Understanding ecological dynamics: Stability metrics and Early warnings

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measuring stability for understanding ecosystem responses to stress

The babel of stability

Grimm & Wissel Oikos 1997

Stability properties/concepts/dimensions/ facets/components/meanings/…

Stability concepts

1970s	1980s	1990s	2000s
Constancy	Stable	Constancy	Nonpoint Attractors
Persistence	Persistence	Persistence	Persistence
Inertia	Resilience	Resilience	Variability
Elasticity	Resistance	Elasticity	Alternative States
Amplitude	Variability	Resistance	
Cyclical Stability		Domain of Attraction	
Trajectory Stability			
(Orian 1975)	*(Pimm 1984)*	*(Grimm & Wissel 1997)*	*(Ives & Carpenter 2007)*

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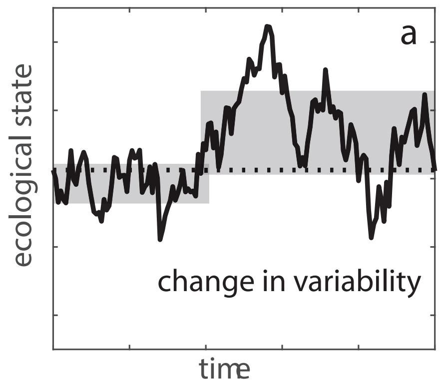
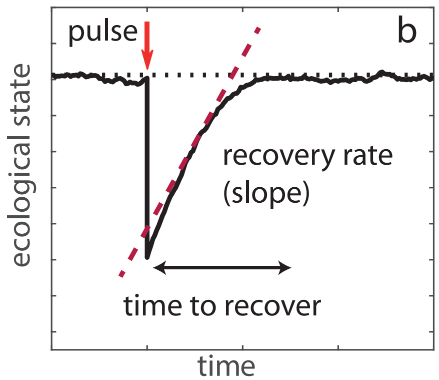
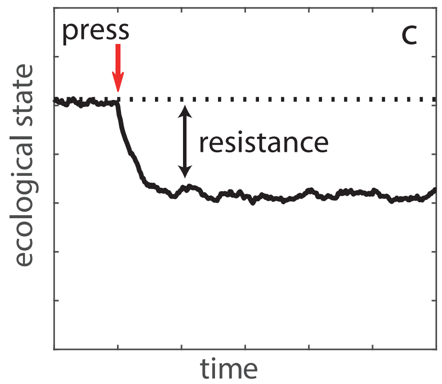
Constancy



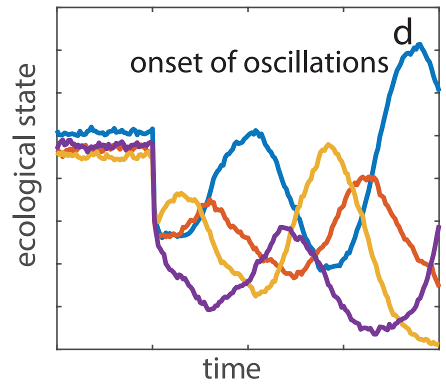
Resilience (engin)



