
# High frequency measurement of phosphate, nitrate, DOC and turbidity for NbS evaluation

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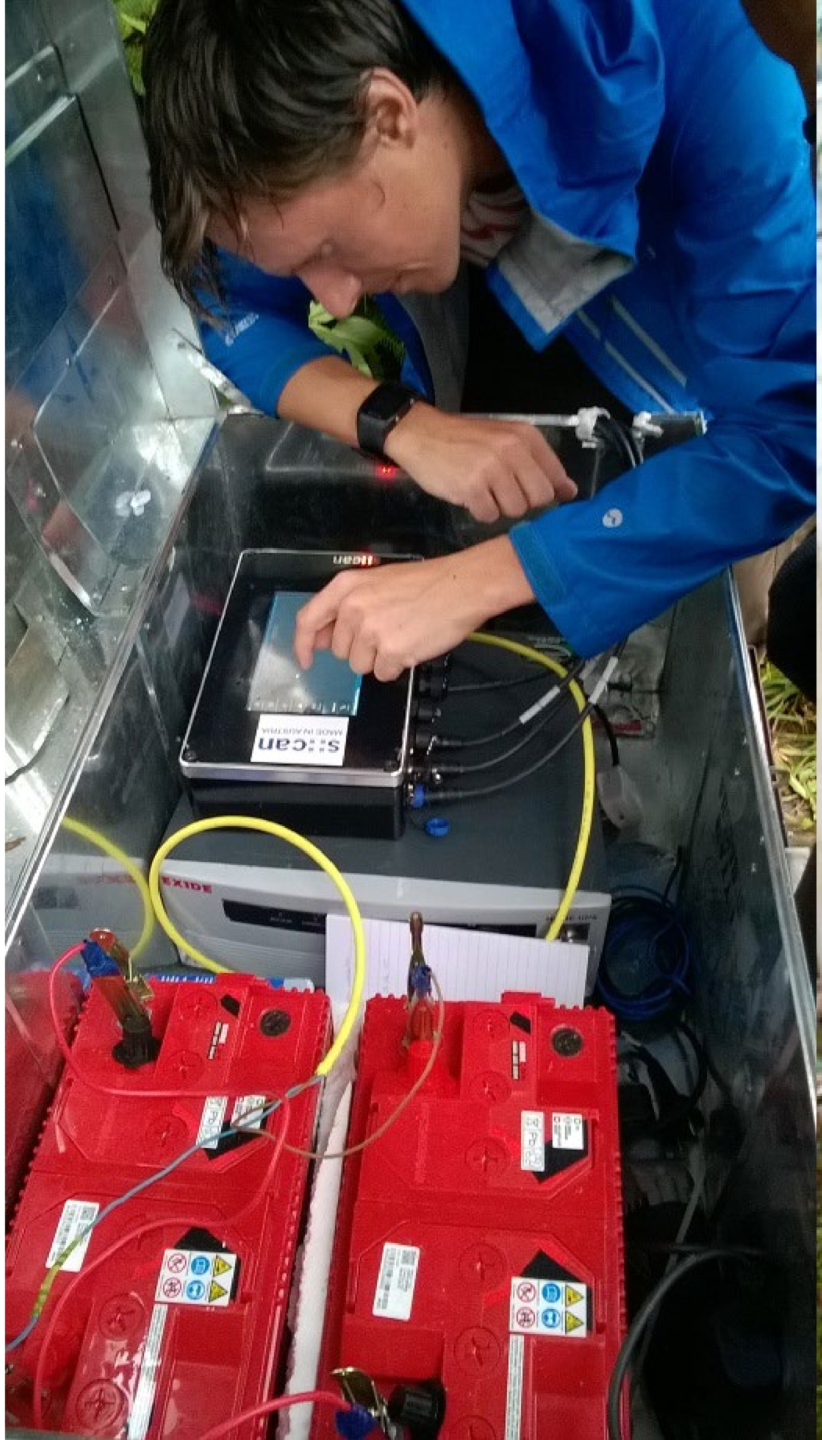
Context of today's presentation:

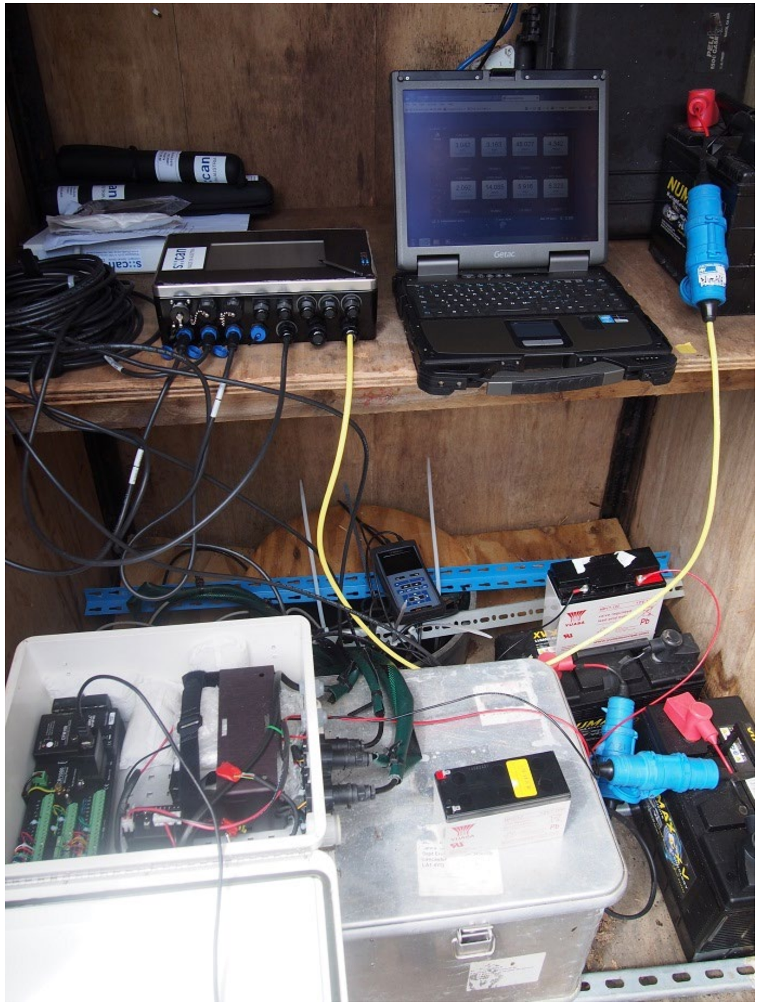
focus on effectiveness of **Nature-based Solutions** to hydrological issues (incl. water quality)

