A framework for detecting anomalies in water-quality variables

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ARCLP Workshop

Outline

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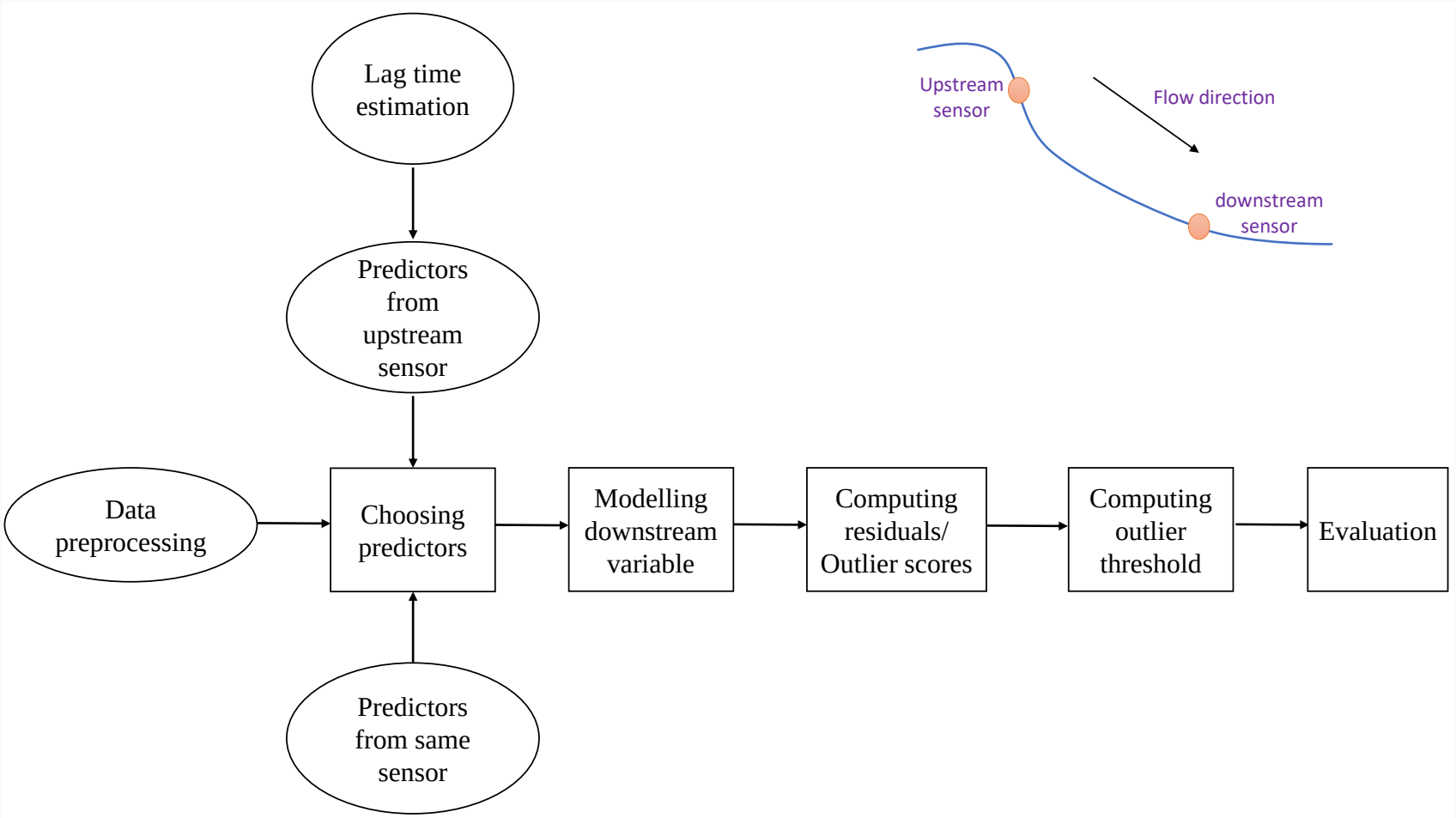
Objectives

An anomaly is an observation that has an unexpectedly low conditional density

Objective

- Developing statistical tools to detect technical anomalies in water-quality variables measured by in-situ sensors
- Utilising temporal correlation and information from multiple sensors

