Causes of False Alarms in Inferential Event Detection Systems for Distribution System Water Quality Monitoring

Ed Roehl, John Cook, Ruby Daamen, and Uwe Mundry
Advanced Data Mining International, LLC
Greenville, South Carolina

Early Results from

WRF PROJECT 4182

Interpreting real-time online monitoring data for water quality event detection

Acknowledgements

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Thanks to Our Utility Partners

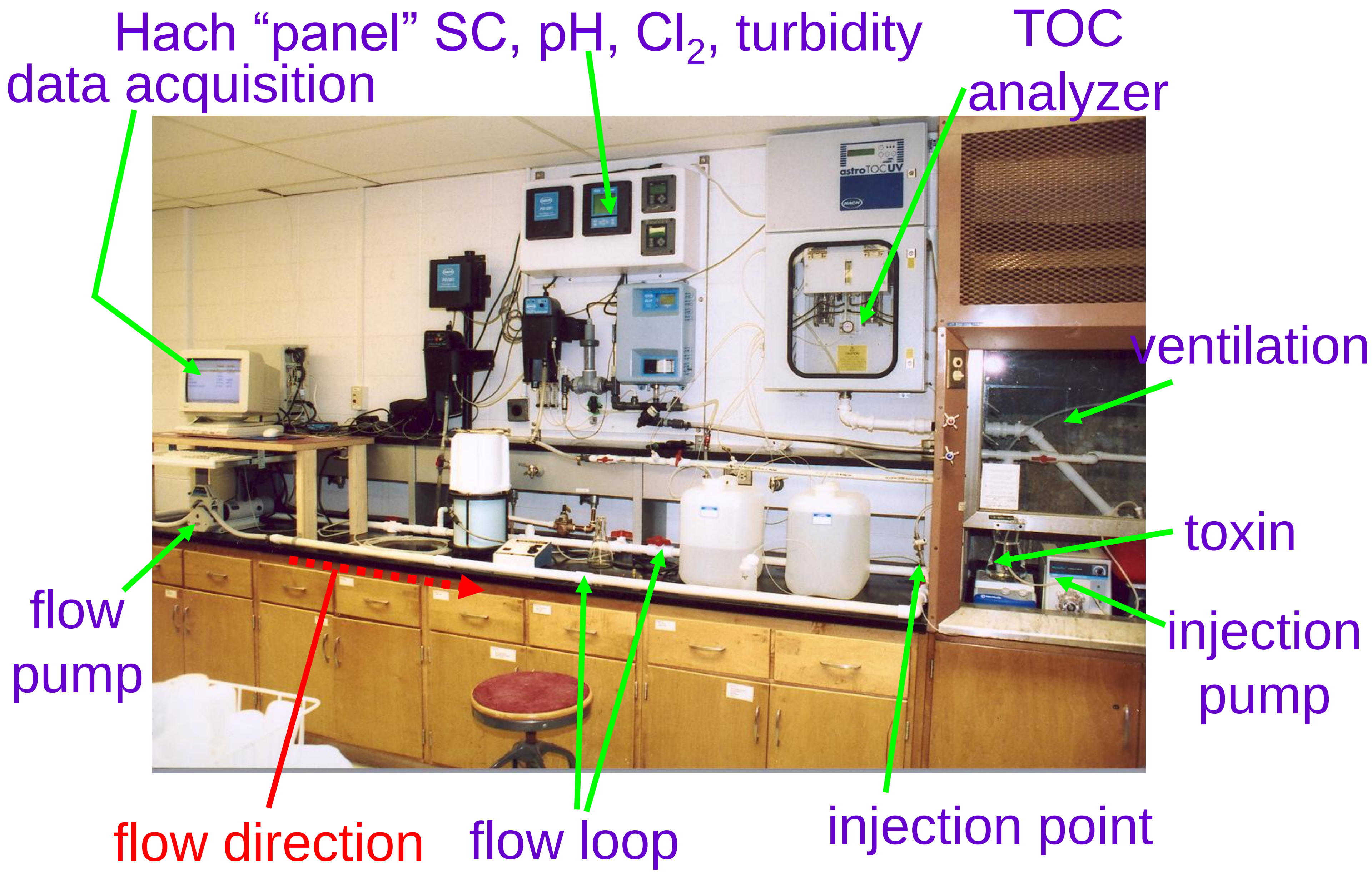
- City of Columbus, Ohio, Division of Power and Water
- Greenville Water System
- Newport News Waterworks
- Oklahoma City Water Department
- Startex Jackson Wellford Duncan Water District (SJWD)

The Concept

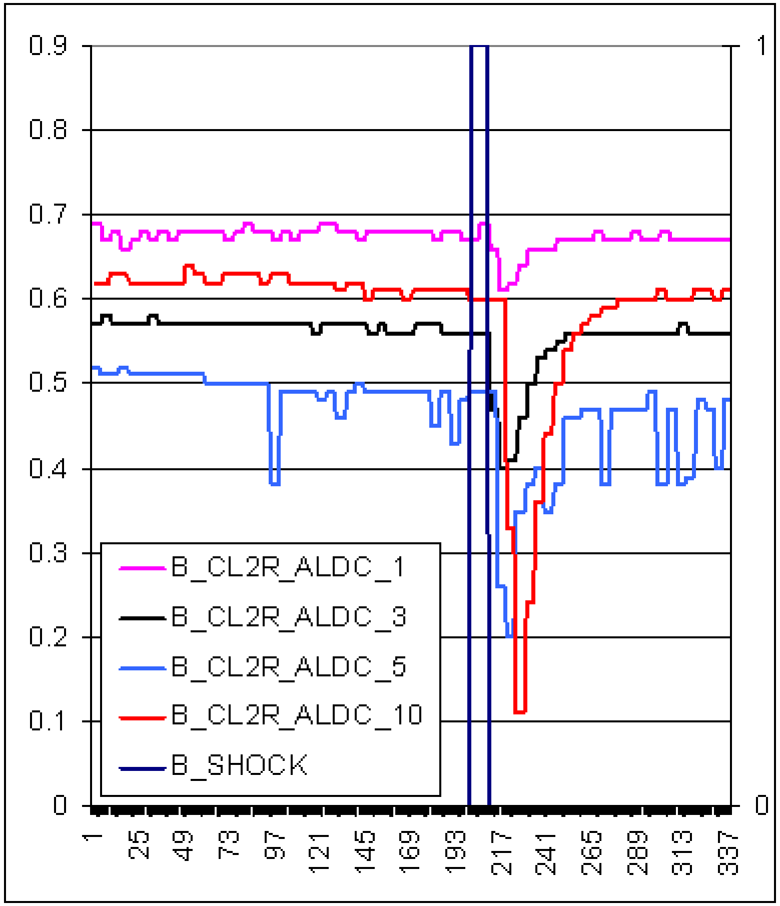
Inferential Event Detection System (IEDS)

- Focus on distribution system security
- Real-time monitoring of “conventional” WQ parameters - CL2, PH, COND/SC, TURB, TOC, TEMP
- Infers an “event” by detecting anomalous patterns of WQ behavior
  - Does not measure concentrations of specific compounds like liquid chromatography
- Systems have been available for a number years

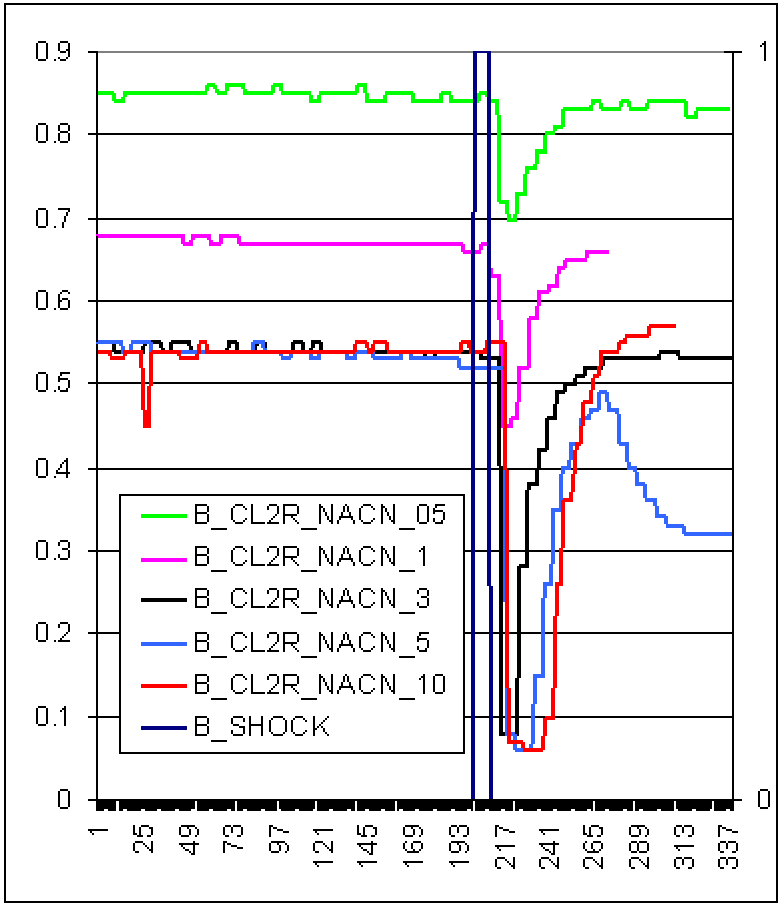
Colorado State pilot loop from Project 3086



CSU pilot loop results

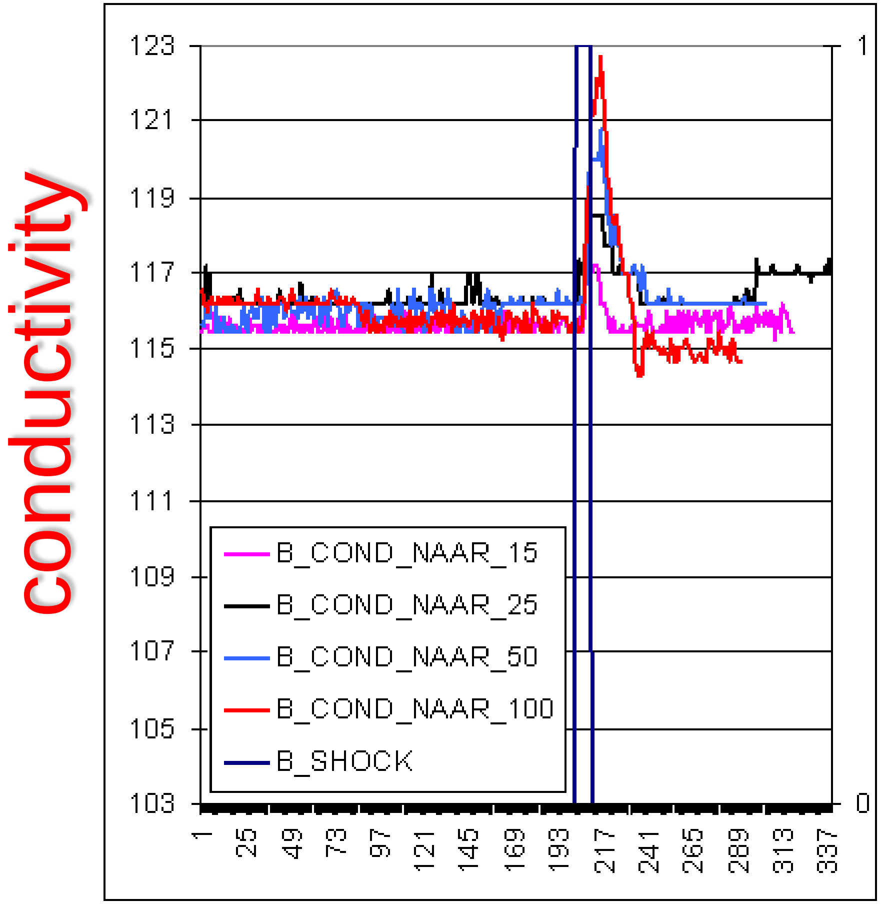


chlorine residual response to Aldicarb

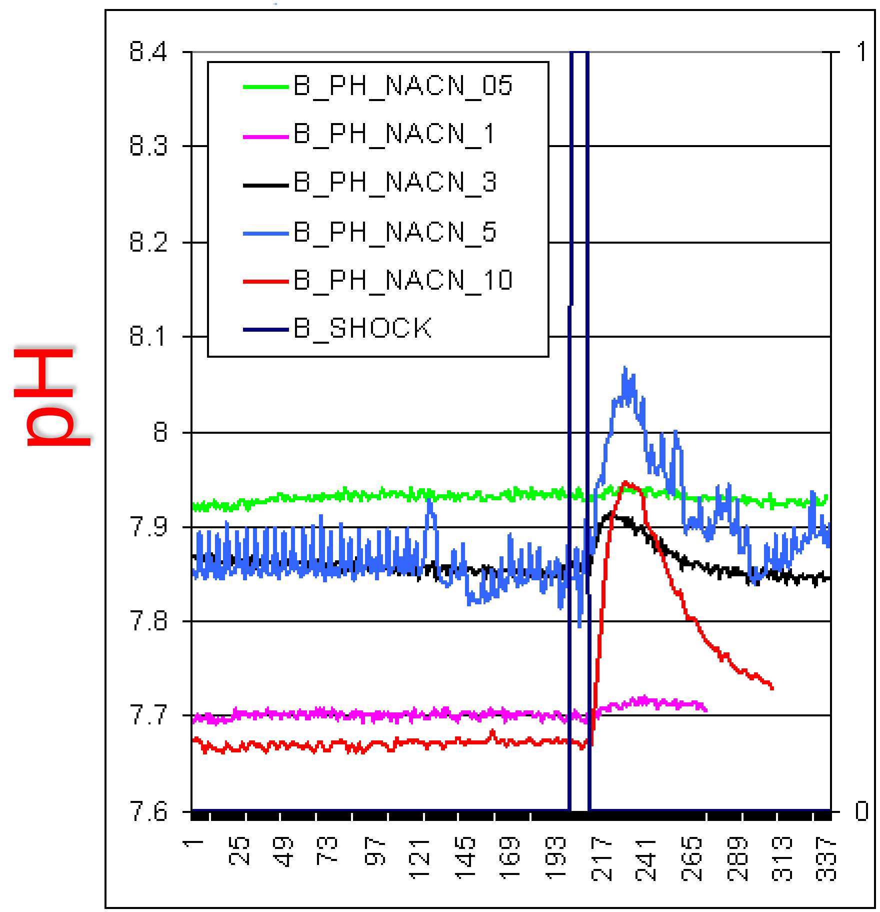


chlorine residual response to Na Cyanide

CSU pilot loop results, cont.