***managed tropical forests***
Malaysia, PNG, India

***managed temperate grasslands and woodland***
United Kingdom



Emphasis in this presentation:



Value of hydrological dynamics to attribute (interpret) high frequency water quality dynamics using System Identification Theory / Tools

**(1) Need continuous water quality observations that are 'accurate'** *– key focus*

**(2) Need System Identification Tools to cope with intrinsically noisy environmental data**

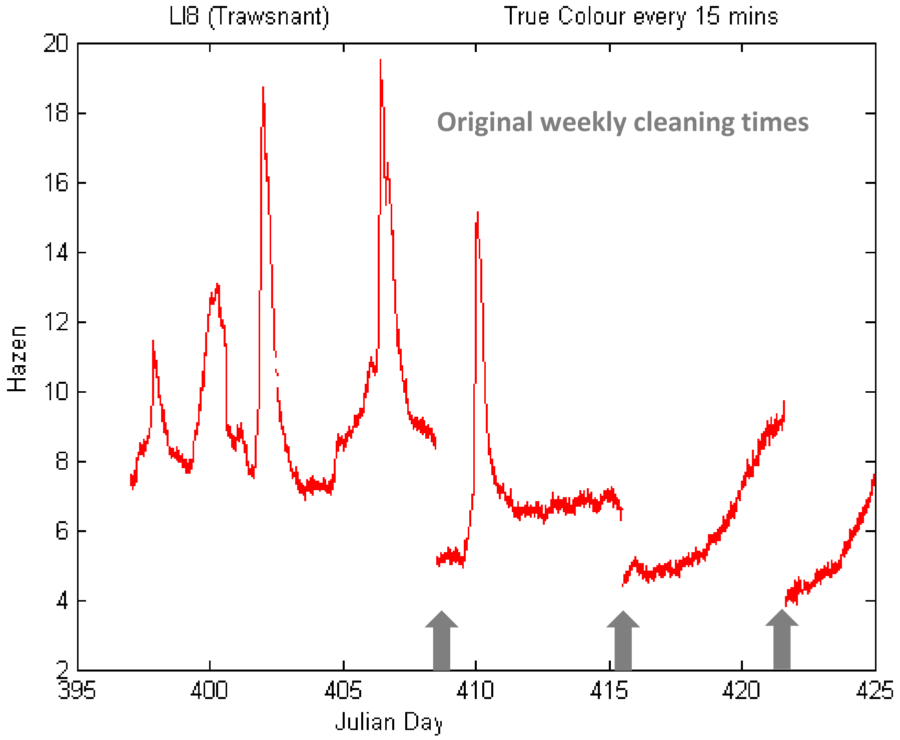
**(3) Need continuous discharge observations synchronous with WQ observations**

If meet these criteria for **SMART monitoring**

**what learning can be achieved?**

**(1) Need continuous water quality observations that are 'accurate'**

i.e., (a) free from **disinformative artefacts** (see e.g., Beven & Westerburg 2011 Hydrol Process)




*weekly clean proved insufficient*

Bi-weekly cleaning (brush 10% HCl) reduce step (eg, < 0.7 mg/L DOC) followed by drift correction