Proposed framework



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Pringle Creek - Texas, USA

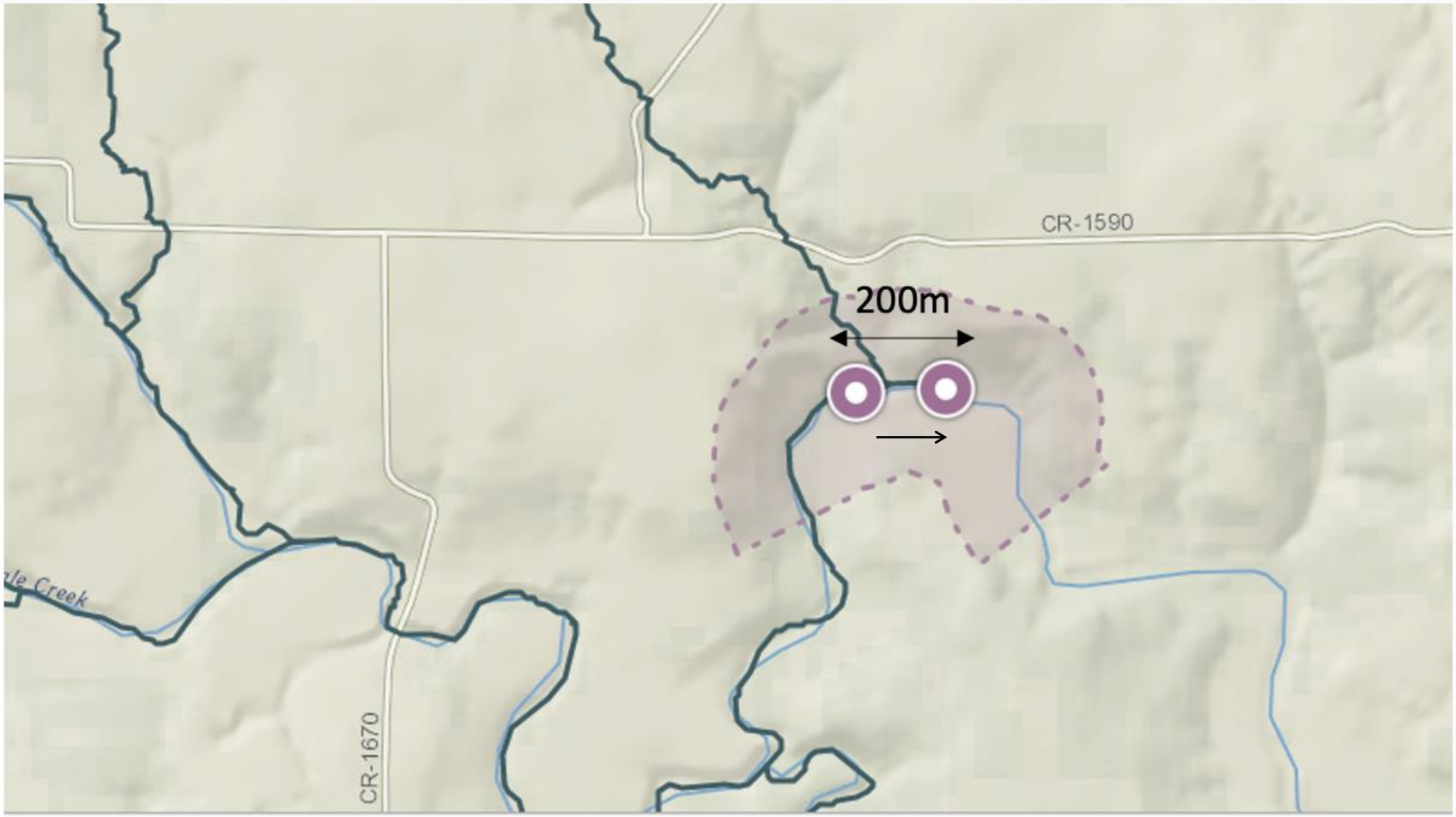
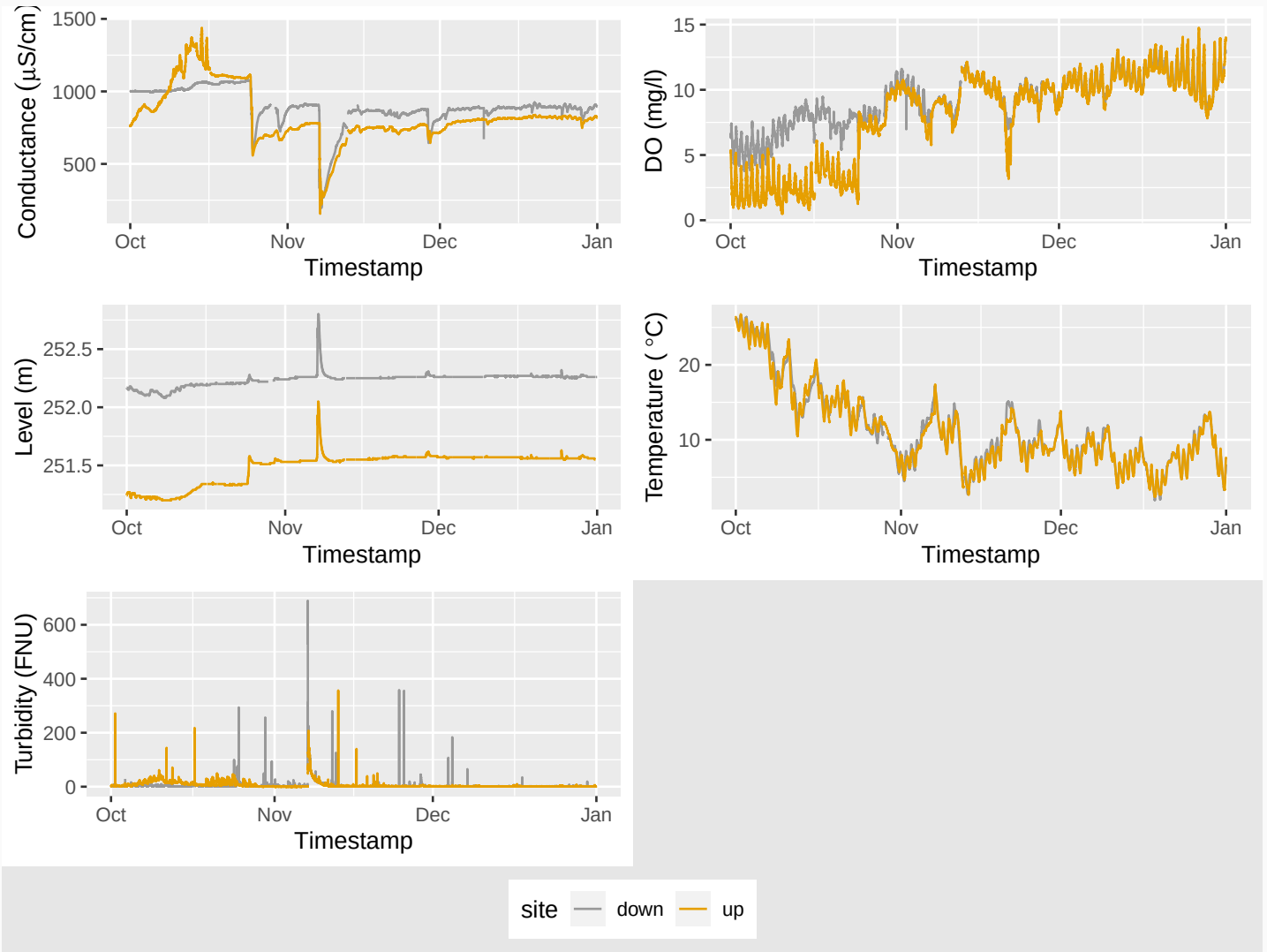