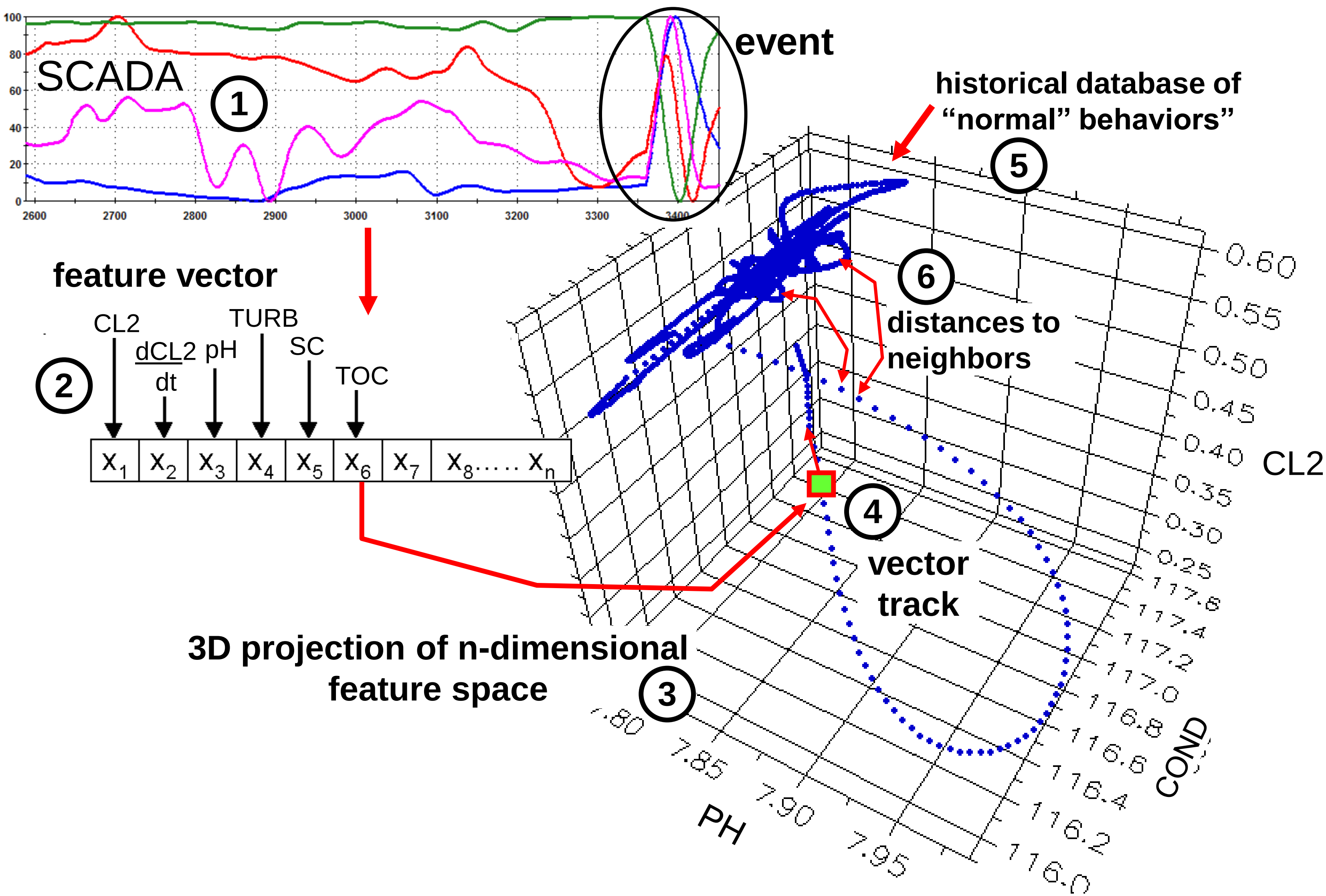


conductivity response to Na Arsenate



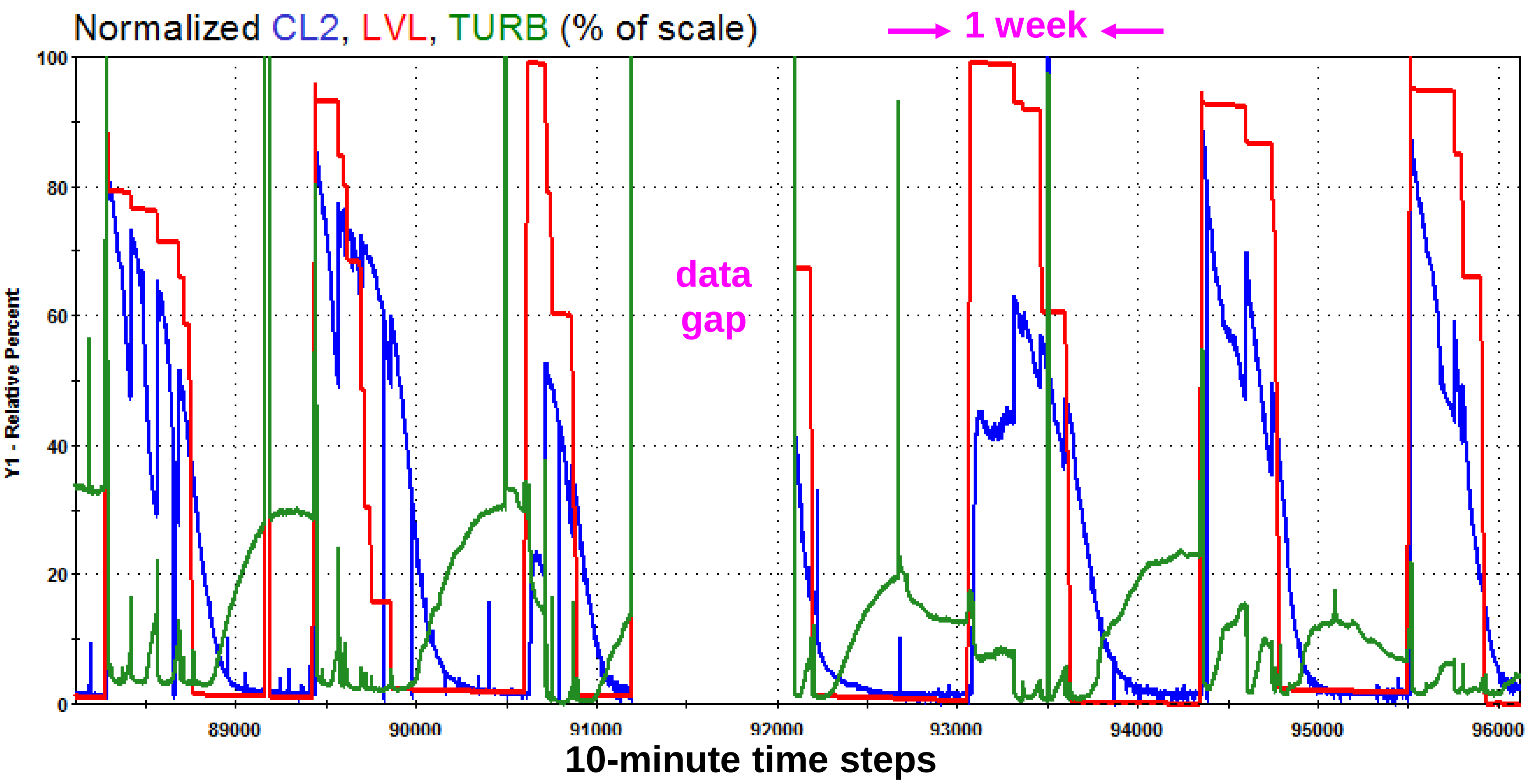
pH response to Na Cyanide

HOW? - event detection



Reality

Measurement errors, tank cycling, etc.



- Fast, full scale change

WRF Project 4182

- Reports of unacceptable numbers of false positives unless sensitivity reduced
  – defeats purpose
- Thesis - a more effective IEDS can be developed by incorporating the effects of operational parameters on water quality variability
  – reduce false positives
  – local ops params – Q, Ps, LVL
- Utility partners provided multi-year data from 40+ monitoring sites

Definitions

- A contaminated slug flowing past a sensor array might only be detectable for a few minutes or less.
  - Here, target detection window $\leq$ 20 minutes
    - event is manifest and detectable

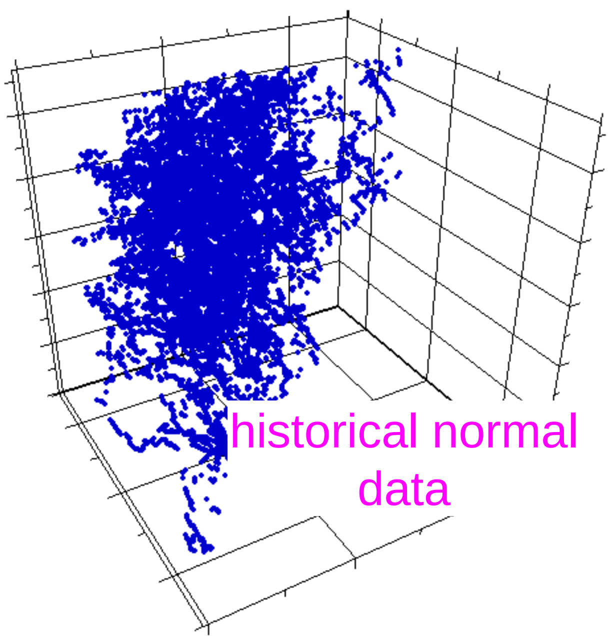
- “Normal” data – all the data here represents normal operations and normal data collection issues.

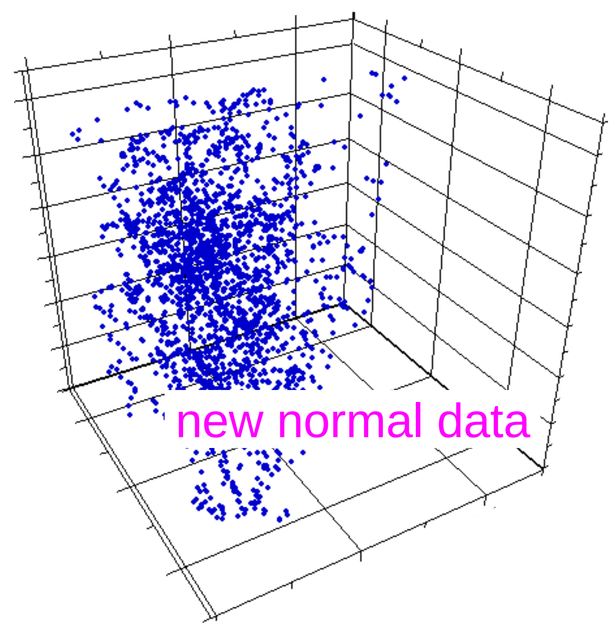
Causes of False Positives

Question 1

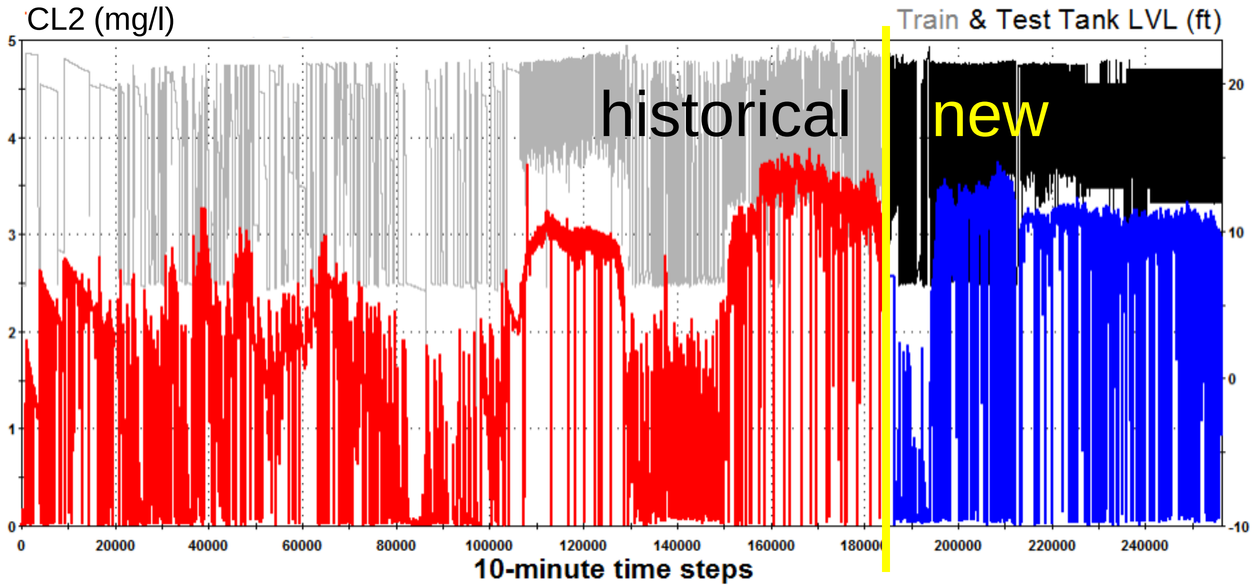
- Q1: If event detection relies on pattern matching vectors, how similar are "normal" new vectors to normal old vectors?
  - "old" = historical database
  - "new" = vectors streaming from process
- Expected A: If both are normal, they should be pretty similar.

