Identifying regime shifts using early warning signals: the univariate and multivariate options

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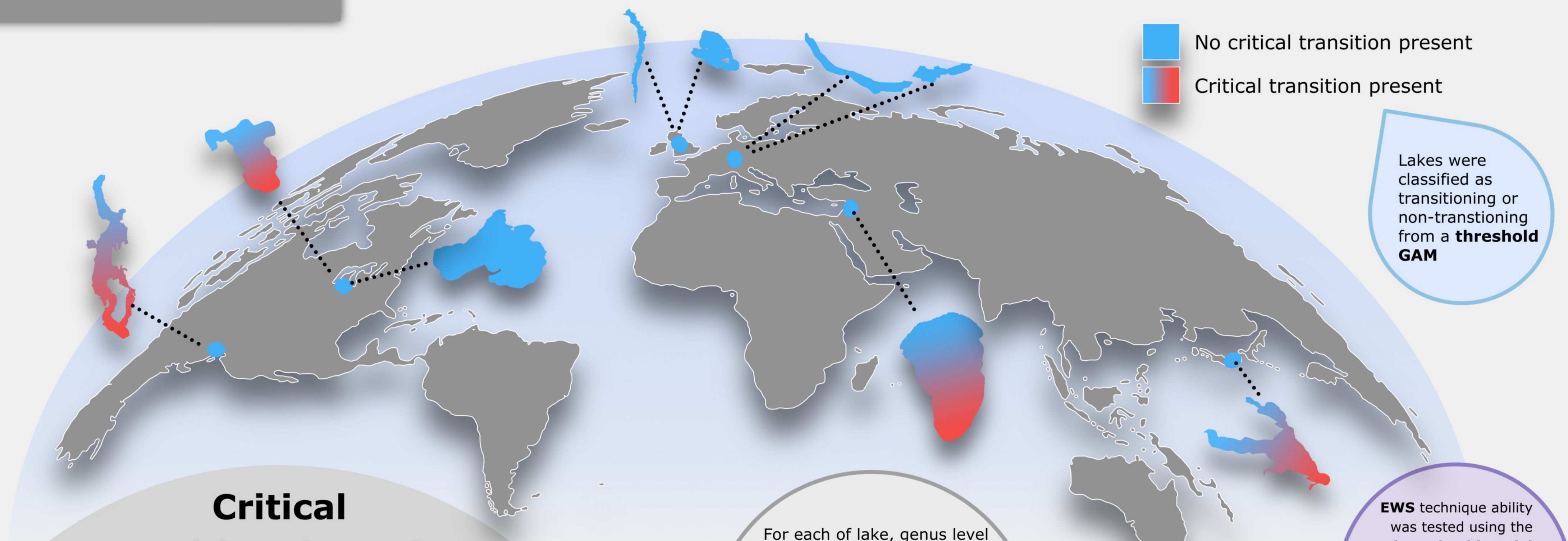
Rationale

Identifying rapid shifts in natural systems is key to their management but is difficult due to the non-linear nature of such changes.

A collection of model-free and generic tools have been suggested to identify these regime shifts using dynamical system theory.

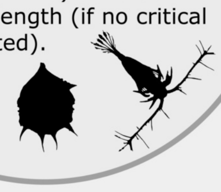
Here, we identify the presence/absence of critical transitions in an international pool of lake plankton communities and compare each tool's efficacy.



Lakes were classified as transitioning or non-transtioning from a **threshold GAM**

For each of lake, genus level phytoplankon and zooplankton monthly densities were assessed using each **technique.**

Data was trimmed prior to the transition (if detected) or to 80% of the time series length (if no critical transition detected).



EWS technique ability was tested using the **bayesian binomial model**:

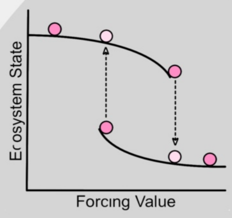
$$success \sim binomial(number\_of\_trials, \pi)$$

$$logit(\pi) = \beta 0 * lake * outcome + \beta 1 * ews\_method$$

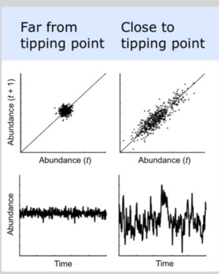
$$\beta 1 \sim normal(0,1)$$

$$\sigma \sim exponential(1)$$

Critical transition detection



Methods for detecting oncoming regime shifts arise from bifurcation mathematics. For these techniques to work, we require specific conditions where a **small change** in a linear forcing value **causes a large change** in the system state i.e a critical transition.