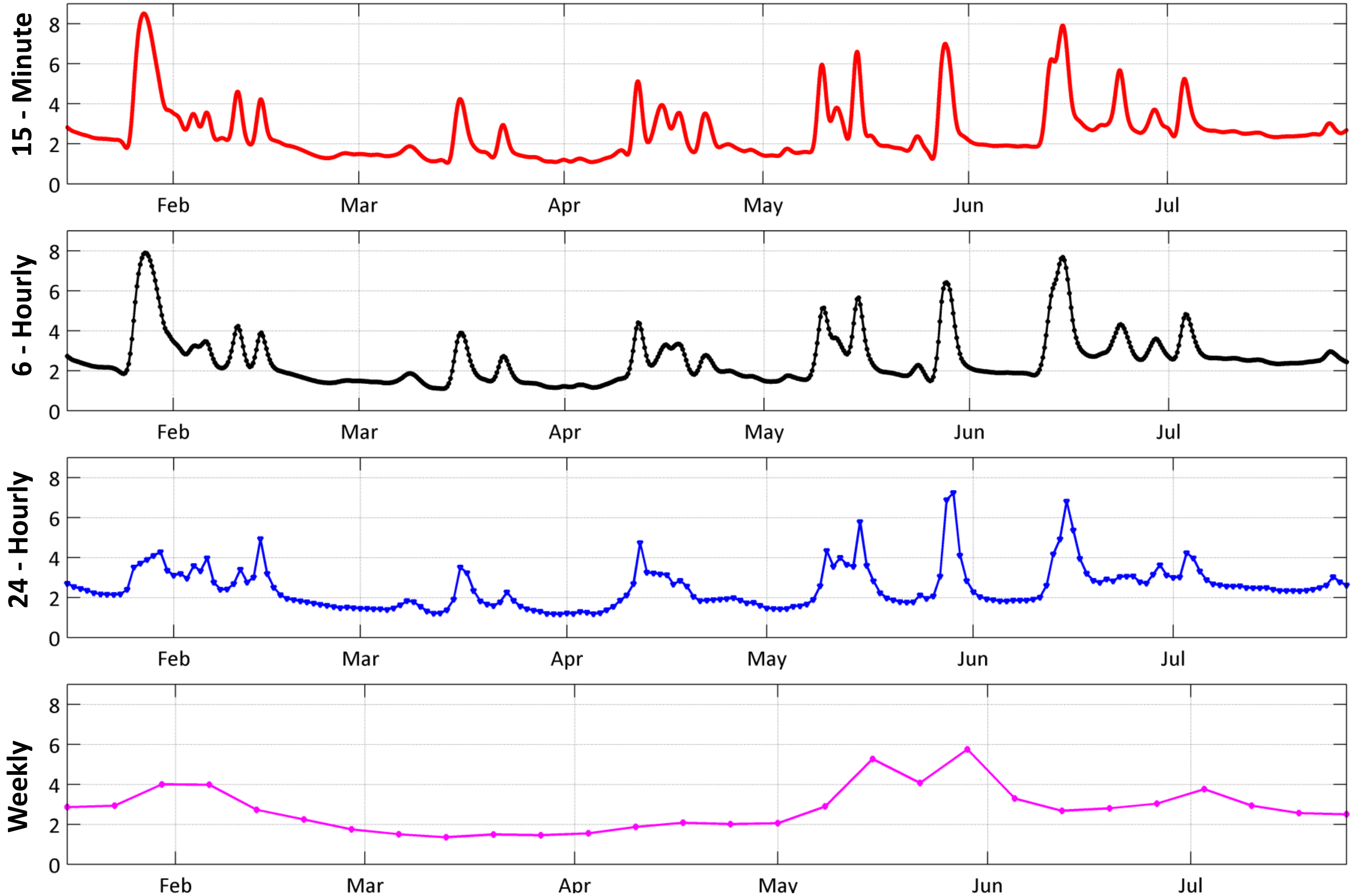
Jones et al 2014 Env Sci Tech

# (1) Need continuous water quality observations that are 'accurate'

i.e., (b) observations not **under-sampled** ('aliased')

LI6 catchment DOC (mg/L) time series

under-sampling **changes shape of chemograph** (time-series of concentration or load)



## (1) Need continuous water quality observations that are 'accurate'

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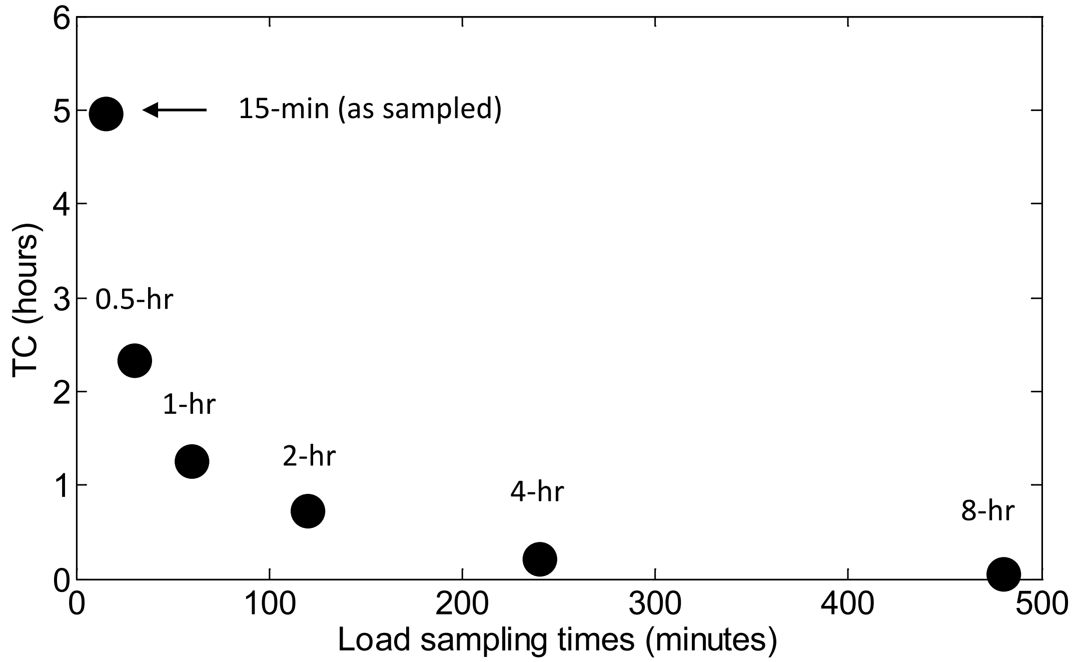



which changes **terms that characterise flood chemograph shape** (ie, Dynamic Response Characteristics, DRCs, fitted to observations)

e.g., **TC = time constant**
(residence time of response)

*Note: process interpretation dependent on DRCs and model order*

eg, $TC_{fast}$ of rainfall to $DOC_{LOAD}$ for LI7 stream where sampling halved progressively

Jones et al (2014 Environ Sci Tech)

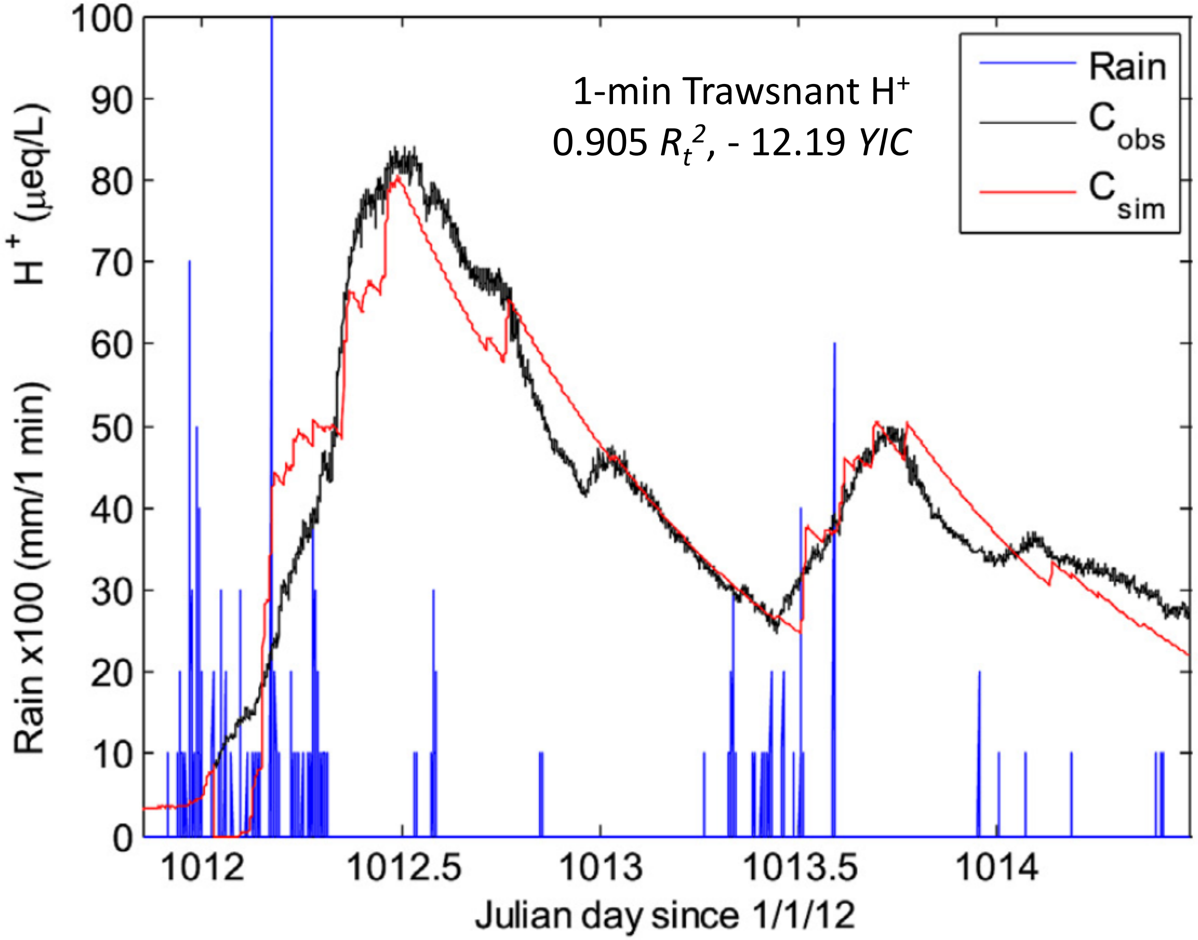
## (1) Need continuous water quality observations that are ‘accurate’