CARTOON



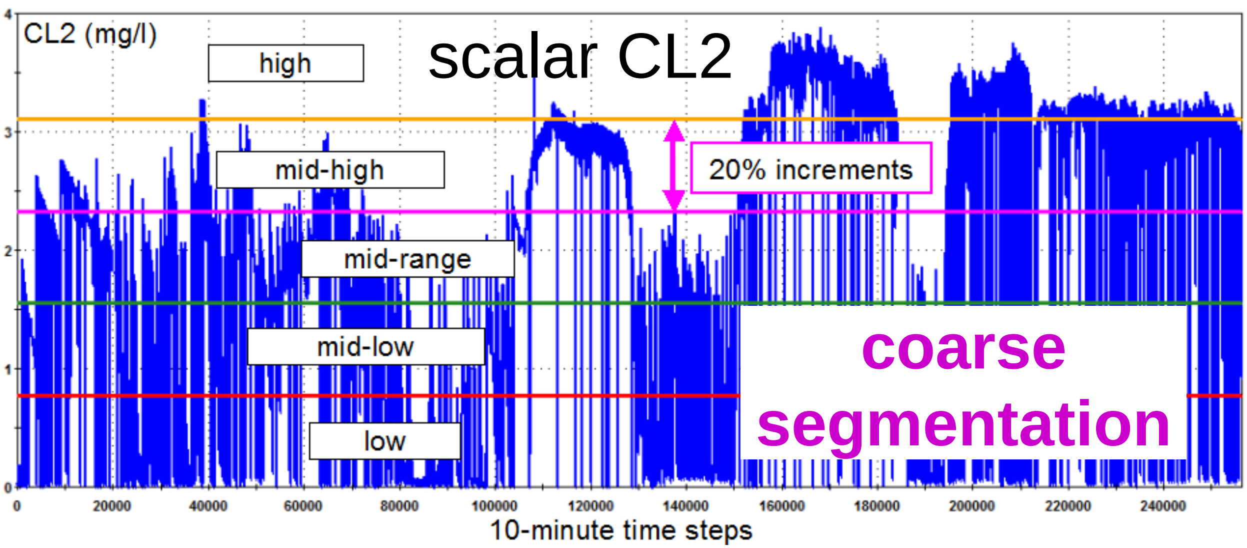


Experiment 1 – determine if old and new vectors cohabitate the same sub-spaces of feature space



1. Divide 4 years of 10-min data into ~70% old and ~30% new

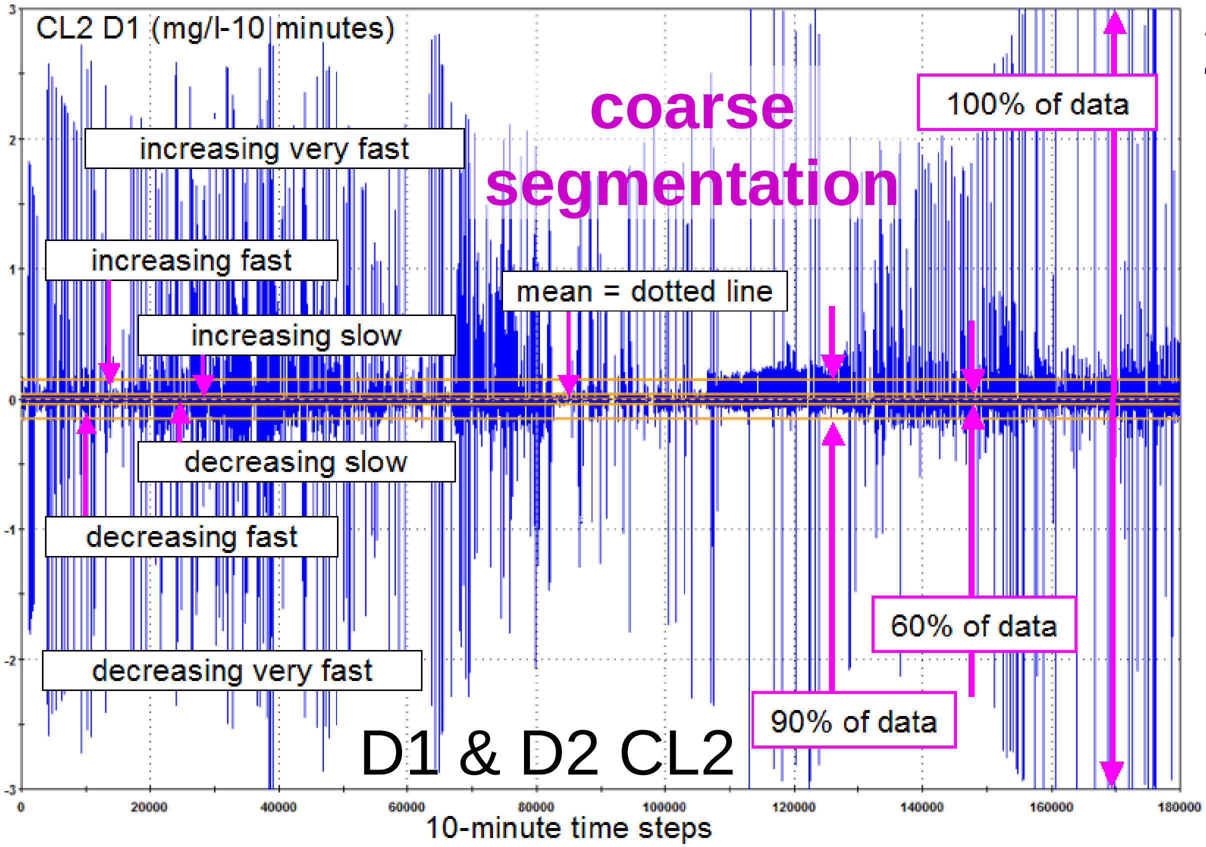
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8….. x_n



2. Define vector features for each WQ parameter
   a. Scalars - divided into 5 20% sub-ranges

cont 1: Experiment 1 - cohabitating hist. and new

x_1	x_2	x_3	x_4	x_5	x_6	x_7	$x_8 \ldots\ldots x_n$



2. cont. - Create features
   b. D1 = 1-time-step difference; sub-divide into 6 sub-ranges
   c. D2 = D1 time-delayed 1 time step

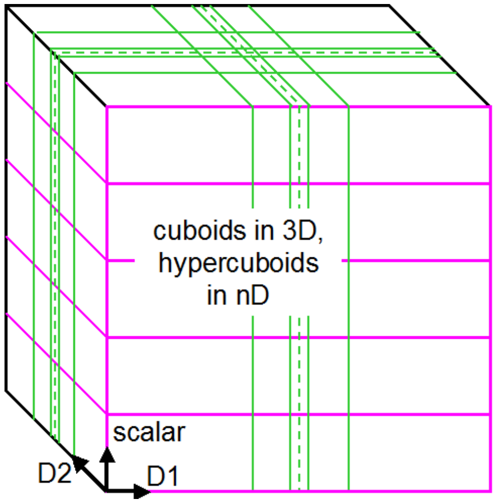
Process Dynamics – scalar+D1+D2 describe parameter’s current position+velocity+acceleration.

cont 2: Experiment 1 – cohabitating old and new

3. Count cohabitating old and new in sub-spaces (hypercuboids) formed by 5 scalar, 6 D1, and 6 D2 sub-ranges

Combinatorial Explosion – even with coarse segmentation

- *3 scalars = 5 x 5 x 5 = 125 cuboids*
- *+ D1 = 125 x 6 x 6 x 6 = 27k hypercuboids*
- *+ D2 = 27k x 6 x 6 x 6 = 5.8 million*



tank site

Params	Case #	Incl. Features Scalar	D1	D2	#Hypercuboids	Old #Vects	New #Vects	% Match	#Vect # Miss
CL2, LVL, TEMP	1	X			125	124,195	68,526	100	339
	2	X	X		27,000	100,083	67,047	73	17,941
	3	X	X	X	5,832,000	84,576	65,949	19	53,410
+ PH	4	X			625	119,651	63,487	85	9,509
	5	X	X		810,000	94,838	61,314	28	43,963
	6	X	X	X	1.05E+09	79,273	59,658	2.6	58,096
+ COND, TURB	7	X			15,625	107,469	60,961	80	12,138
	8	X	X		729,000,000	79,830	56,911	10	50,970
	9	X	X	X	3.40E+13	62,150	53,606	0.11	53,546

cont 3: Experiment 1 – cohabitating hist. and new

booster pump station away from tanks

Params	Case #	Incl. Features Scalar	D1	D2	#Hyper cuboids	Old #Vects	New #Vects	% Match	# Miss
CL2, PH, COND, TURB	1	X			625	119,278	48,892	100	59
	2	X	X		810,000	114,986	48,174	88	5,628
	3	X	X	X	1,049,760,000	111,152	47,624	24	36,143

next experiment

Back to Question 1

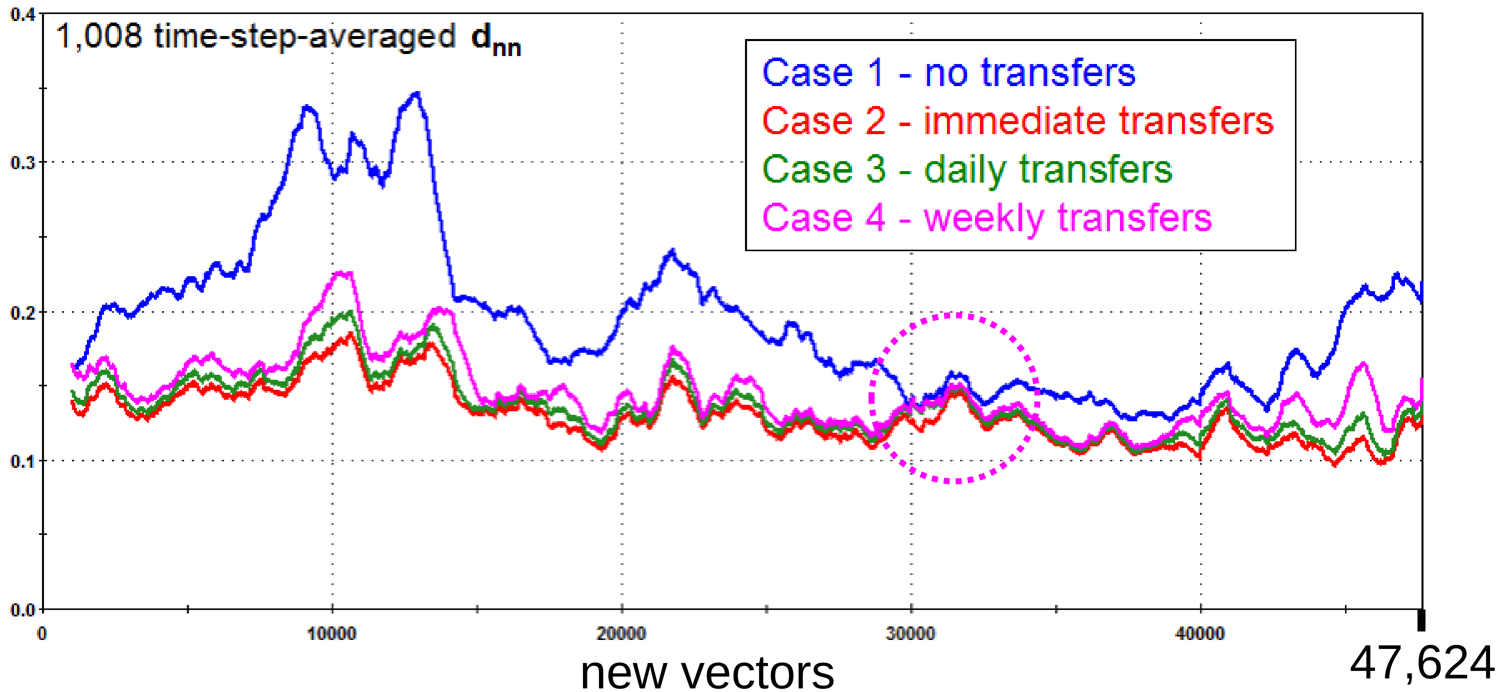
- Q1: How similar are “normal old” and “normal new” vectors?
- Expected A: If both are “normal”, they should be pretty similar.
- Real A: Not very - numerous false alarms may be unavoidable without desensitizing IEDS

Question 2

- Q2: What would happen if we periodically transfer “new” vectors to the historical database?
  - Experiment 1 – static old & new