Figure 1: image courtesy neonscience.org

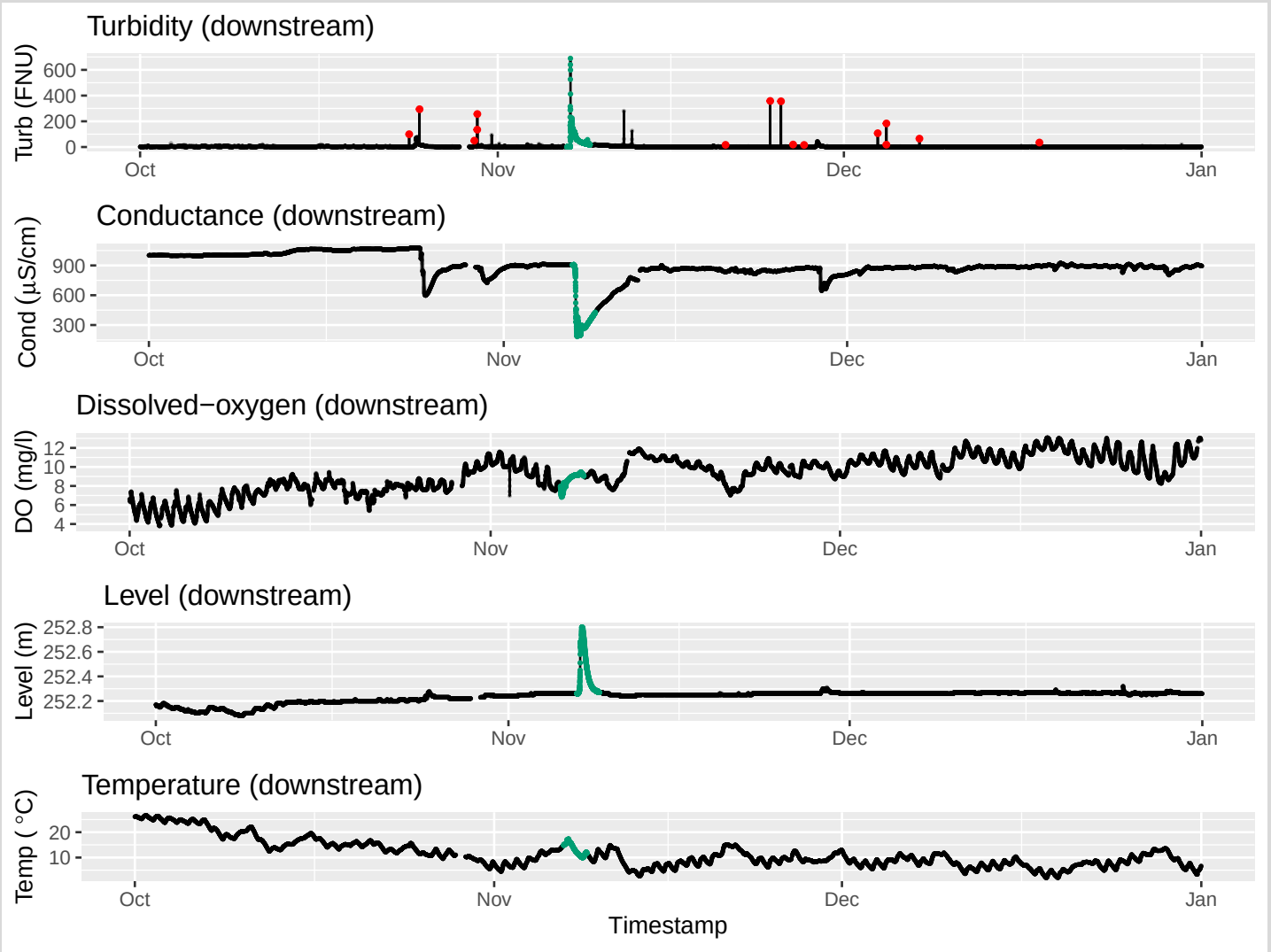
Data

- **Variables** - Turbidity, Conductivity, Dissolved oxygen, Level and Temperature
- **Time span** - 01-10-2019 to 31-12-2019
- **Frequency** - 5 minute intervals
- [`https://data.neonscience.org/data-products`]