Resistance



Dynamical attractors

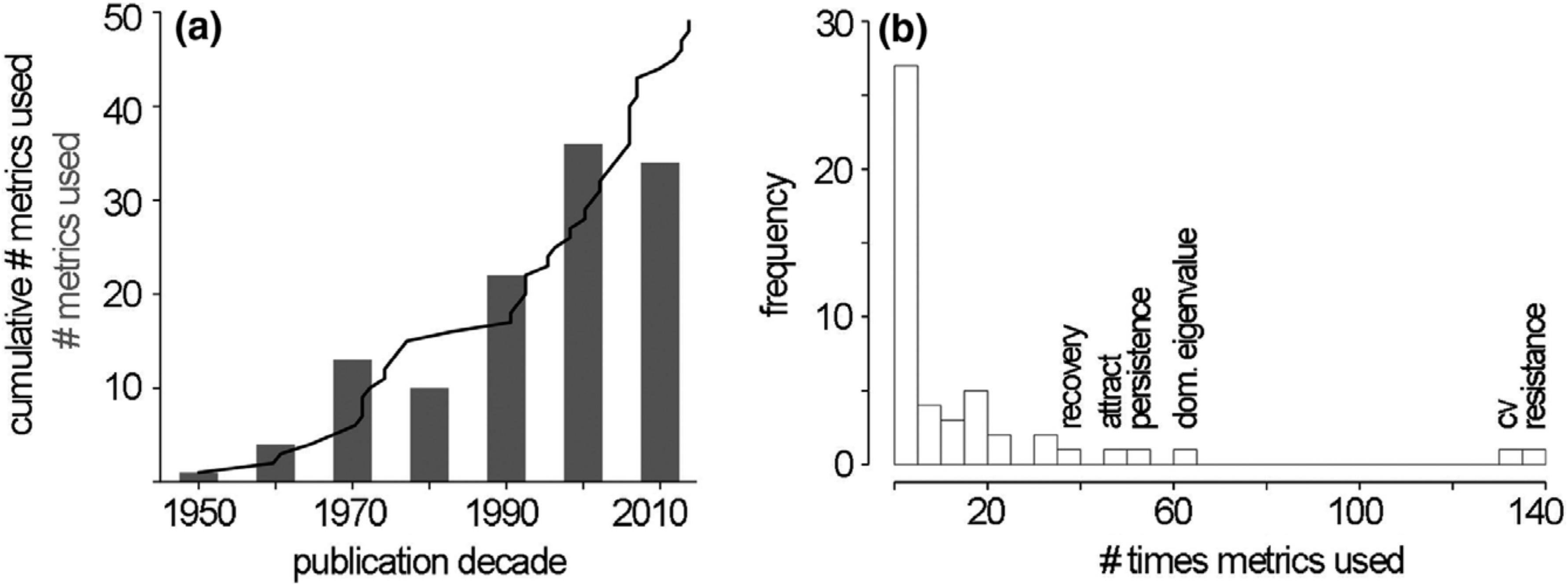


how do we measure Stability - a review

- 459 papers reviewed 1900-2018 from 9 ecological journals
- empirical and theoretical papers (focusing on communities)

Kefi et al 2019 Ecol Lett

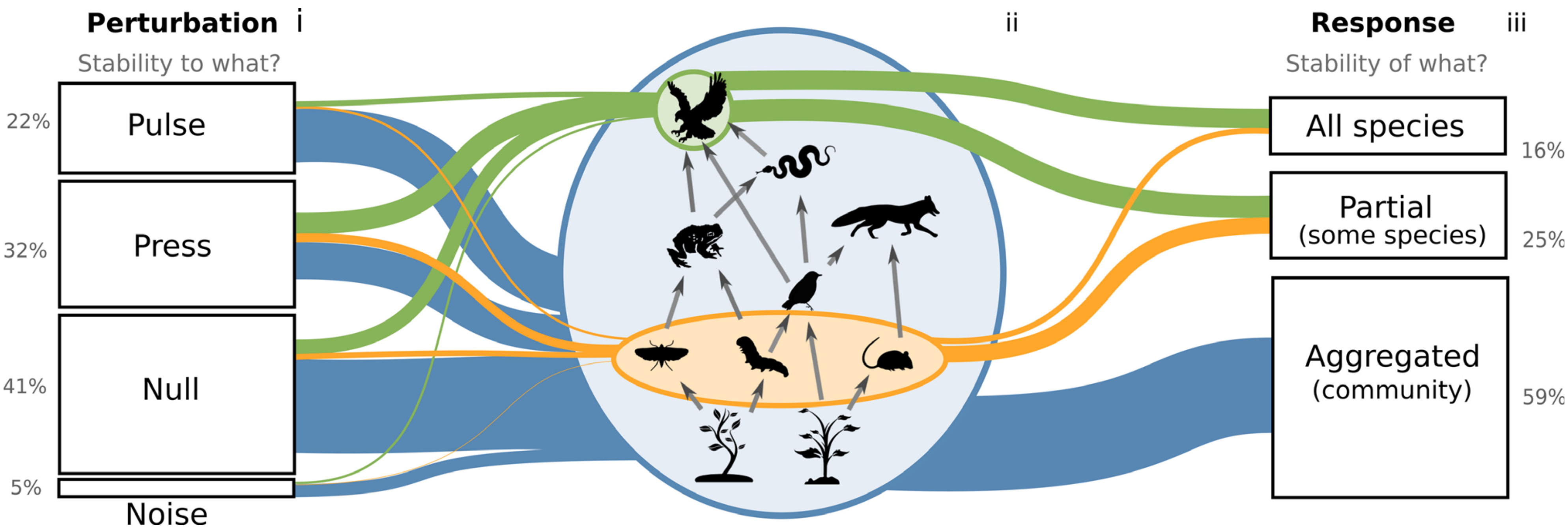
how do we measure Stability - a review



- 459 papers reviewed 1900-2018 from 9 ecological journals
- empirical and theoretical papers (focusing on communities)
- 34 different metrics used since 2010
- some metrics used more than others