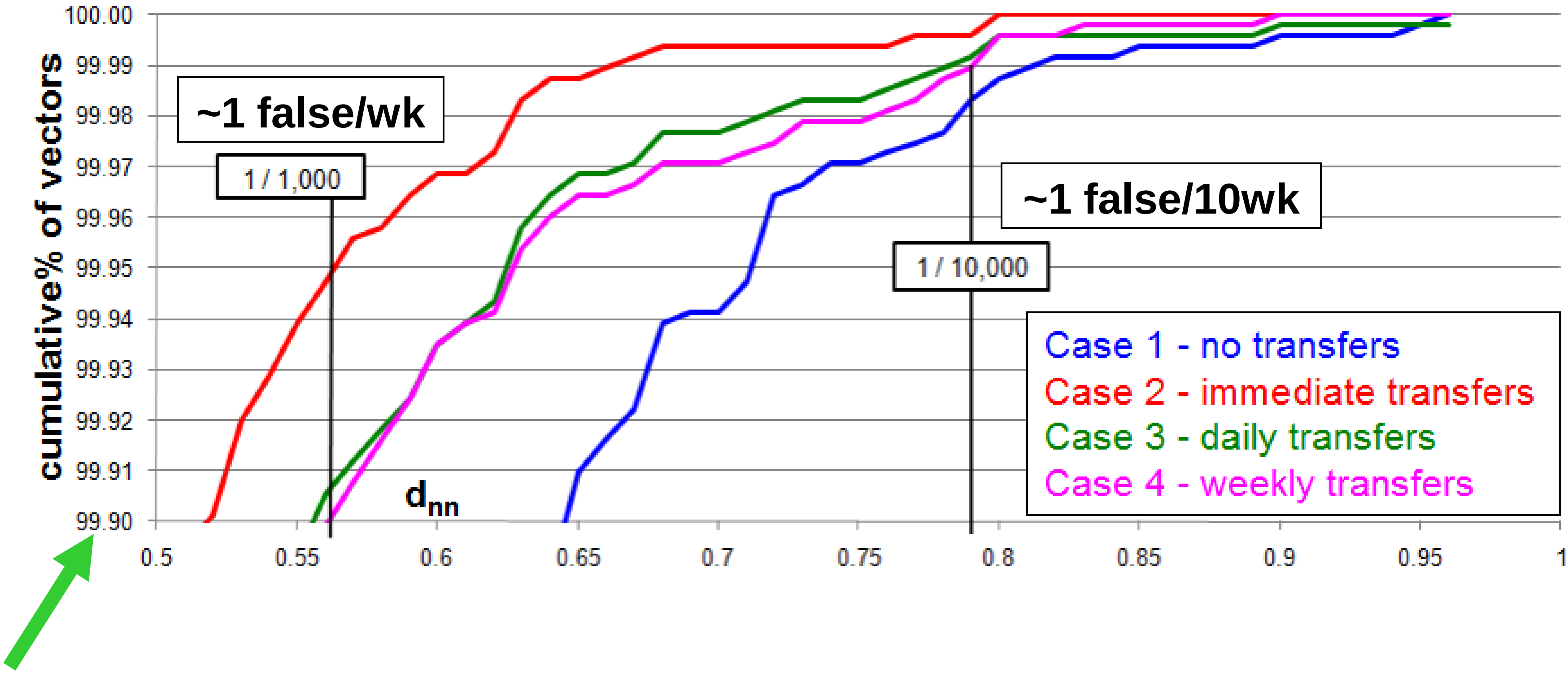
- Expected A: False alarms should decrease.

Experiment 2 – simulate updating hist. database



- Simulations used the site away from tanks
  - features = CL2, SC, COND, TURB scalars+D1s+D2s
- d_{nn} = distance of new vector to “nearest neighbor” old vector
  - In IEDS d_{nn} > specified limit triggers alarm
- Findings
  1. Transfer cases are high percentage of no-transfer case
  2. Little difference between transfer cases
  3. Indicates that successive “normal” vectors can be far apart

cont: Experiment 2



- Weekly transfers
  - 1 false/wk: d_{nn} = 42 x avg(d_{nn})
  - 1 false/10wks: d_{nn} = 59 x avg(d_{nn})

Back to Question 2

- Q2: What would happen if we periodically transfer “new” vectors to the historical database?
- Expected A: False alarms should decrease.
- Real A: False alarms might not fall to acceptable levels.

Question 3

- Q3: Why are successive vectors so far apart?

- A: To come.

Experiment 3 – correlation matrices

- Cross-correlation matrix – correlates changes among multiple ops & WQ parameters
  - change = Dx = current value – value x time steps ago

- Utility B stand alone site
  - 86-sec time step
  - Mix of WQ and operational parameters

1 time-step

R^2	Q-D1	P-D1	LVL-D1	TURB-D1	PH-D1	COND-D1	TOC-D1	CL2-D1
Q-D1		0.033	0.000	0.000	0.000	0.000	0.000	0.000
P-D1	0.033		0.000	0.000	0.004	0.000	0.000	0.000
LVL-D1	0.000	0.000		0.000	0.000	0.000	0.000	0.000
TURB-D1	0.000	0.000	[illegible]	[illegible]	[illegible]	[illegible]	0.000	0.000
PH-D1	0.000	0.004	[illegible]	[illegible]	[illegible]	[illegible]	0.000	0.000
COND-D1	0.000	0.000	0.000	0.000	0.001		0.000	0.000
TOC-D1	0.000	0.000	0.000	0.000	0.000	0.000		0.000
CL2-D1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

3 time-step (4.3 min) change

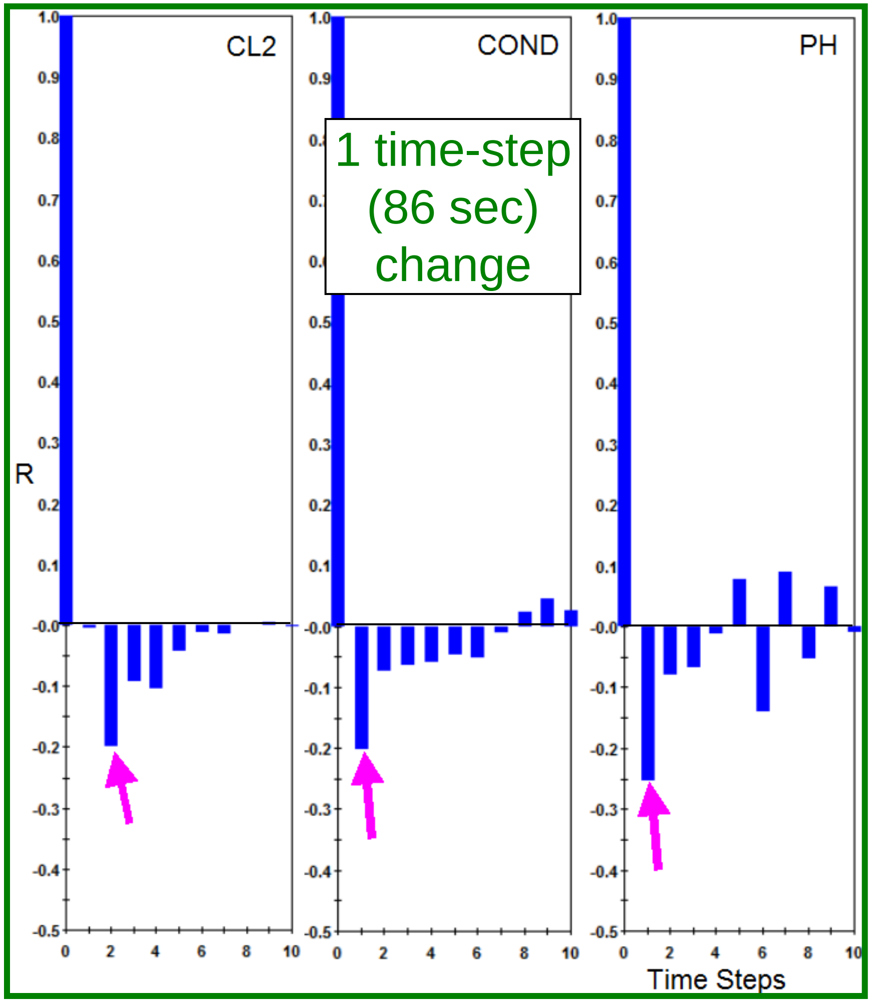
R^2	Q-D3	P-D3	LVL-D3	TURB-D3	PH-D3	COND-D3	TOC-D3	CL2-D3
Q-D3		0.056	0.001	0.001	0.000	0.000	0.000	0.000
P-D3	0.056		0.000	0.000	0.002	0.000	0.000	0.000
LVL-D3	0.001	0.000		0.000	0.000	0.000	0.000	0.000
TURB-D3	0.001	0.000	0.000		0.000	0.000	0.000	0.000
PH-D3	0.000	0.002	0.000	0.000		0.003	0.000	0.000
COND-D3	0.000	0.000	0.000	0.000	0.003		0.000	0.000
TOC-D3	0.000	0.000	0.000	0.000	0.000	0.000		0.000
CL2-D3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

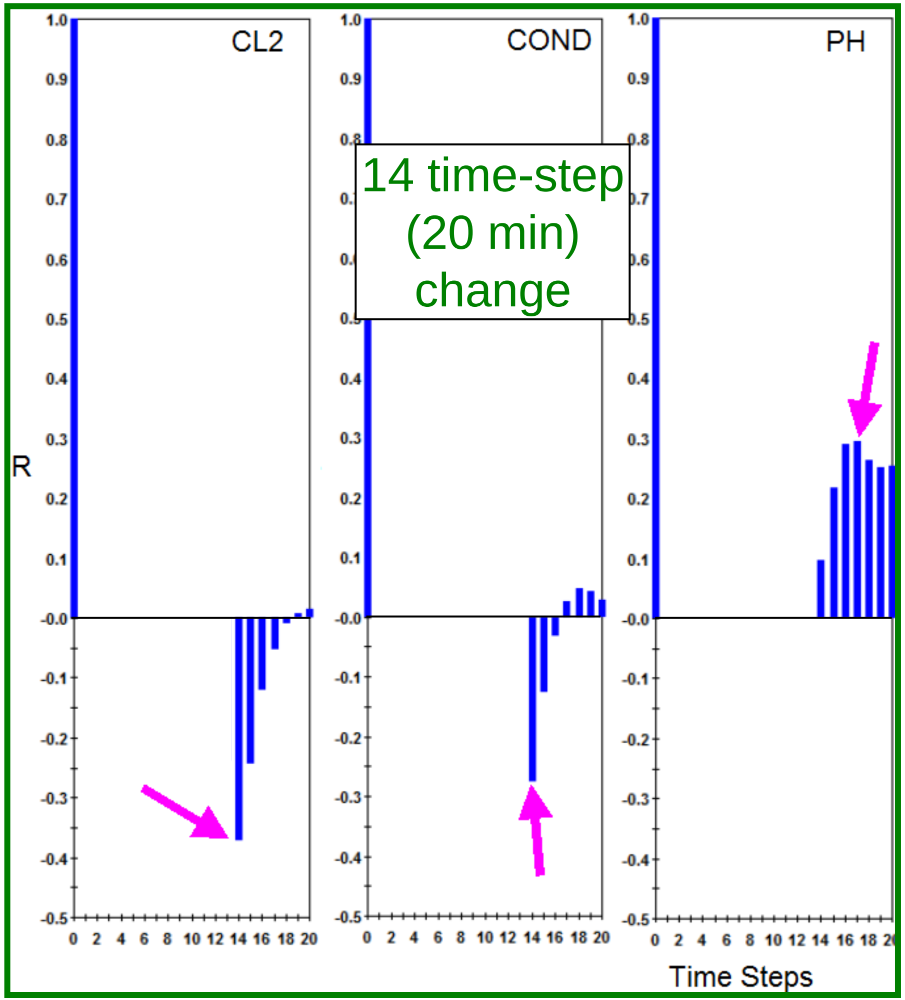
7 time-step (10 min) change

R^2	Q-D7	P-D7	LVL-D7	TURB-D7	PH-D7	COND-D7	TOC-D7	CL2-D7
Q-D7		0.105	0.002	0.008	0.001	0.000	0.000	0.000
P-D7	0.105		0.001	0.000	0.002	0.000	0.000	0.000
LVL-D7	0.002	0.001		0.000	0.000	0.000	0.000	0.000
TURB-D7	0.008	0.000	0.000		0.000	0.000	0.000	0.001
PH-D7	0.001	0.002	0.000	0.000		0.003	0.000	0.000
COND-D7	0.000	0.000	0.000	0.000	0.003		0.000	0.000
TOC-D7	0.000	0.000	0.000	0.000	0.000	0.000		0.000
CL2-D7	0.000	0.000	0.000	0.001	0.000	0.000	0.000	

Experiment 4 – autocorrelation of Dx

- Autocorrelation function correlates a signal to itself to determine how deterministic / random it is.
  - determinism = current behavior depends somewhat on past
  - randomness = current behavior unrelated to past