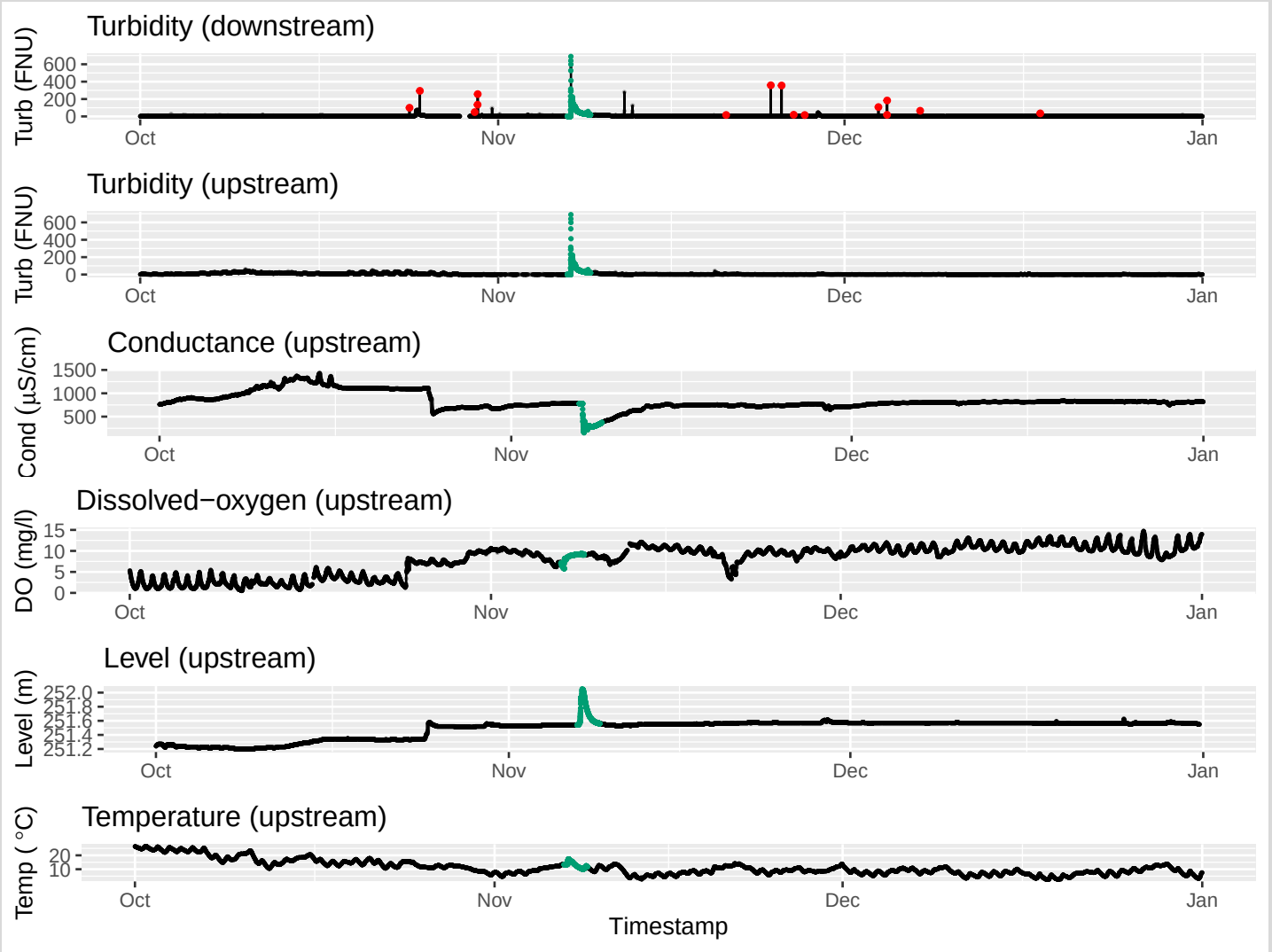
Time plots


Conductance (µS/cm)
1500
1000
500
Oct
Nov
Dec
Jan
Timestamp
DO (mg/l)
15
10
5
0
Oct
Nov
Dec
Jan
Timestamp
Level (m)
252.5
252.0
251.5
Oct
Nov
Dec
Jan
Timestamp
Temperature (°C)
20
10
Oct
Nov
Dec
Jan
Timestamp
Turbidity (FNU)
600
400
200
0
Oct
Nov
Dec
Jan
Timestamp
site
down
up

Turbidity downstream vs other downstream variables



Turbidity downstream vs other upstream variables



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Modeling downstream turbidity

$$turbidity\_down_t = \phi_0 + \sum_{i=1}^{p} g_i(z_{i,t_l}) + \sum_{j=1}^{q} h_j(turbidity\_down_{t-j}) + \varepsilon_t$$

Choices for z_{i,t_l}

Model	Predictors
GAM-down	other downstream variables
GAM-down-AR	other downstream variables + lagged responses
GAM-up	upstream variables
GAM-up-AR	upstream variables + lagged responses
GAM-up-down	upstream variables + downstream variables

Lag time estimation

- Assume the lag time between two sensor locations depends on the upstream river behavior
- Use *conditional cross-correlations* to estimate the lag time
- let x_t : Turbidity upstream, y_t : Turbidity downstream and $\boldsymbol{z}_t$: {level upstream, temperature upstream}
- $x_t^* = \frac{x_t - \mathrm{E}[x_t|\boldsymbol{z}_t]}{\sqrt{\mathrm{V}[x_t|\boldsymbol{z}_t]}}$ and $y_t^* = \frac{y_t - \mathrm{E}[y_t|\boldsymbol{z}_t]}{\sqrt{\mathrm{V}[y_t|\boldsymbol{z}_t]}}$

Conditional cross-correlation

$$r_k(\boldsymbol{z}_t) = \mathrm{E}[x_t^* y_{t+k}^* | \boldsymbol{z}_t] \quad \text{for} \quad k = 1, 2, \ldots$$