i.e., (b) observations not **under-sampled** (‘aliased’)

SI-method to **identify minimum sampling rate** before DRCs shift significantly

need System Identification (SI) Tools capable of high efficiency and high parsimony models

high $R_t^2$ and strong -*YIC*, particularly for highest res data



**(1) Need continuous water quality observations that are 'accurate'**

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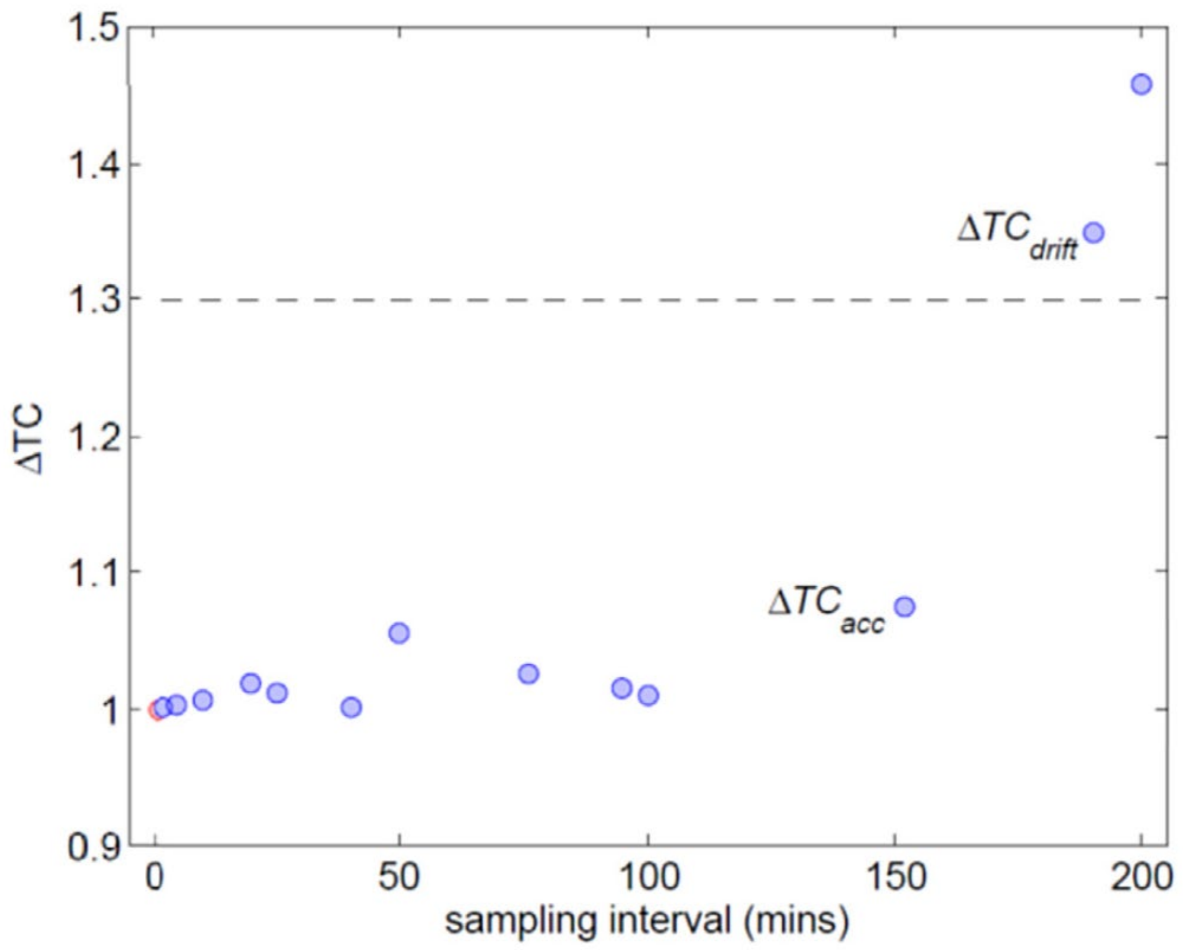
SI-method to **identify minimum sampling rate** before DRCs shift significantly