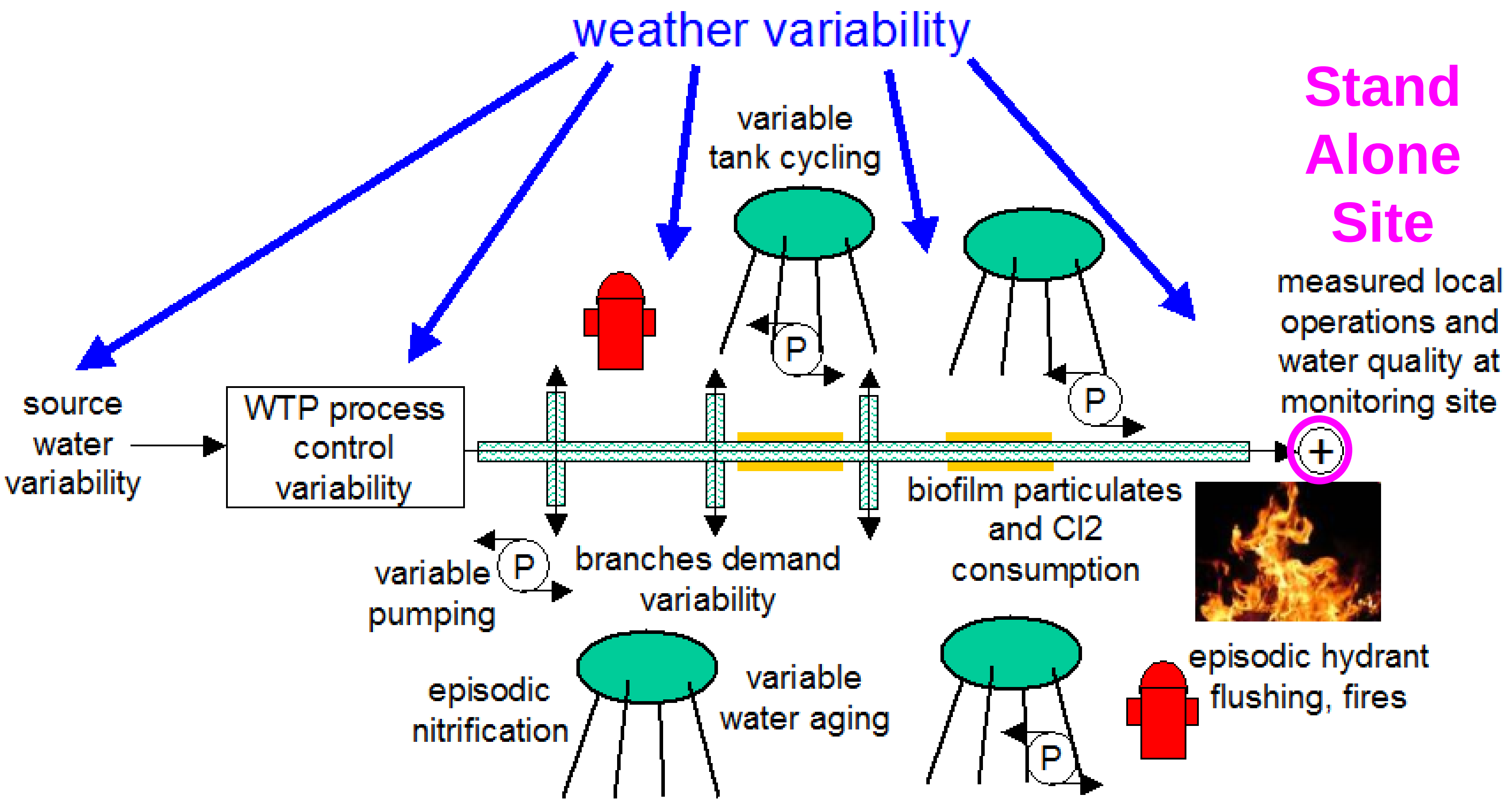
Back to Question 3

- Q3: Why are successive vectors so far apart?

- A: WQ change on time scales ≤ 20 minutes can be "apparently random".
  - Exp. 3 (x-matrices) - WQ & ops parameter changes are poorly correlated
  - Exp. 4 (autocorr.) - individual WQ parameter change is non-deterministic
  - Same findings at multiple sites & utilities

- non-determinism = randomness = noise

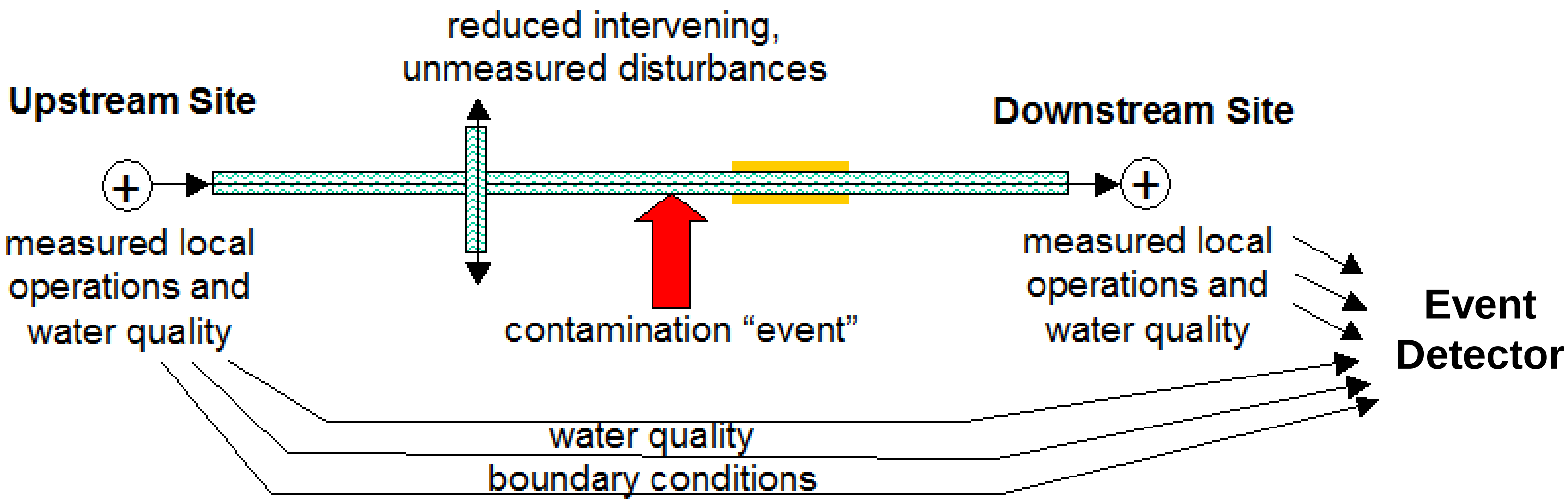
Causes of WQ variability



- Unmeasured disturbances
  - pressure & flow transients
- Measurement errors

Current Research

Alternative to stand-alone site monitoring



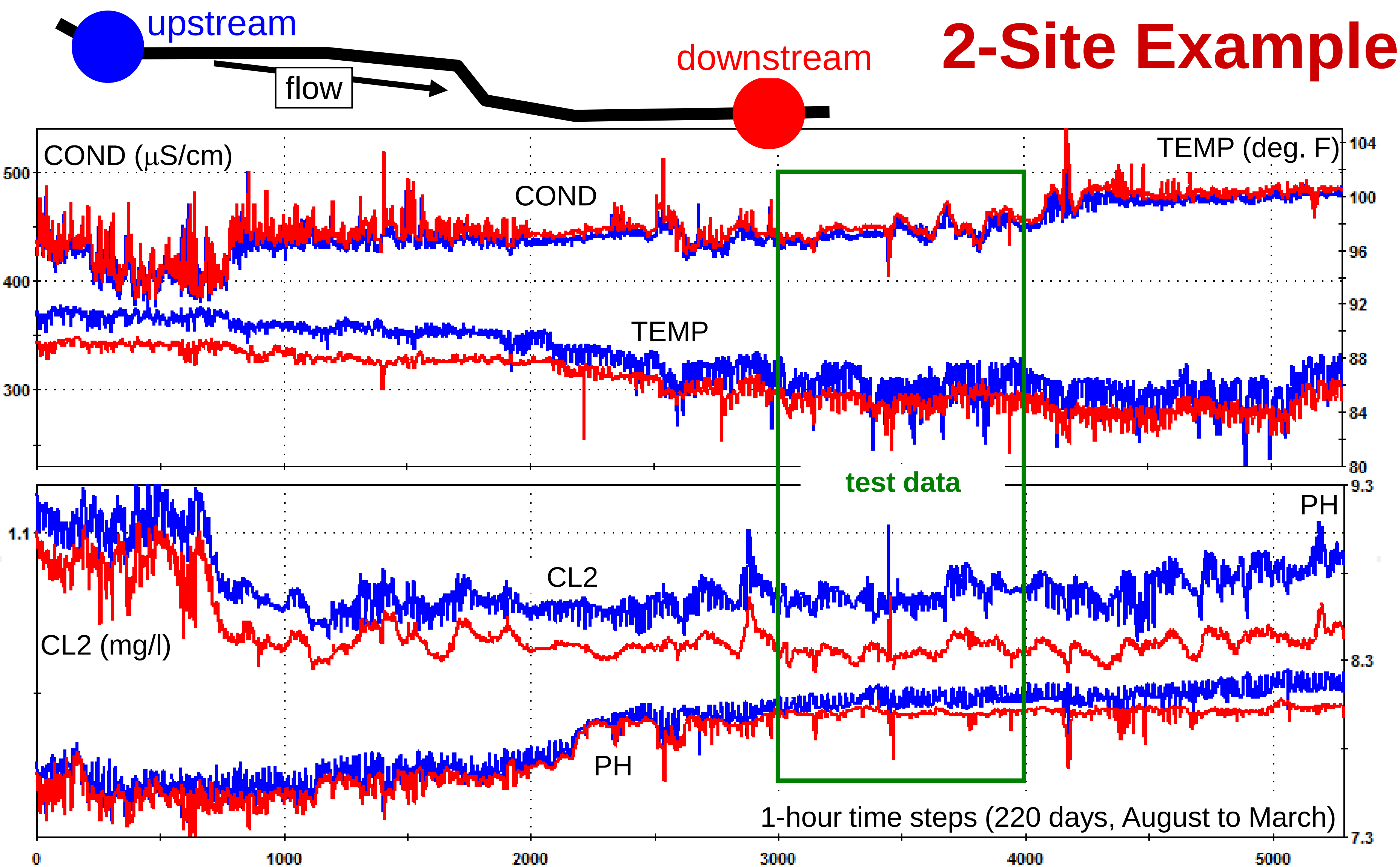
- Upstream / downstream sites
- Upstream site provides
  - boundary conditions for downstream WQ
  - more operational parameters

Multi-Site Concept

- Event detection performed on filtered signals
  - model-based filtering of downstream WQ signals
  - modeling = accounting of causes of variability
  - filtered signals less variable

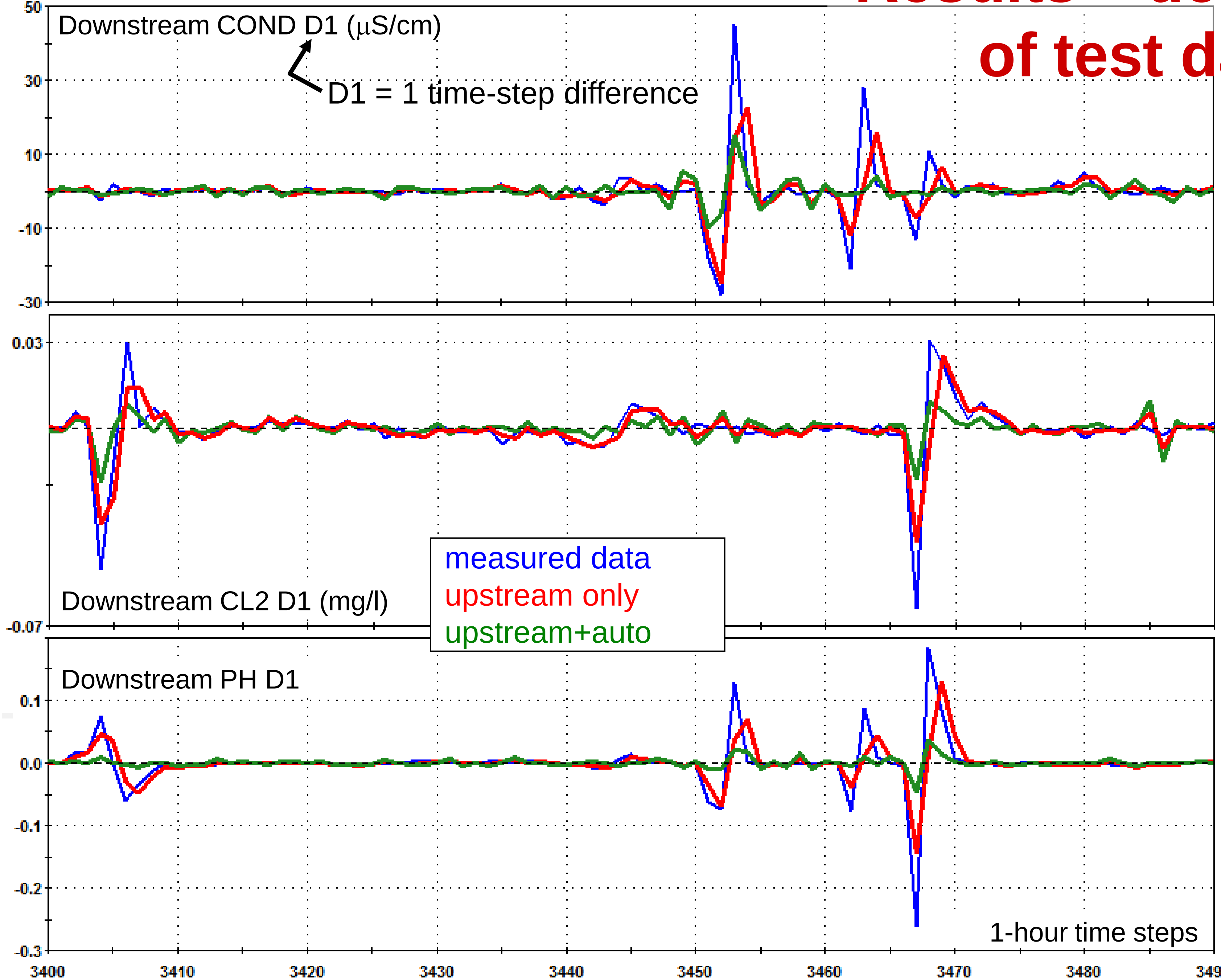
- Modeling technique
  - multivariate, nonlinear curve fitting by (multi-layer perceptron) artificial neural networks (ANN)
    - “machine learning” from AI
  - inputs - upstream and “local” WQ and ops
    - spectrally decomposed into components
    - autoregressive “local” WQ inputs time delayed to be outside detection window (e.g., 20 minutes)
    - co-linear inputs decorrelated
  - ANN “learns” best predictor components