- To estimate $r_k(\boldsymbol{z}_t)$ we fit the following GAMs
- Let $x_t^* y_{t+k}^* | \boldsymbol{z}_t \sim \mathrm{N}(r_k(\boldsymbol{z}_t), \sigma_r^2)$,

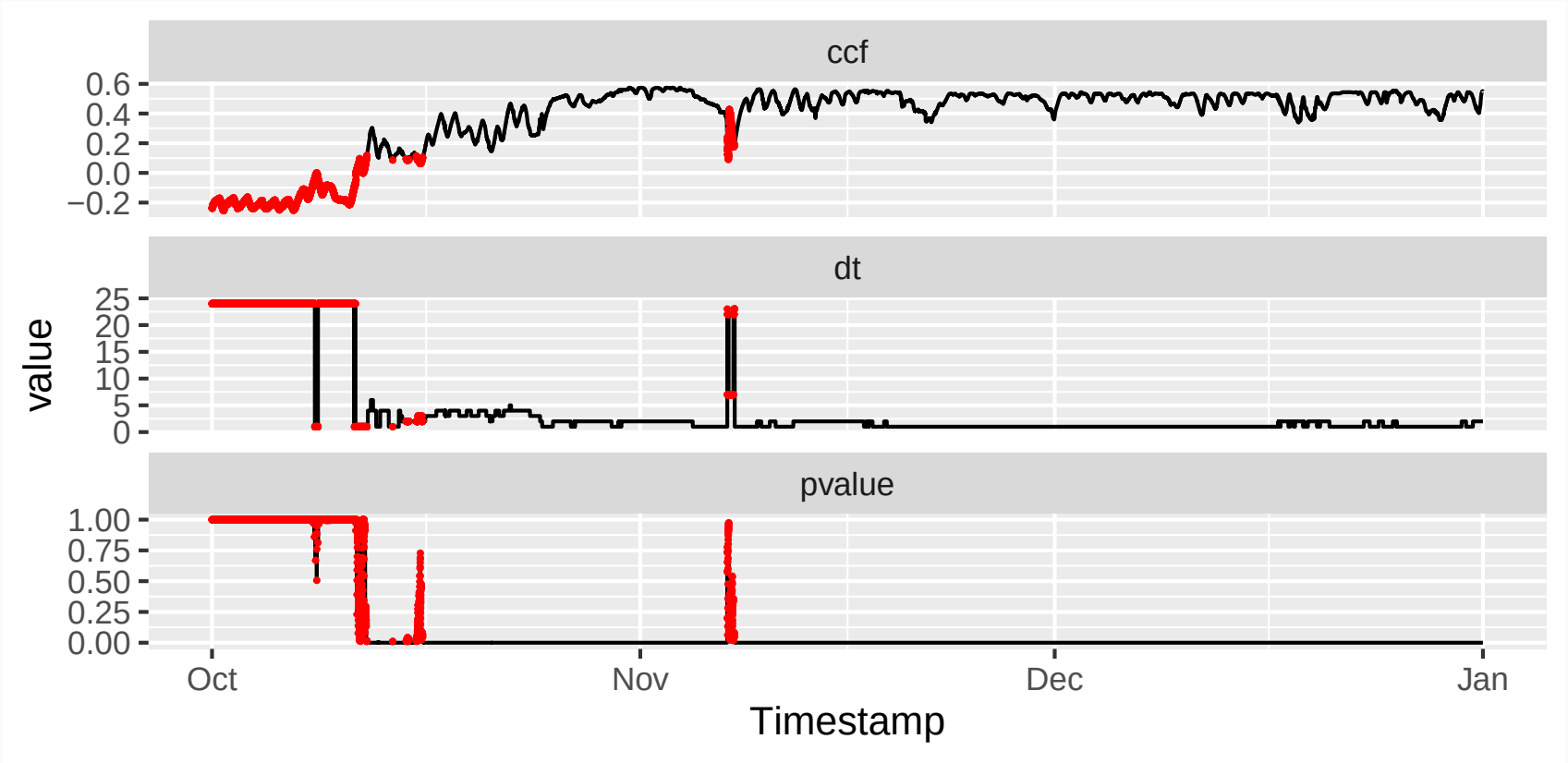
$$g(r_k(\boldsymbol{z}_t)) = \gamma_0 + \sum_{i=1}^{p} h_i(z_{i,t}) + \varepsilon_t$$

$$\hat{r}_k(\boldsymbol{z}_t) = g^{-1}(\hat{\gamma}_0 + \sum_{i=1}^{p} \hat{h}_i(z_{i,t}))$$