Kefi et al 2019 Ecol Lett

how do we measure Stability - a review



- 1.4 perturbations per study
- most responses measured on higher level
- mostly 1 metric per study
- only 2% combine theoretical with empirical measures

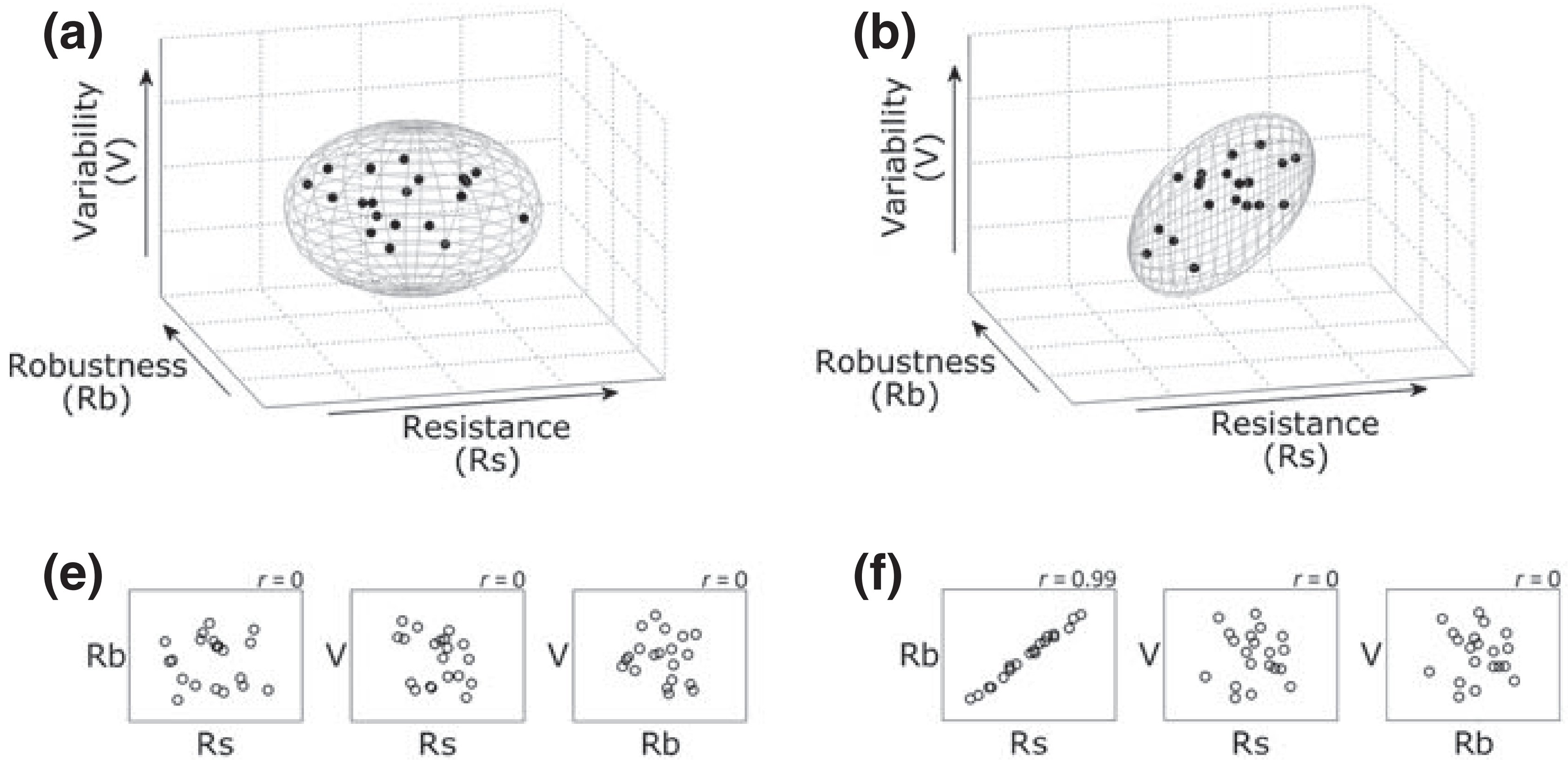
Kefi et al 2019 Ecol Lett

but, which metric(s) describe the overall stability of a community?