2-Site Example

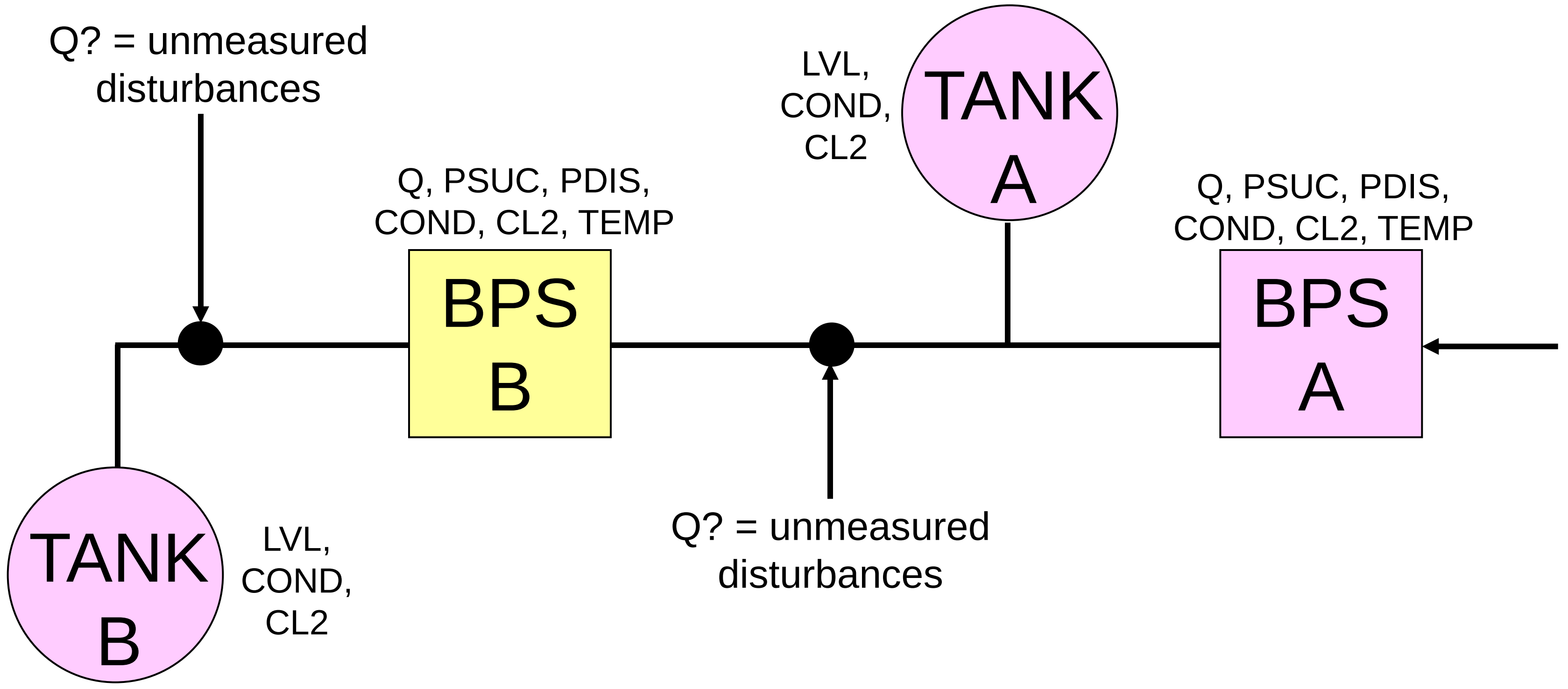


- Raw WQ variability is similar but not identical
  - differences caused by unmeasured disturbances
- 1-hour time step too big for 20-minute detection window
  - exploratory research on multi-site

Results – detail of test data

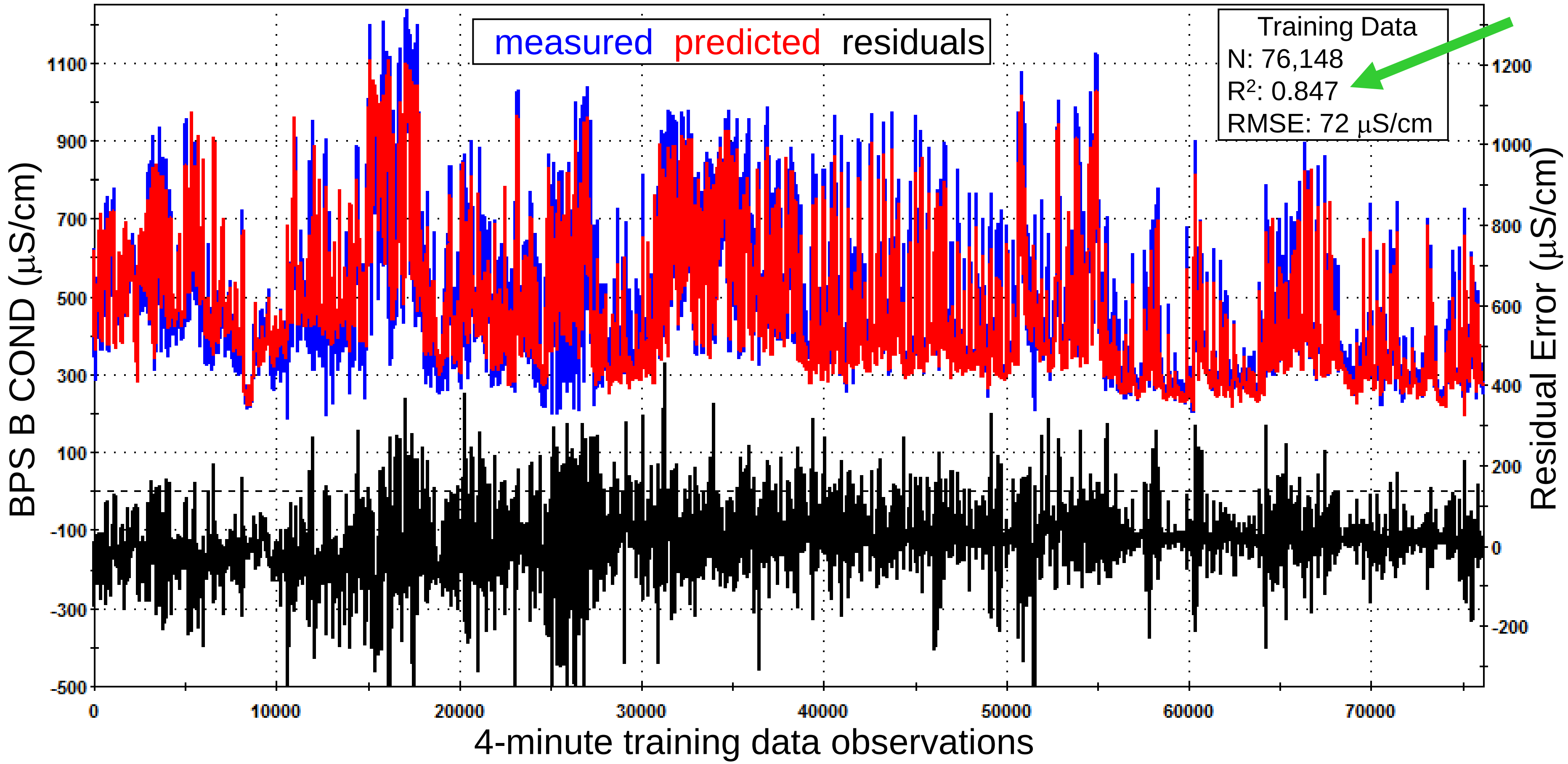


More Complicated 4-Site Example



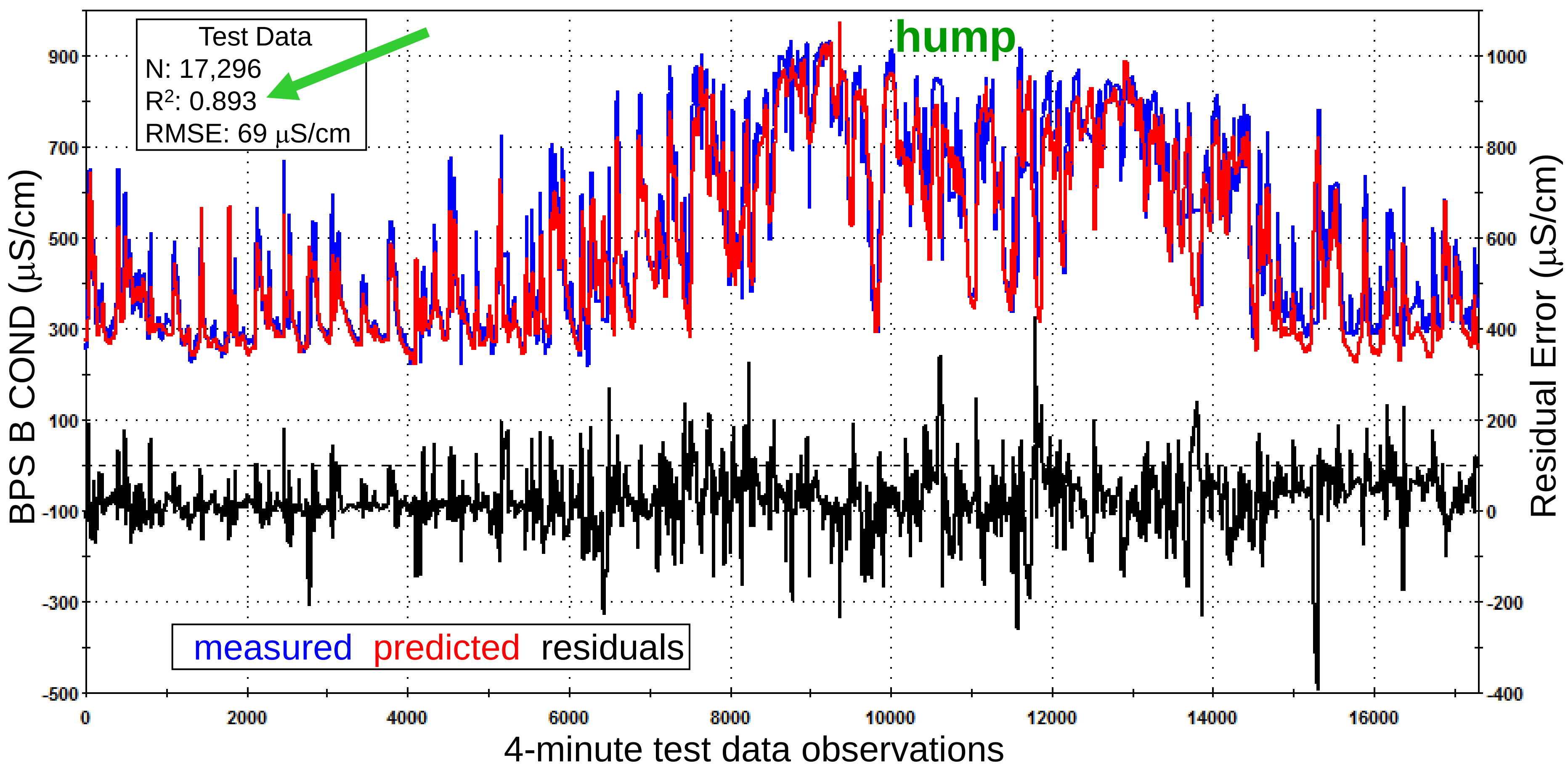
- BPS B is “target” site
- Utility operates multiple WTPs with different sources
- 1 year of data (1-min reduced to 4-min)
  - first 10 month = training
  - last 2 months = test