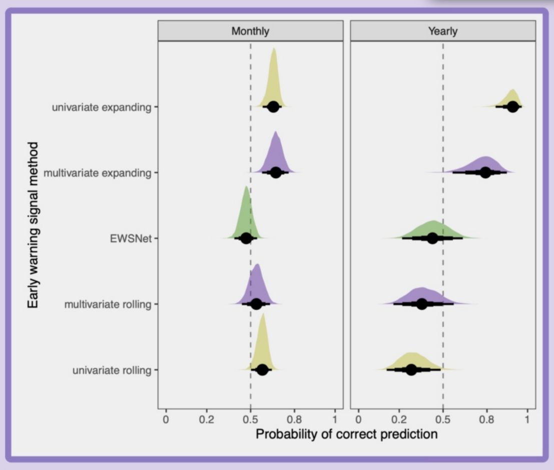


Approaching this 'tipping point', the recovery time of the system takes longer. This slowing down results in increasing autocorrelation and variance: a.k.a **early warning signals**' (**EWSs**) (Dakos *et al.* 2012).

EWSs can be calculated in two ways (**rolling** vs **expanding** windows) in both **univariate** and **multivariate** data (Weinans *et al.* 2021).

New machine learning techniques have also emerged e.g. **EWSNet** (Deb *et al.* 2022). These models classify the probability of a form of tipping point (none, critical or smooth).

Results

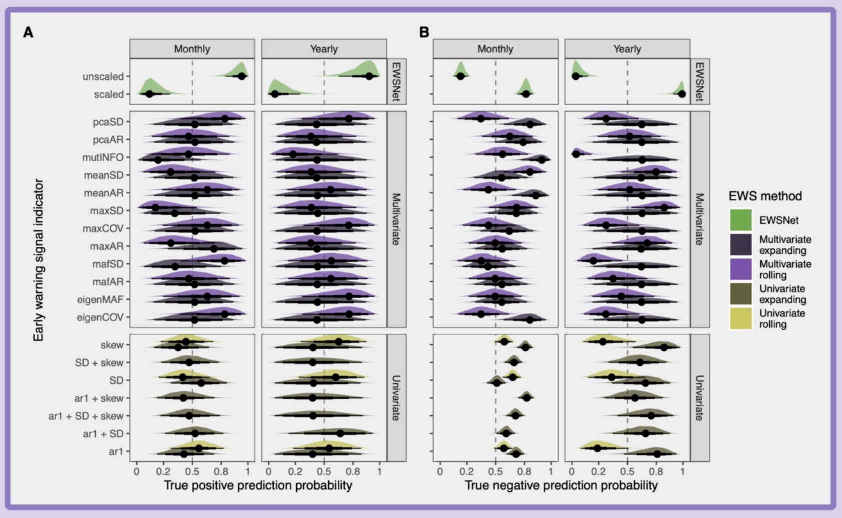


Method level comparisons

Multivariate and expanding windows generally yield superior predictions to univariate.

EWSNet consistently underperforms.

Longer time series (Monthly) improve probability of a correct prediction across methods.



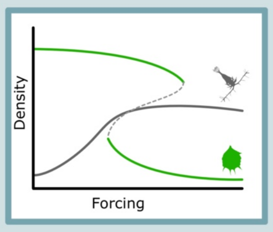
Individual indicator comparisons

Most indicators show greater true negative rates than true positive.

Larger variability in multivariate indicators compared to univariate.

meanAR, maxAR and pcaAR display best perform in Monthly data, whereas maxCOV, mafAR and ar1+SD+skew are the best performers in Yearly data.

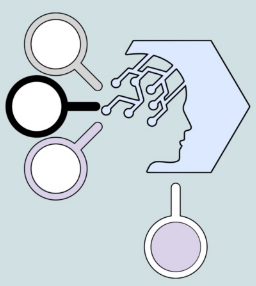
Conclusion



Post hoc detection of critical transitions is difficult in natural systems - Some cross validation of time series to a hypothesised driver is required for a critical transition to be disentangled from a smooth or linear transition.

Separate transitions are observable in the two plankton trophic levels - As ecoystem functioning is an emergent property, it may be sensible to perform assessements at genus/trophic level rather than at the species.

Exploiting maximum information from the system improves EWS assessments - Multivariate and composite early warning signals yield higher probabilities of a correct prediciton than single information methods.



Machine learning yields promise but is hampered by their training data - EWSNet displayed the highest true positive rates but also the highest false positive rates. This implies that its training has been biased towards transitioning datasets. This is remediable.

Info

All methods were computed in the new R package **EWSmethods**. The package can be found here:

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References: Dakos *et al.* 2012 *PLoS One*; Deb *et al.* 2022 *R. Soc. Open Sci.*; Weinans *et al.* 2021 *Sci. Rep.*