$$\Delta TC = \frac{\max(TC_O, TC_i)}{\min(TC_O, TC_i)}$$

$$\mathbf{1.3(\Delta \mathit{TC})}$$



## (1) Need continuous water quality observations that are 'accurate'

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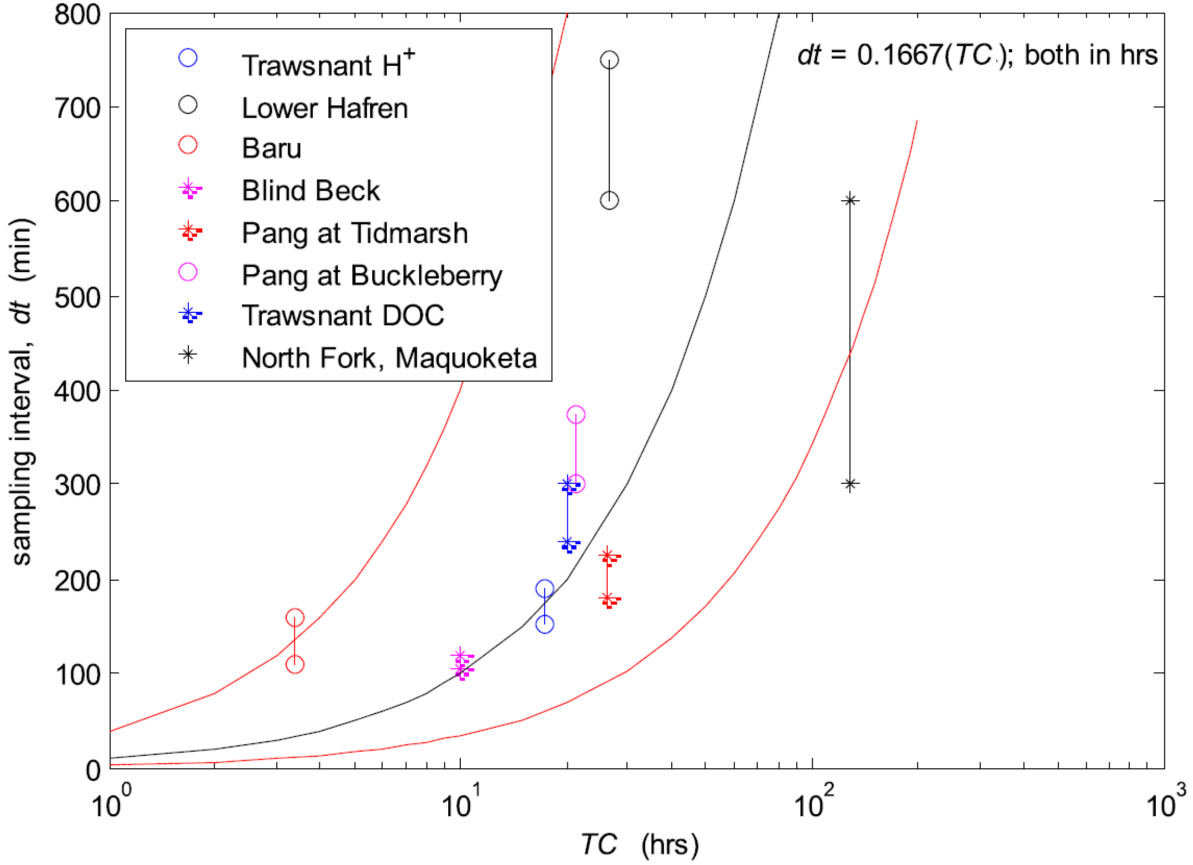
SI-method to **identify minimum sampling rate** before DRCs shift significantly

# $1.3(\Delta TC)$

Chappell et al (2017 Water Res)

consistent with but more reliable than existing

1/6(*TC*) of Young (2010 BHS)



## (1) Need continuous water quality observations that are 'accurate'

i.e., (b) observations not
**under-sampled** ('aliased')

Chappell et al (2017 Water Res)

| site | variable | sampling interval | |
|---|---|---|---|
| | | $T_{acc}$ (min) | $T_{drift}$ (min) |
| Trawsnant | $H^+$ | 152 | 190 |
| Hafren | $H^+$ | 600 | 750 |
| Baru | $H^+$ | 110 | 160 |
| Blind Beck | $H^+$ | 105 | 120 |
| Pang at Tidmarsh | $H^+$ | 180 | 225 |
| Pang at Buckleberry | $H^+$ | 120 | 300 |
| Trawsnant | DOC | 240 | 300 |
| North Fork | $NO_3$-N | 300 | 600 |

**i.e., 1.8 – 10 hours**

# (2) Need System Identification Tools to cope with intrinsically noisy environmental data

## e.g., RIVC algorithm

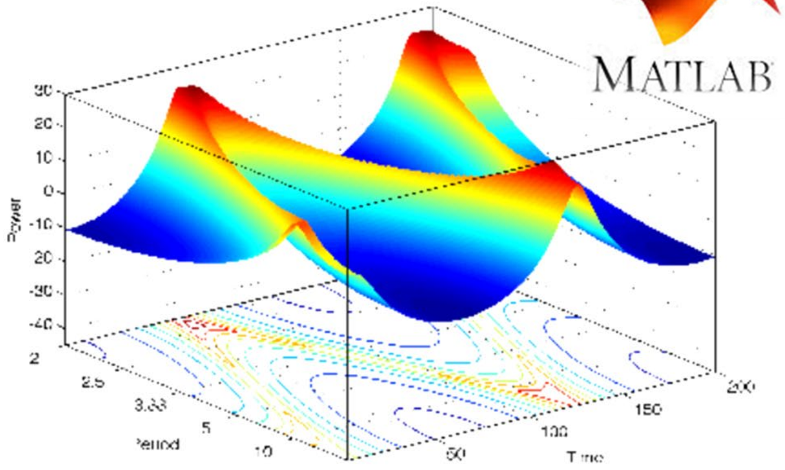
***R***efined ***I***nstrumental ***V***ariable ***C***ontinuous-time Box-Jenkins identification algorithm

Model estimation involves **iterative pre-filtering of signals to remove high frequency noise inherent within environmental data** (even within quality assured data) that affects identification of accurate parameter values (Jones et al 2014 Environ Sci Tech)

Freely available at https://wp.lancs.ac.uk/captaintoolbox

THE CAPTAIN TOOLBOX

Time-frequency plot produced when the Dynamic Auto-Regression (DAR) routine in CAPTAIN is applied to a 'chirp' signal. The analysis is fully automatic and based on the Kalman Filter and Fixed Interval Smoothing algorithms, with the 'hyper para-meters' optimized by maximum likelihood using prediction error decomposition.

