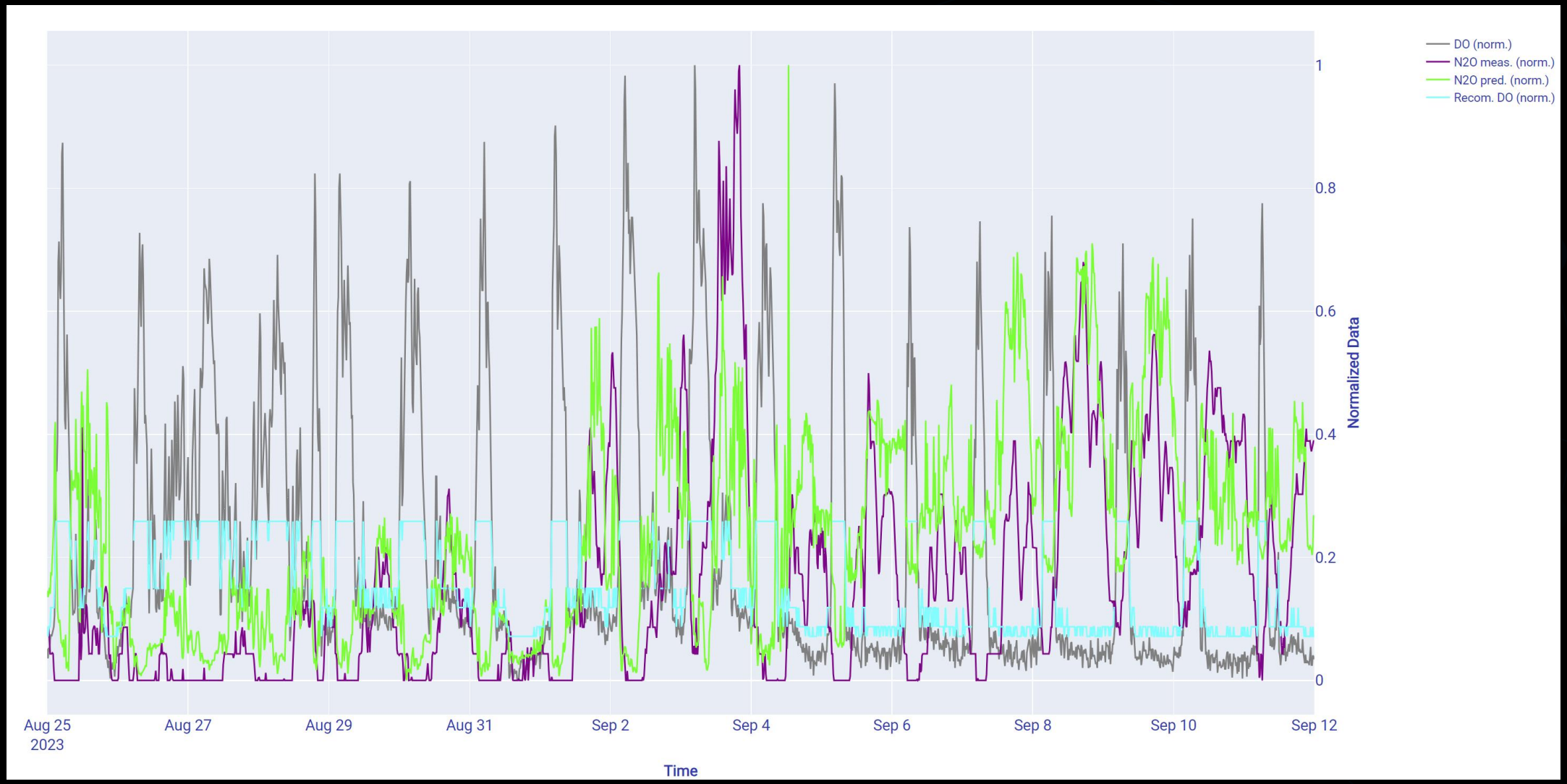


Monitoring N2O in other lanes w/ ML



We can rely on predicted N2O and predicted N2O corresponding with risk

Monitoring N2O in other lanes w/ ML



If we can rely on predicted N2O corresponding with risk, then we can rely on DO recommendations (cyan) and that bringing current DO (grey) closer to recommended can reduce N2O

Conclusions

- *AI/ML approach can help through each step of the N20 reduction journey - from planning to monitoring after reducing*
- *Reliable physical measurements are essential*
- *There is no perfect tool, but we can put the pieces together for an overall robust solution*
  - *AI/ML for assessing*
  - *In-situ meaurements for reactor level (in one reactor)*
  - *AI/ML with measurement data for monitoring in all reactors*
  - *Mobile measurements at site-level for verifying AI/ML*
- *<u>We need to start Now</u>. We cannot wait for perfection.*
- *Research needs to pick up where we left off, not 10 yrs behind, while we continue to learn from practice in parallel*

Questions

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