multidimensionality of stability

Community A

Community B



Donohue et al 2013 Ecol Lett

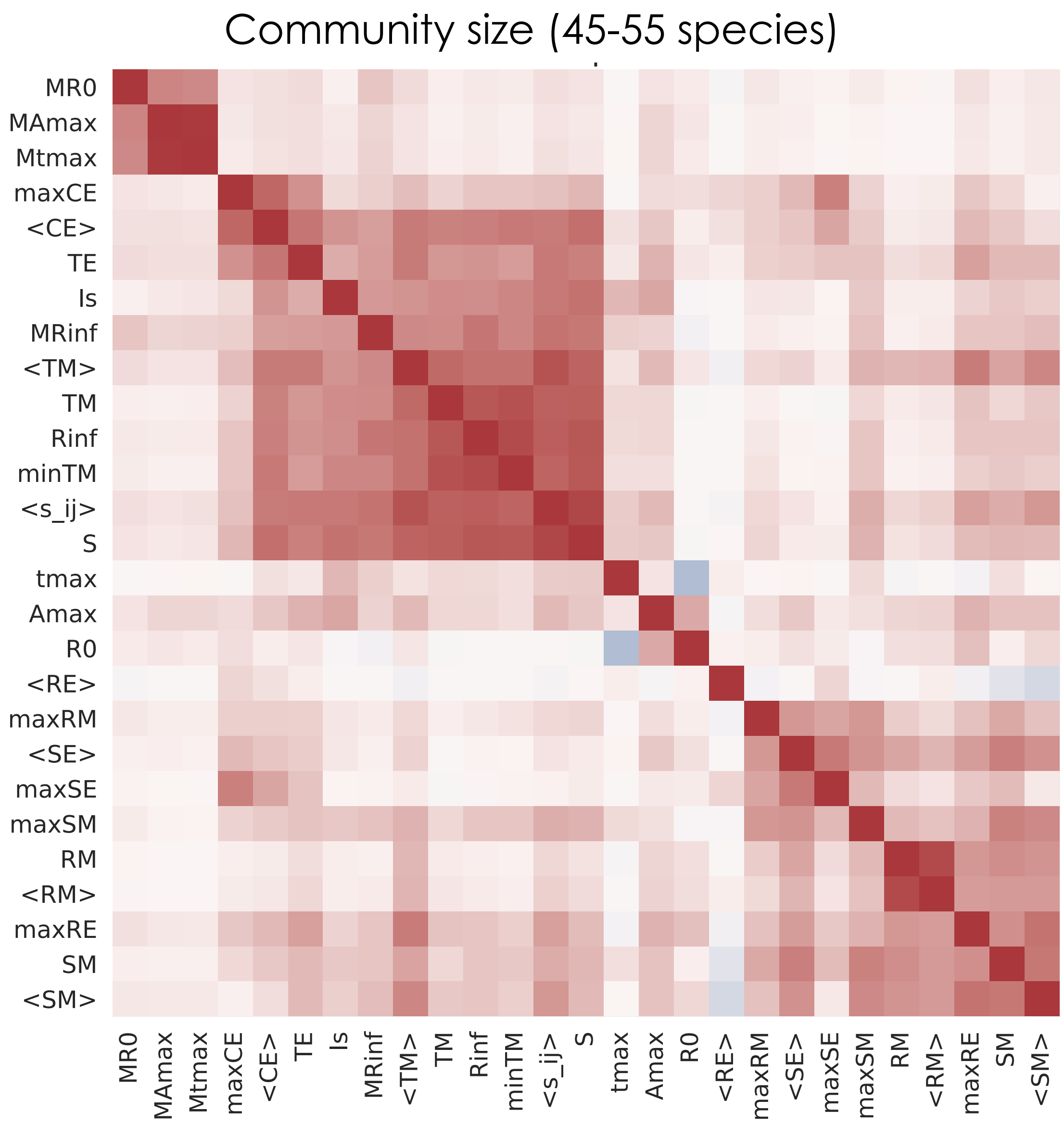
Can we quantify the dimensionality of stability based on metric correlations?

Can we quantify the dimensionality of stability based on metric correlations?