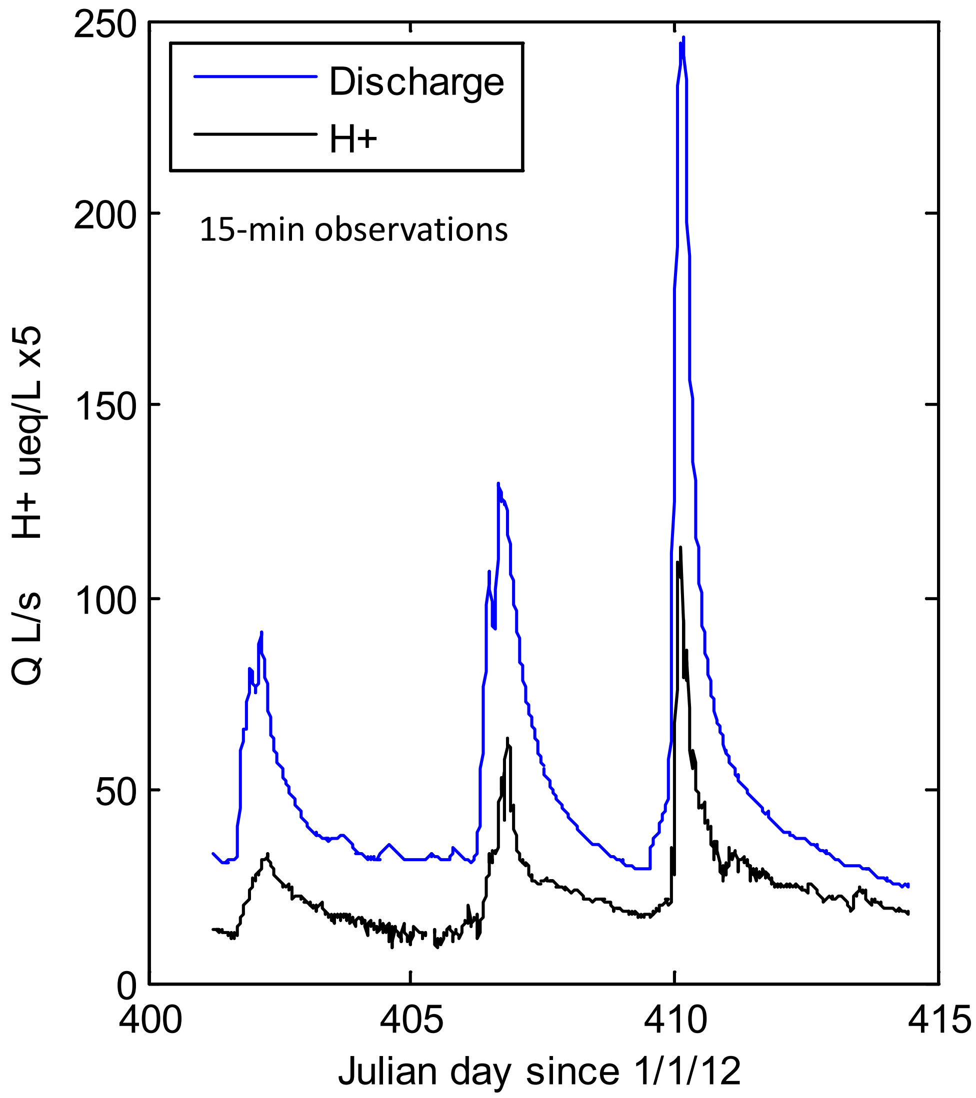


The **C**omputer-**A**ided **P**rogram for **T**ime-series **A**nalysis and **I**dentification of **N**oisy Systems (CAPTAIN) Toolbox

## (3) Need continuous discharge observations synchronous with the WQ observations


Concentration dynamics strongly associated with storm changes in waterflow dynamics (eg, channel discharge)