BPS B COND Process Model – training data



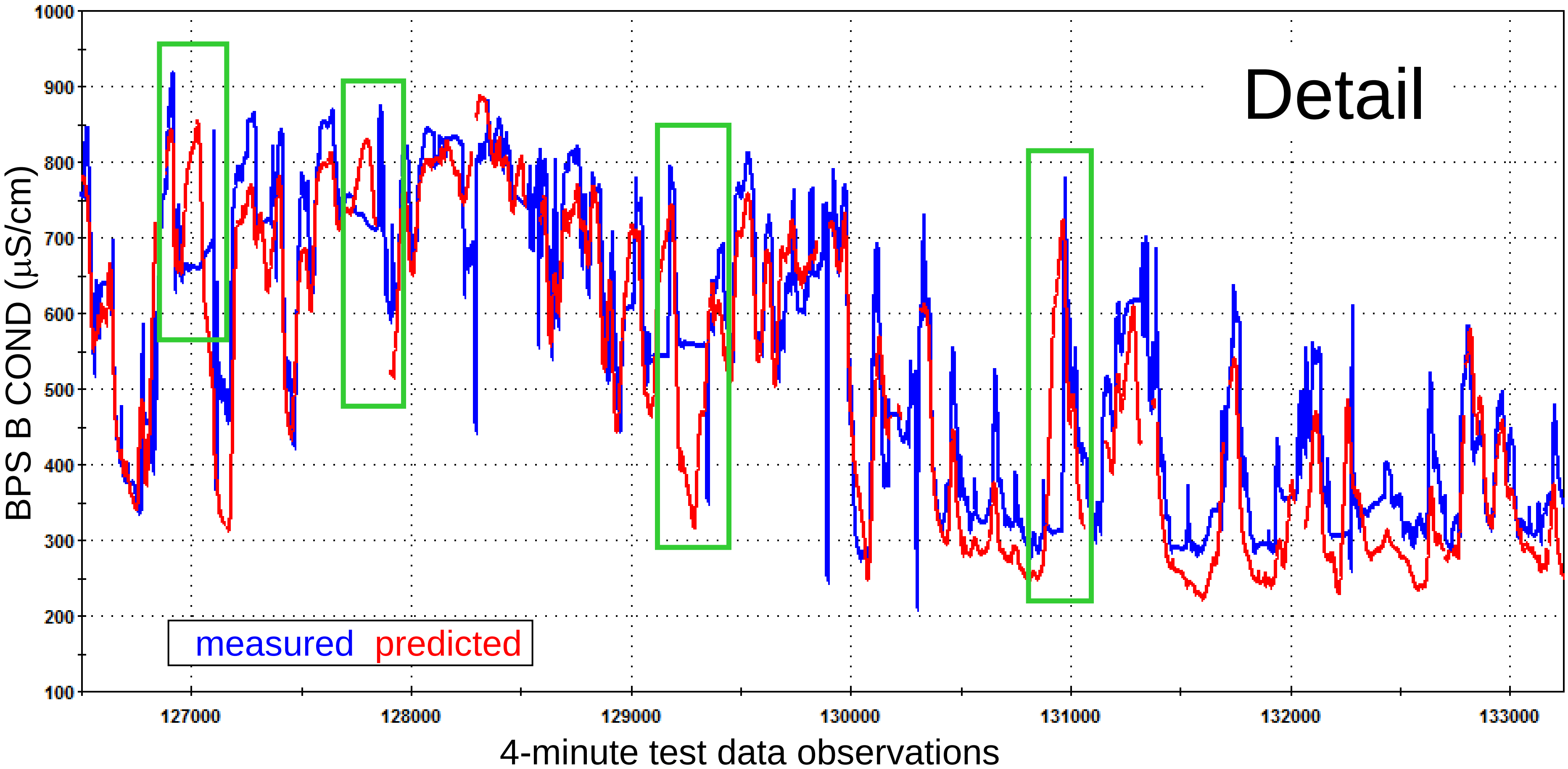
- Looks Good!

BPS B COND Process Model – test data



- Hump may be from different WTP/source
- Looks Good!

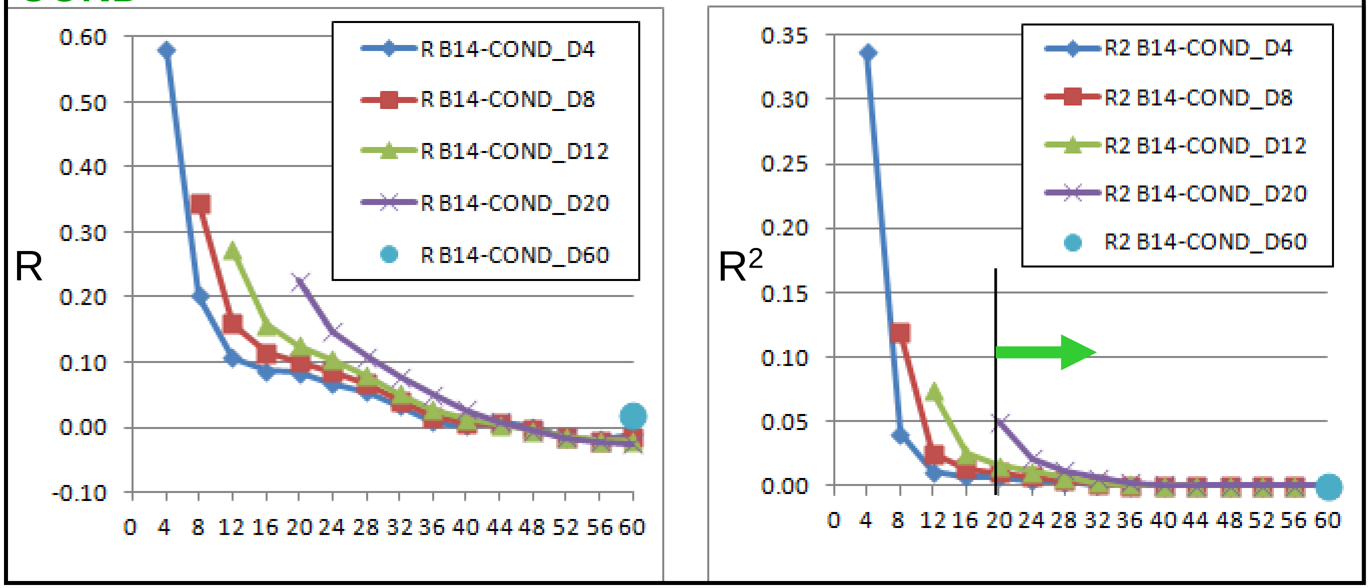
BPS B COND Process Model – test data



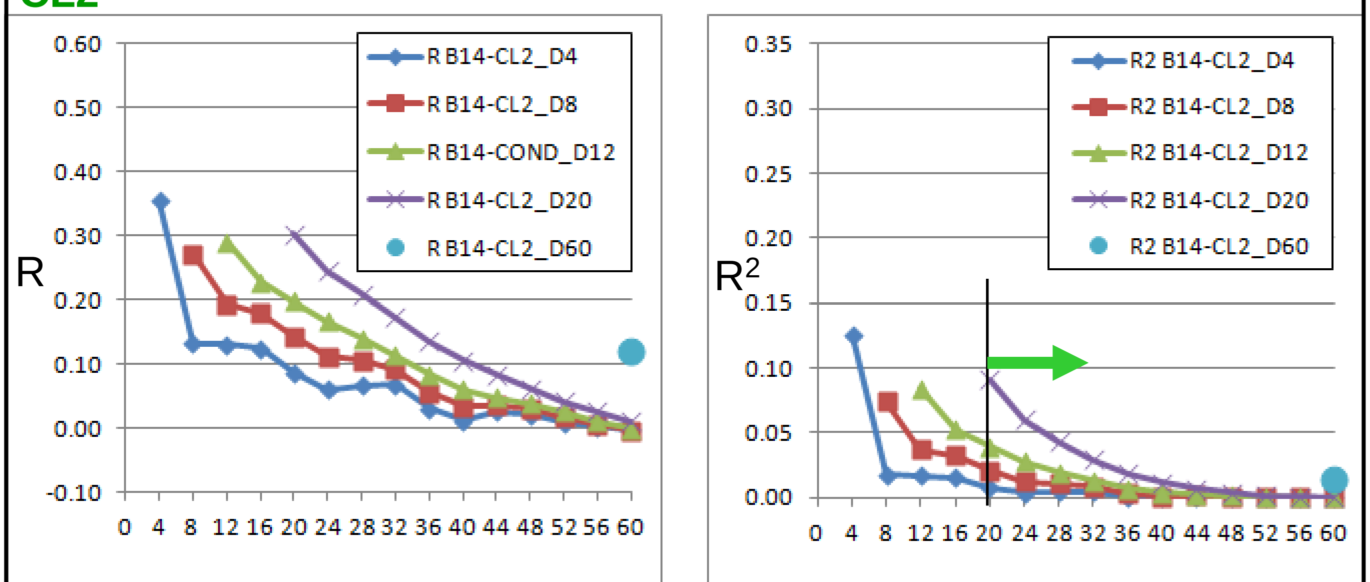
- Looks Bad!
- Process model misses some periods - maybe from unmonitored flows through junctions