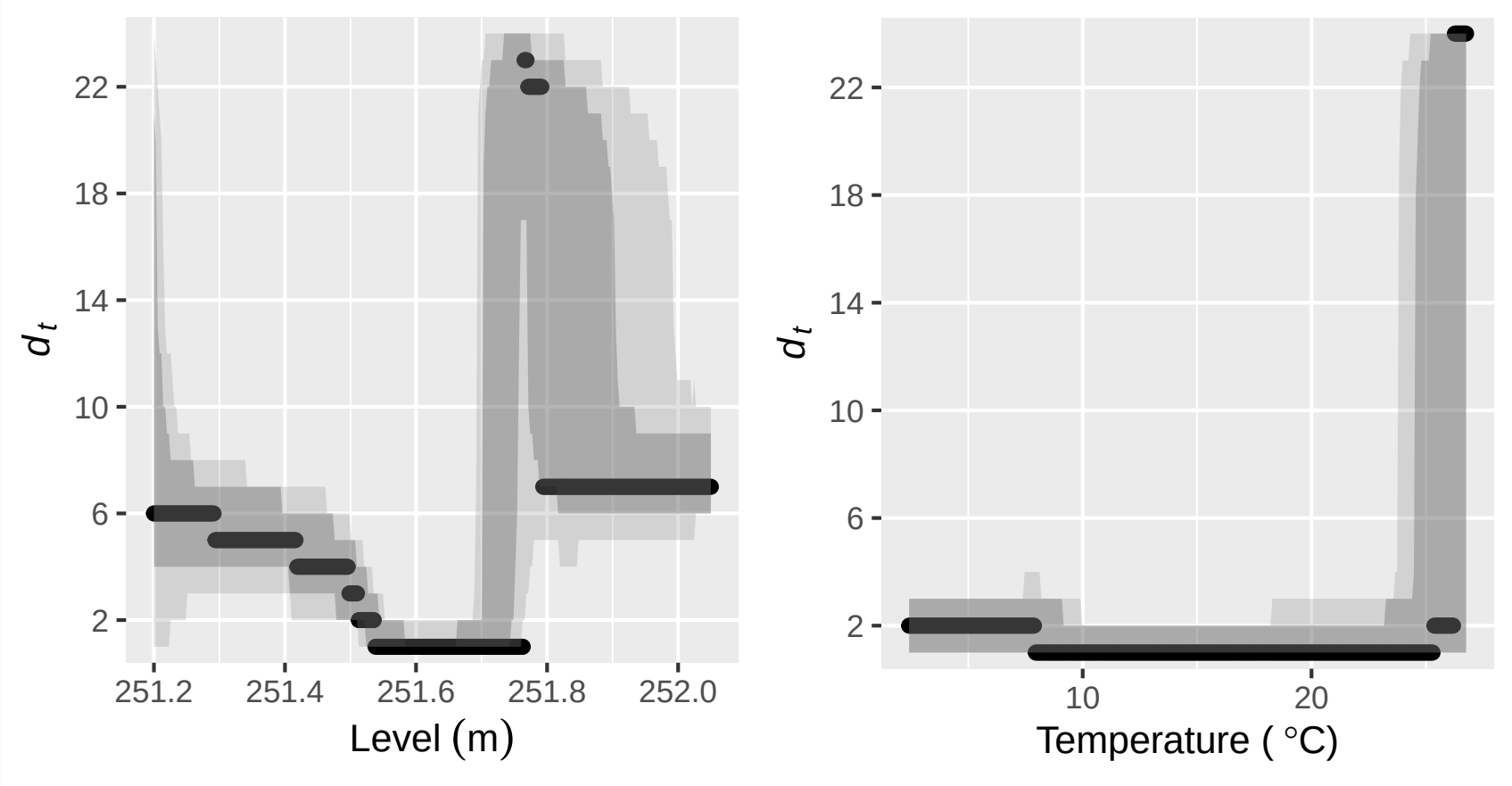
Estimating time delay

$$\hat{d}_t(\boldsymbol{z}_t) = \underset{k}{\operatorname{argmax}} \quad \hat{r}_k(\boldsymbol{z}_t)$$