eg, Jones & Chappell (2014 Hydrol Res) $H^+$ study



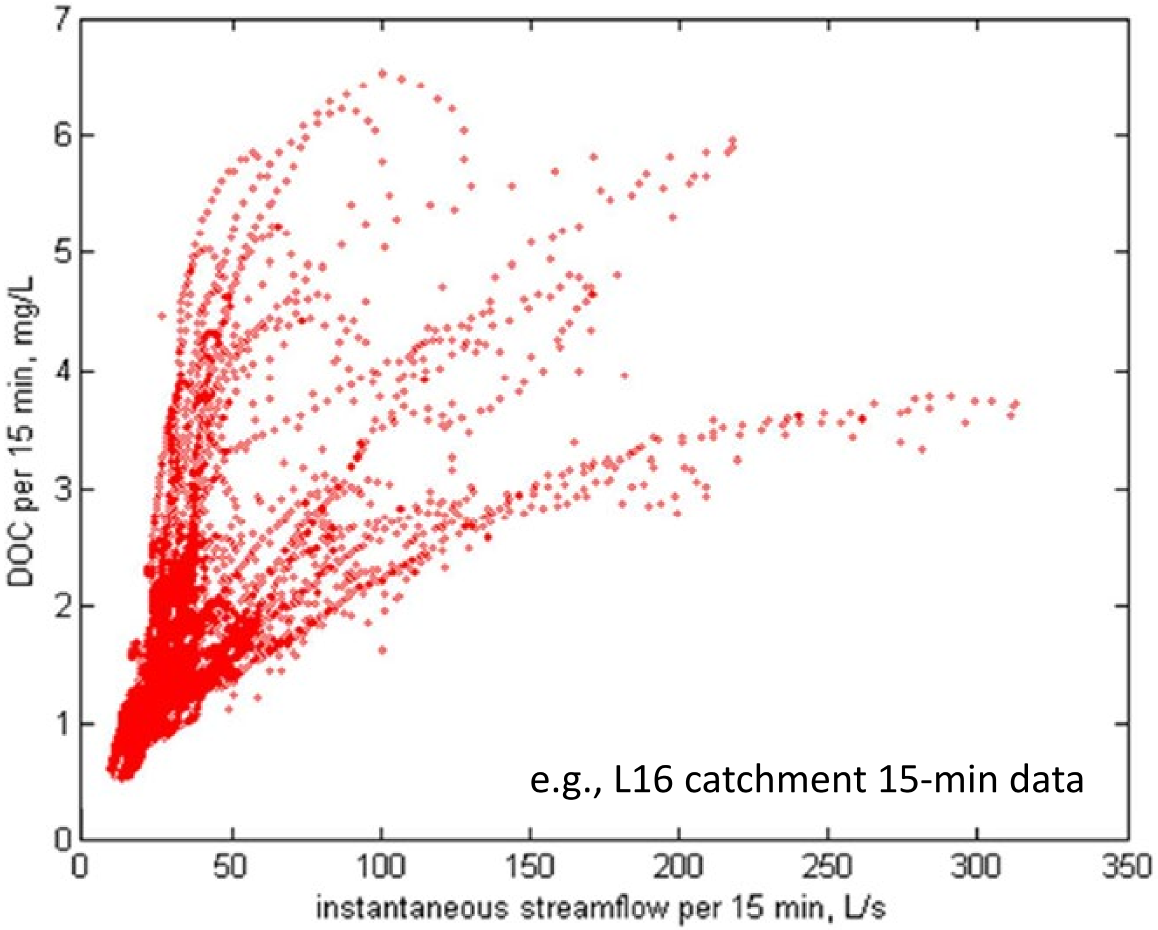

thus should measure discharge to attribute (and simulate) concentration dynamics

**(3) Need continuous discharge observations synchronous with the WQ observations**

C-Q relationships hysteretic; with loops very different between storms events

eg, Jones et al (2014 Environ Sci Tech) DOC study

Thus should measure discharge (and concentration) continuously



**(3) Need continuous discharge observations synchronous with the WQ observations**

Similarly accurate derivation of discharge required

i.e., use a **control structure**

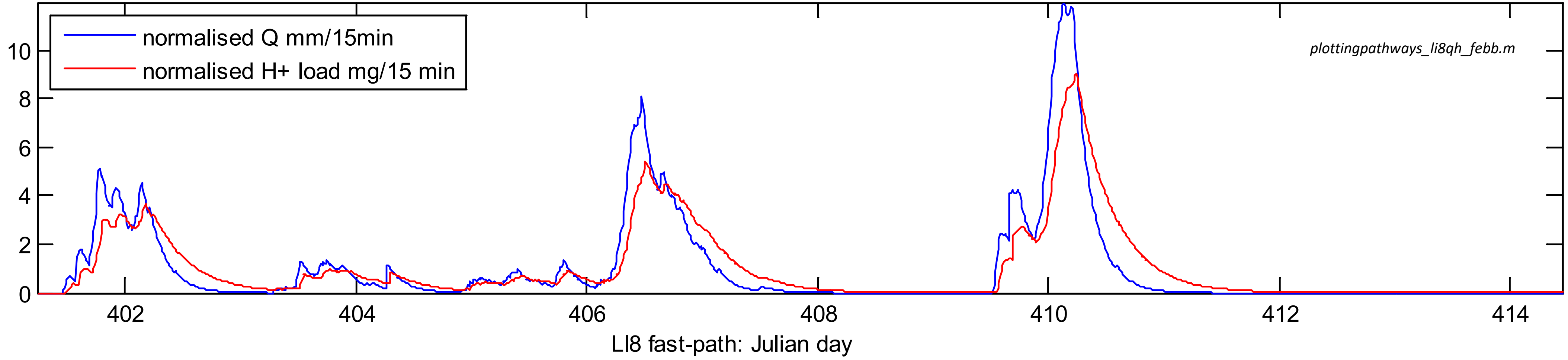
(stable calibration & with measurement at point of critical flow)

If meet these criteria for

# SMART monitoring

## what learning can be achieved?

**Visually contrast timing** of chemical flux against reference of water flux:




$H^+$ load and streamflow (Brianne LI8)

If meet these criteria for

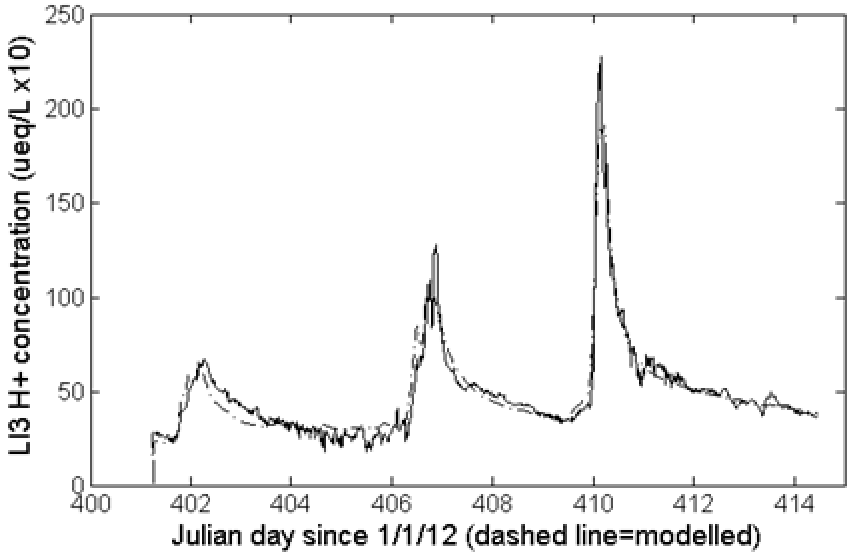
# SMART monitoring

## what learning can be achieved?

**Quantify dynamics:**

87-99% of dynamics in $H^+$ concentration explained purely by dynamics in streamflow (Jones & Chappell, 2014 Hydrol Res)

*15-min observations through contiguous storms*




e.g., 2nd order CT-TF model for a simulated period for streamflow to $H^+$ concentration in the LI3 basin, Llyn Brianne

If meet these criteria for

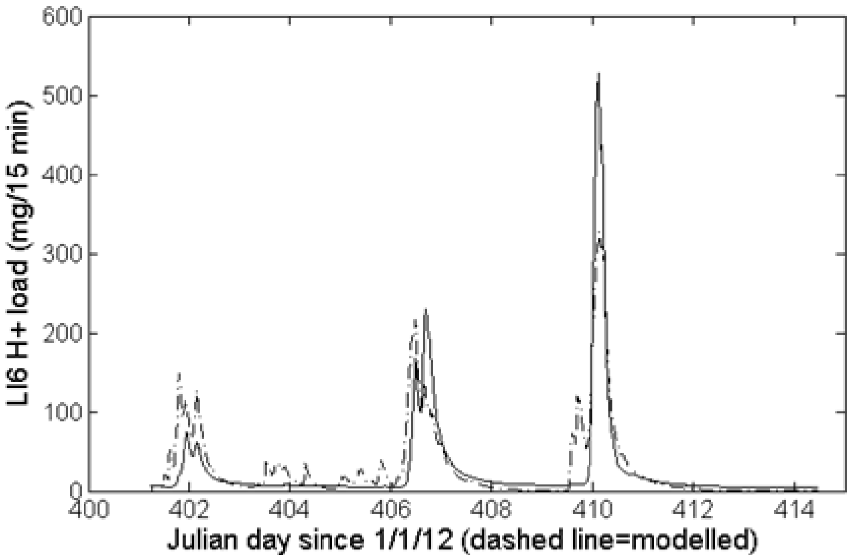
# SMART monitoring

## what learning can be achieved?

**Quantify dynamics**:

71-75% of dynamics in $H^+$ load explained purely by dynamics in rainfall (Jones & Chappell, 2014 Hydrol Res)