BPS B COND Dx autocorrelations

COND

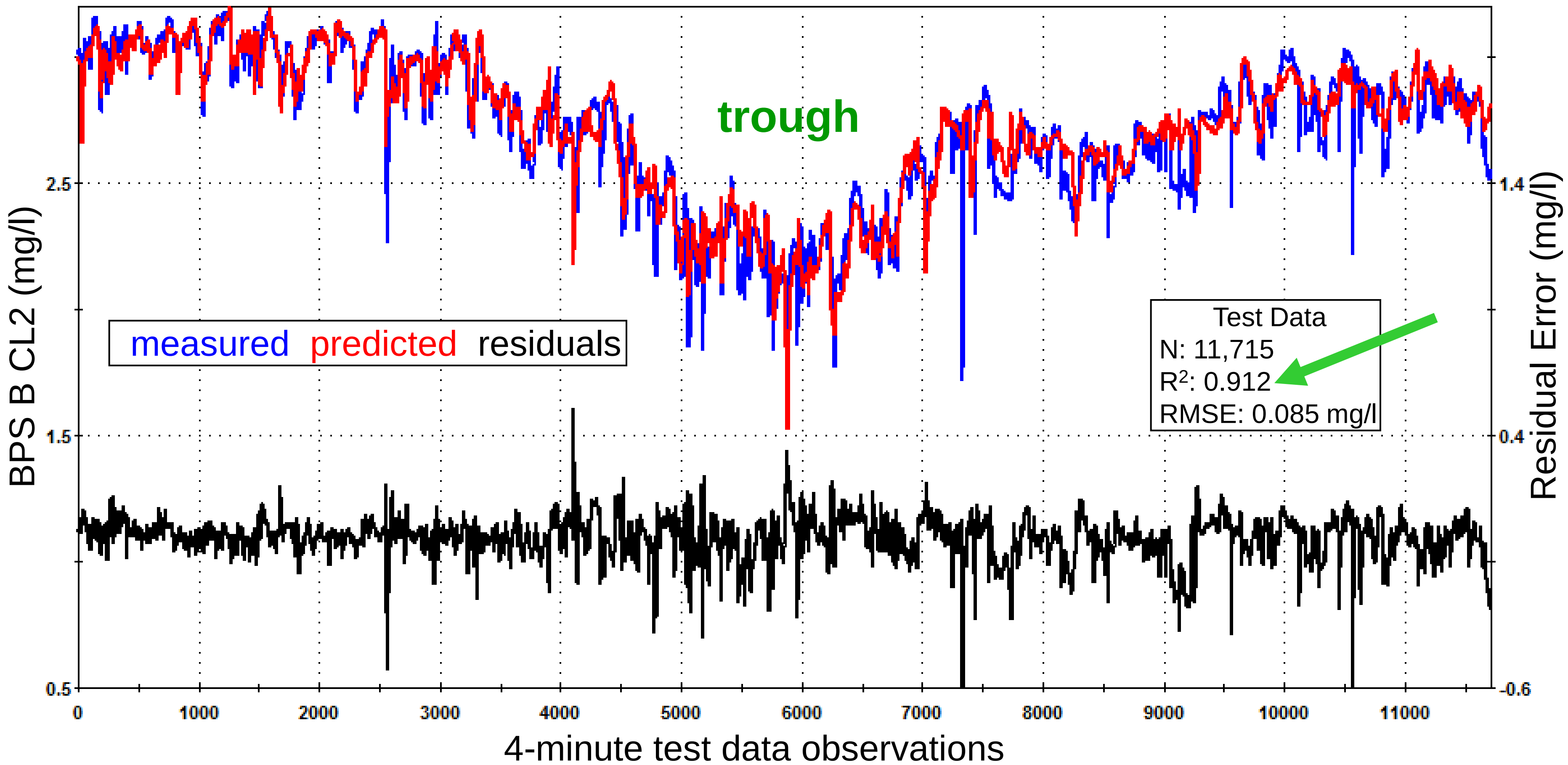


CL2



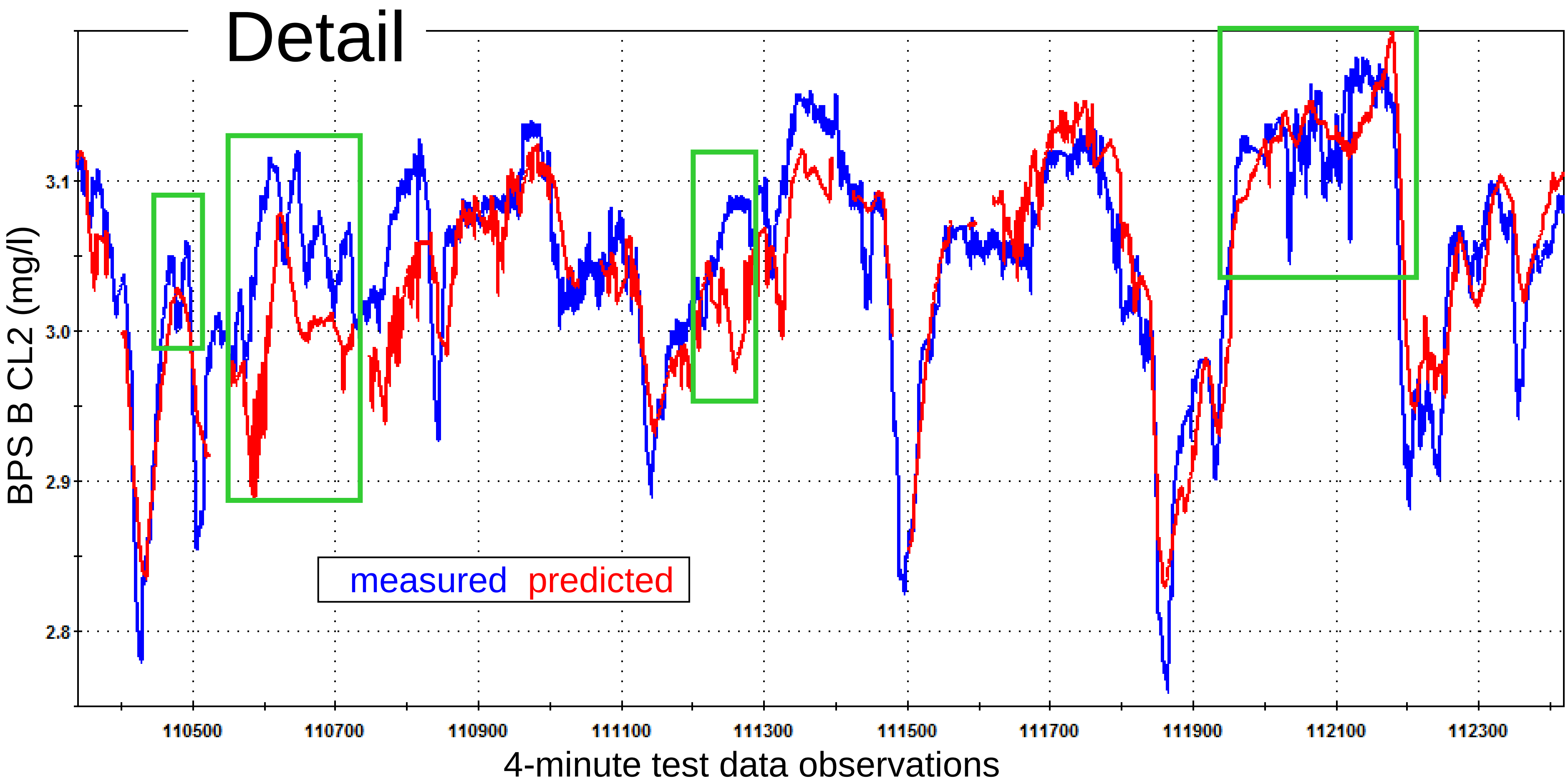
- Dx = Δ over x number of minutes
- R^2s are low

BPS B CL2 Process Model – test data



- trough may be from different WTP/source
- Looks Good!

BPS B CL2 Process Model – test data



- Looks Bad!
- Process model missing some periods - maybe from unmonitored flows through junctions

Conclusions

IEDS - Conclusions

- Practical problems
  - data reliability
  - no guarantees that contamination event would “look” different than “normal” because
    - “normal” is so highly variable
    - WQ sensors being used might not provide the “information” necessary to discriminate
  - Where to put / how many?

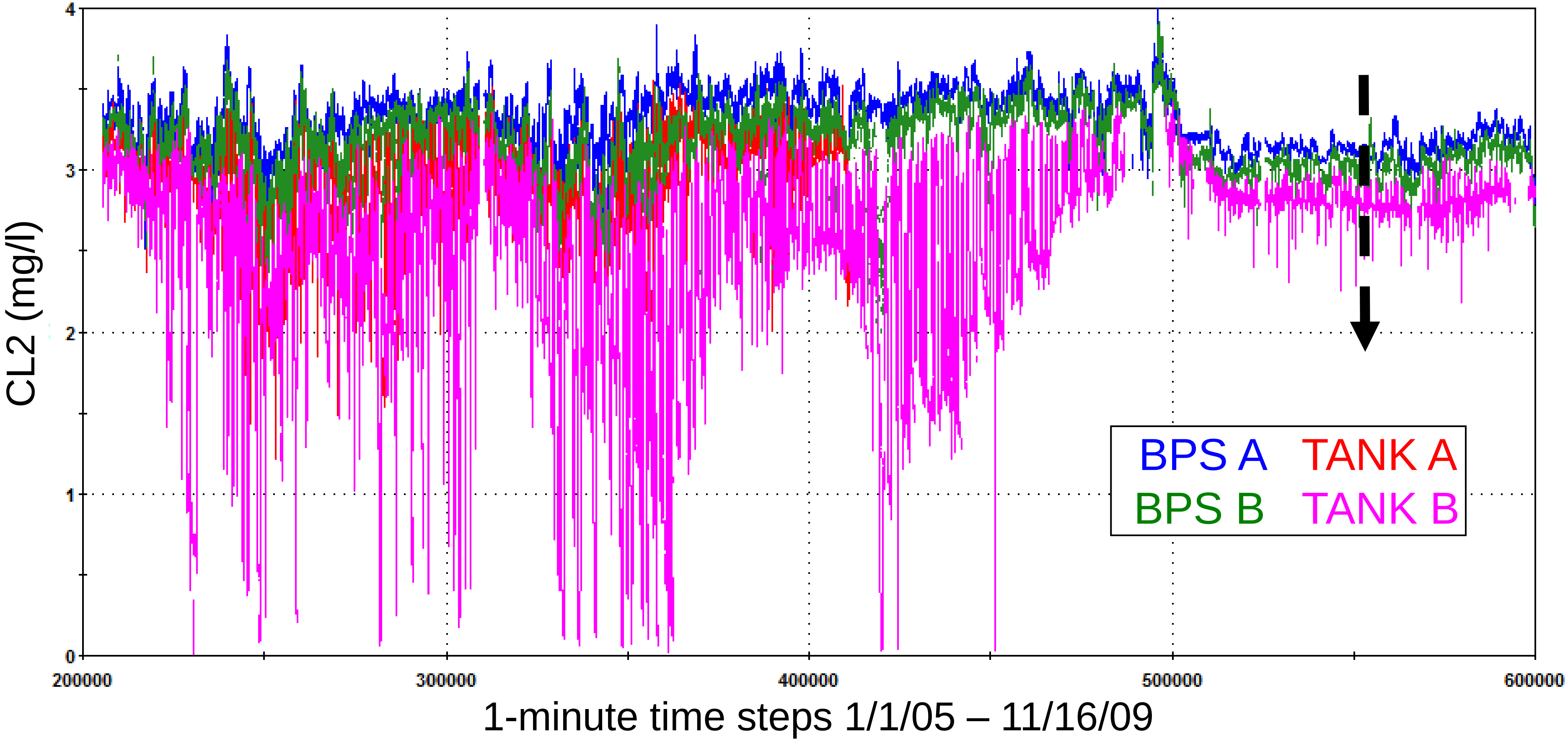
- Stand-Alone Sites
  - face widely ranging random variability from unknown disturbances, a.k.a. normal operations
  - high alarm limits needed to reduce false positives - defeats purpose

cont - Conclusions

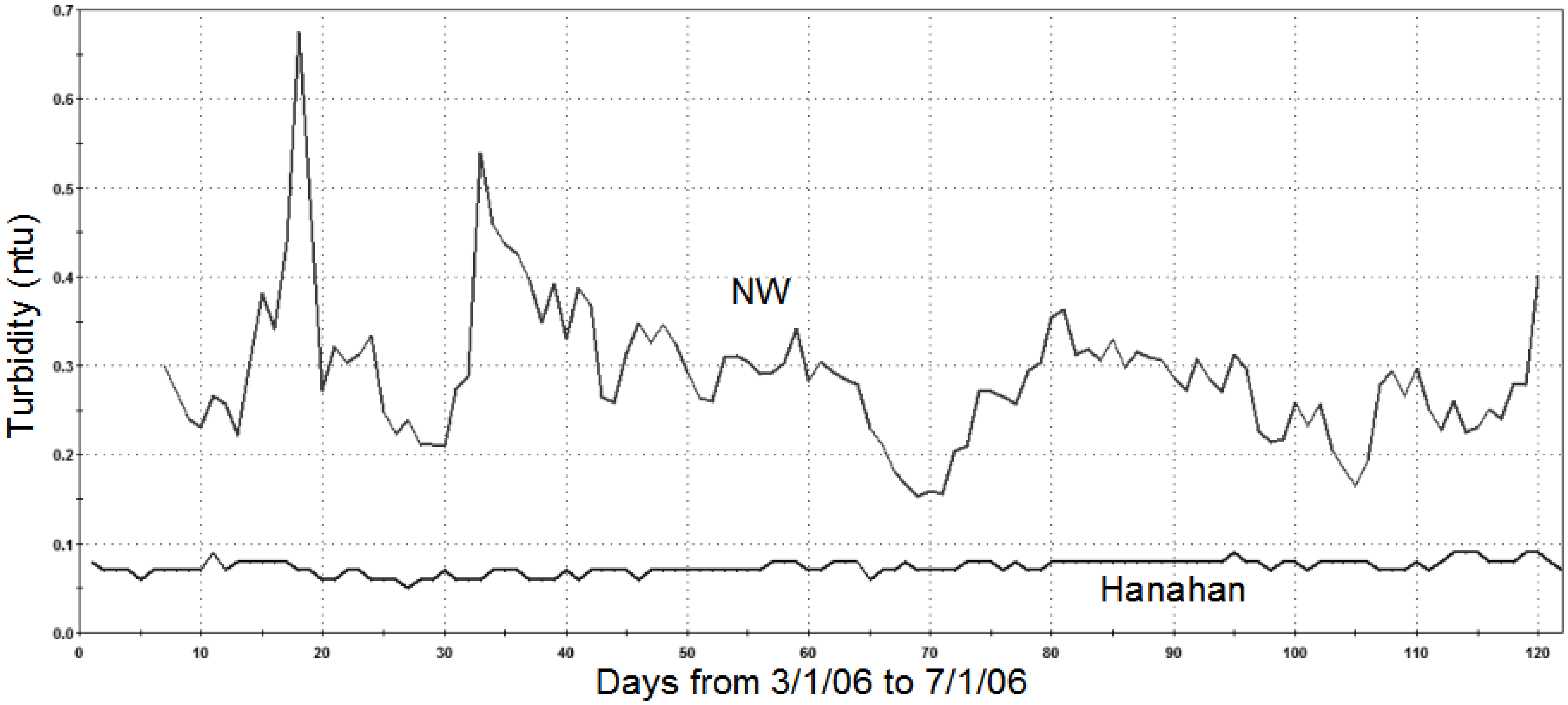
- Multi-Site approach
  - Can account for/explain 80-90% of downstream WQ variability
  - unproven on $\leq$ 20 min detection window
  - diminished when too much complexity
  - field testing to be done at GWS and SJWD

cont - Conclusions

- Other reasons to monitor distribution system WQ
  - control processes at WTP to improve WQ at points of delivery
  - detect common problems - low total chlorine, nitrification, line integrity, DBPs, biofilm sloughing, incipient complaint detection

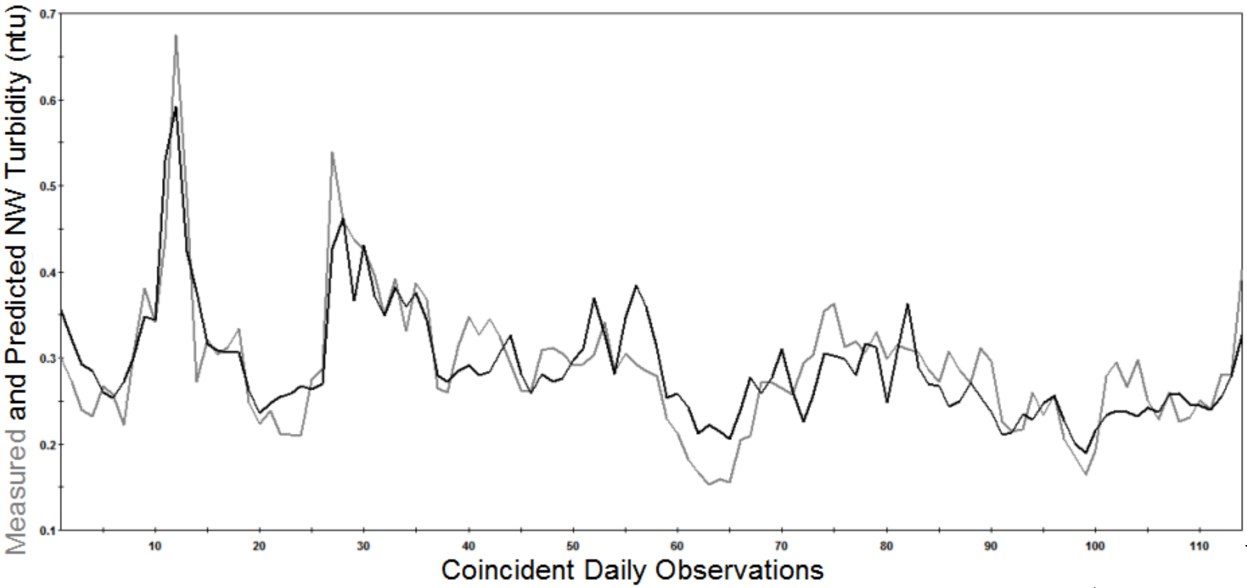


Compare WTP with DS turbidity



- **Little variability in WTP turbidity, < 0.1 NTU !**

Correlate DS turbidity with WTP WQ



- **ANN process model**
- **Inputs = finished water alkalinity, hardness, color, and source blend ratio**
- **$R^2 = 0.71$**