Conditional cross-correlation and lag time estimation



Estimated lag time vs upstream predictors



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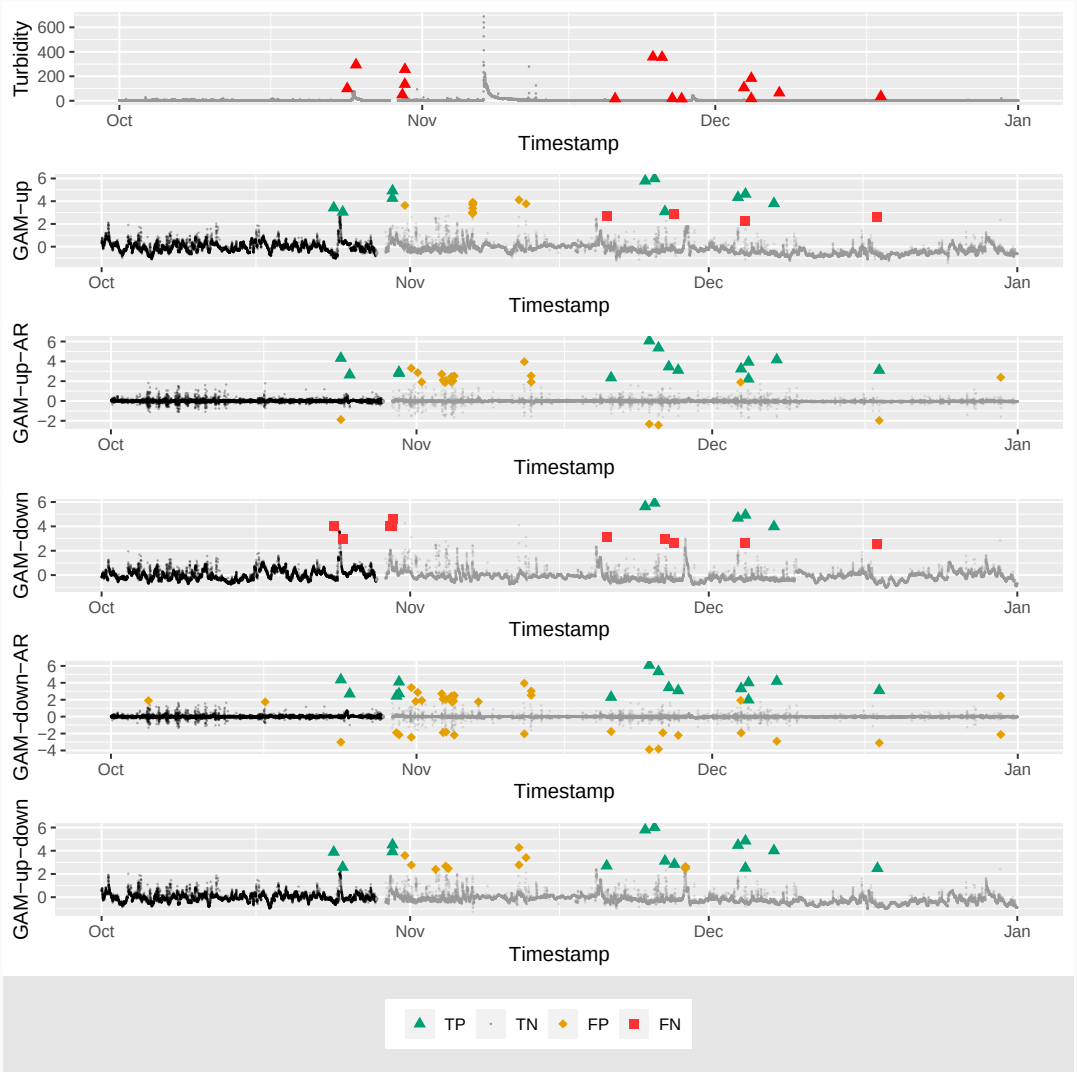
Outlier detection using Peak over Threshold method



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Performance Evaluation

method	TP	TN	FP	FN	OP
GAM-down-AR	15	25948	39	0	0.9977
GAM-up-down	14	25916	14	1	0.9652
GAM-up-AR	14	25837	21	1	0.9651
GAM-up	10	25920	10	5	0.7996
stray(p=0.5, k=1)	9	26007	5	6	0.7497
stray(p=0.5, k=5)	6	26011	1	9	0.5711
stray(p=0.75, k=5)	6	26011	1	9	0.5711
GAM-down	5	26012	0	10	0.4996
stray(p=0.75, k=1)	15	9835	16177	0	-0.0728

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Conclusions

- A new framework to detect technical anomalies
- Uses temporal correlation between the water-quality variables to detect anomalies
- Utilising information from the nearby sensors improves the performance of the algorithm
- Place low-cost sensors close together

Thank You!

Slides: https://github.com/PuwasalaG/ARCLP-workshop/tree/main/presentation

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