*15-min observations through contiguous storms*




e.g., $2^{nd}$ order CT-TF model for a simulated period for rainfall to $H^+$ load in the LI6 basin, Llyn Brianne

If meet these criteria for

# SMART monitoring

## what learning can be achieved?

**Quantify dynamics**:

Jones et al (2014 Environ Sci Tech) DOC study

Relative to water flux, more DOC flux in faster component

| site | $DOC_{LOAD}/Q$ | model[a] | YIC | $R_t^2$ | $TC_{fast}$ (h) | $TC_{slow}$ (h) | fast % | slow % | SSG |
|---|---|---|---|---|---|---|---|---|---|
| LI8 | Feb load | [2 2 2] | −5.27 | 0.870 | 5.09 ± 0.14 | 46 ± 21 | 47.4 ± 14 | 52.6 ± 14 | 2.155 |
| | Feb Q | [2 2 2] | −6.35 | 0.883 | 3.48 ± 0.16 | 63 ± 120 | 16.3 ± 32 | 83.7 ± 32 | [illegible] |
| | May load | [2 2 8] | −8.52 | 0.972 | 10.98 ± 0.13 | 372 ± 94 | 34.9 ± 6.6 | 65.1 ± 6.6 | 4.315 |
| | May Q | [2 2 1] | −9.46 | 0.949 | 7.77 ± 0.35 | 441 ± 120 | 6.5 ± 27 | 93.5 ± 27 | 2.589 |

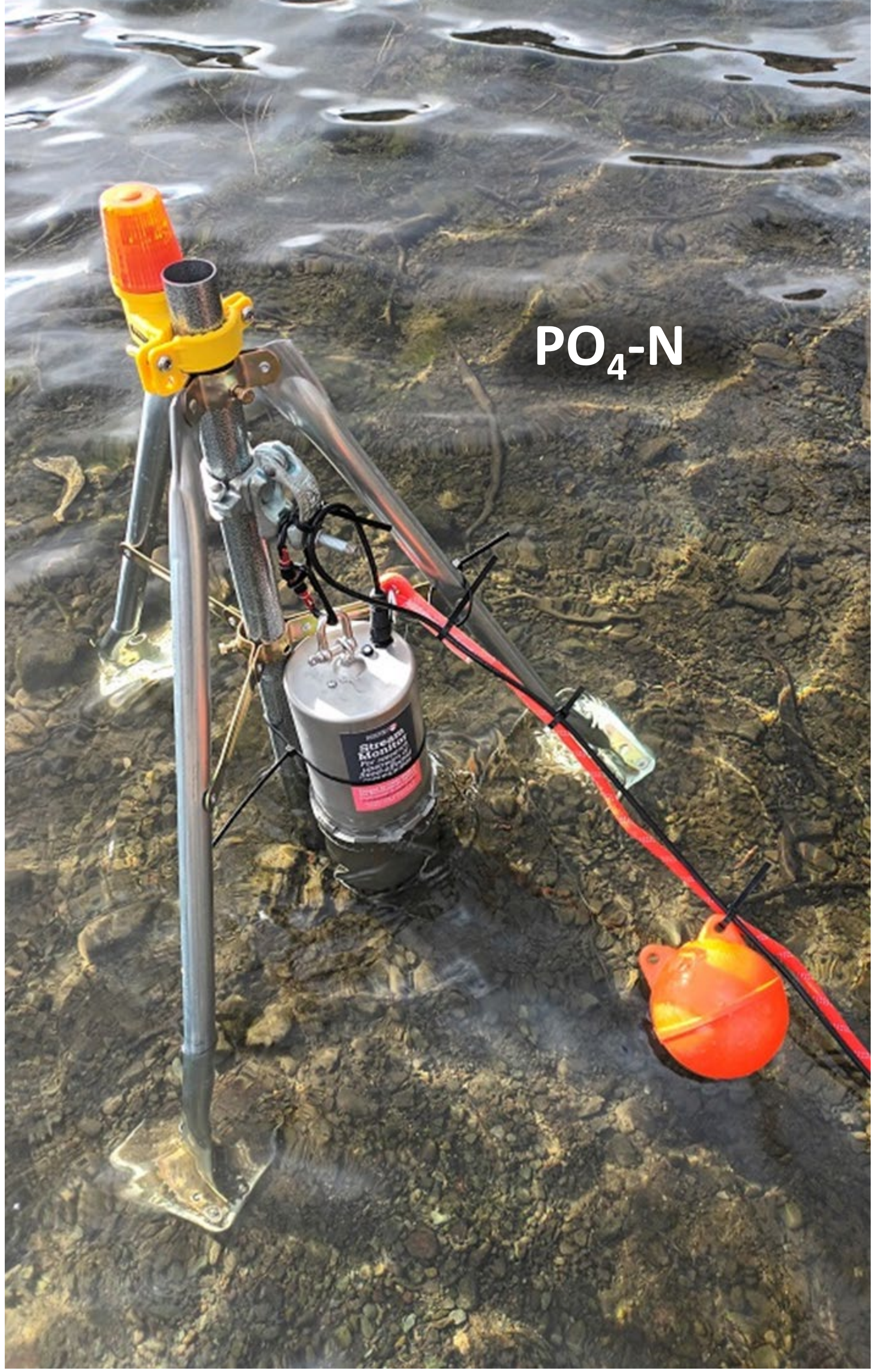
Greater pure time delay of DOC mobilisation in spring

Greater DOC flux per unit rain input in spring


**Current applications of SMART monitoring approach**

e.g., NFM co-benefits

**turbidity (SSC)**

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www.es.lancs.ac.uk/people/nickc/npub.htm

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