- generated foodwebs with niche model
- bioenergetic model with allometric scaling
- simulated communities from 5 to100 species
- using random parameter distributions
- only focused on stable equilibrium solutions
- estimated 27 metrics from the literature
- measured pairwise rank cross-correlations

Dominguez-Garcia, Dakos, Kefi (in revision)

pair-wise Spearman ranked correlations



E.g.

<CE>: Cascading extinctions

Rinf: asymptotic resilience

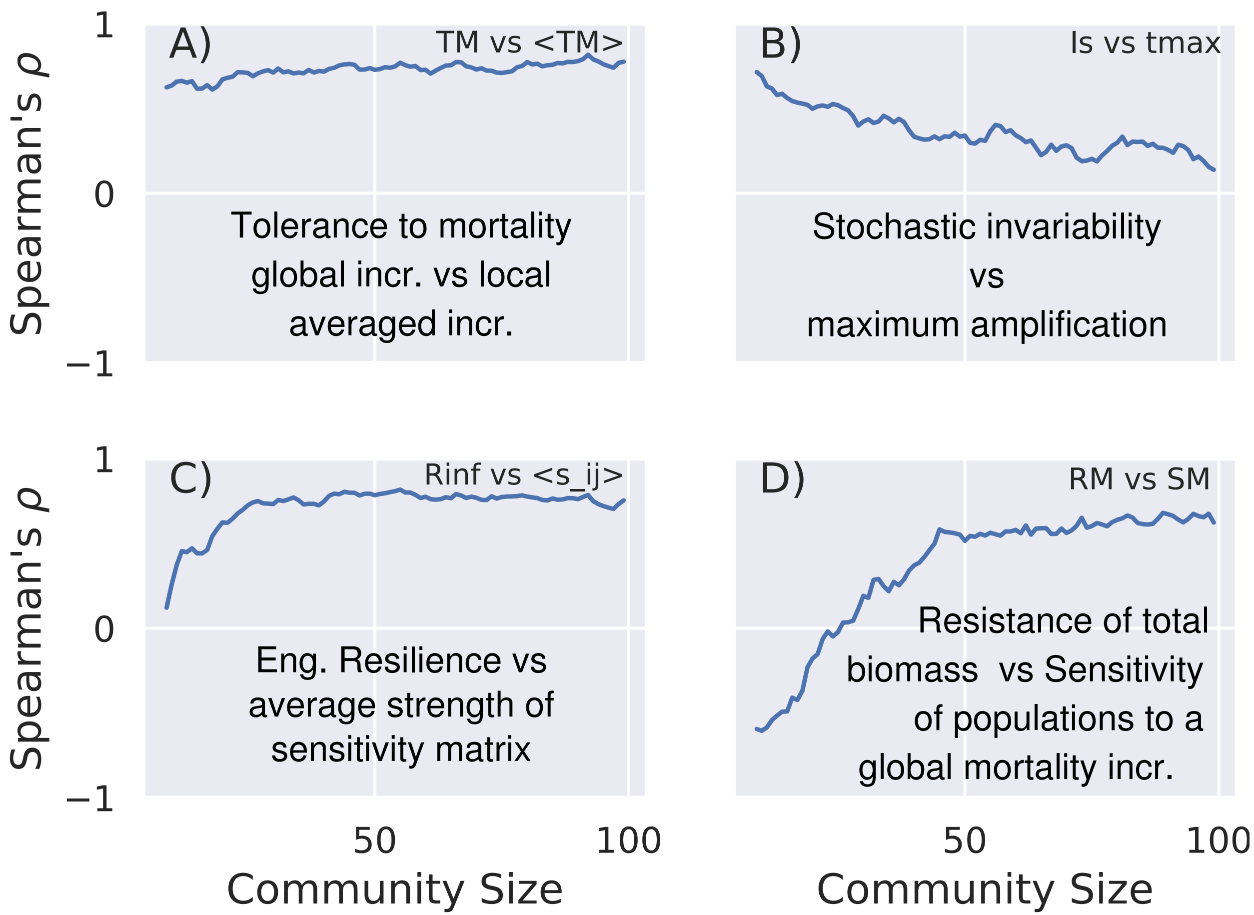
Is: invariability

RE: resistance of total biomass to extinctions

TM: Tolerance to mortality (Structural stability)

Dominguez-Garcia, Dakos, Kefi (in revision)

correlations depended on community size



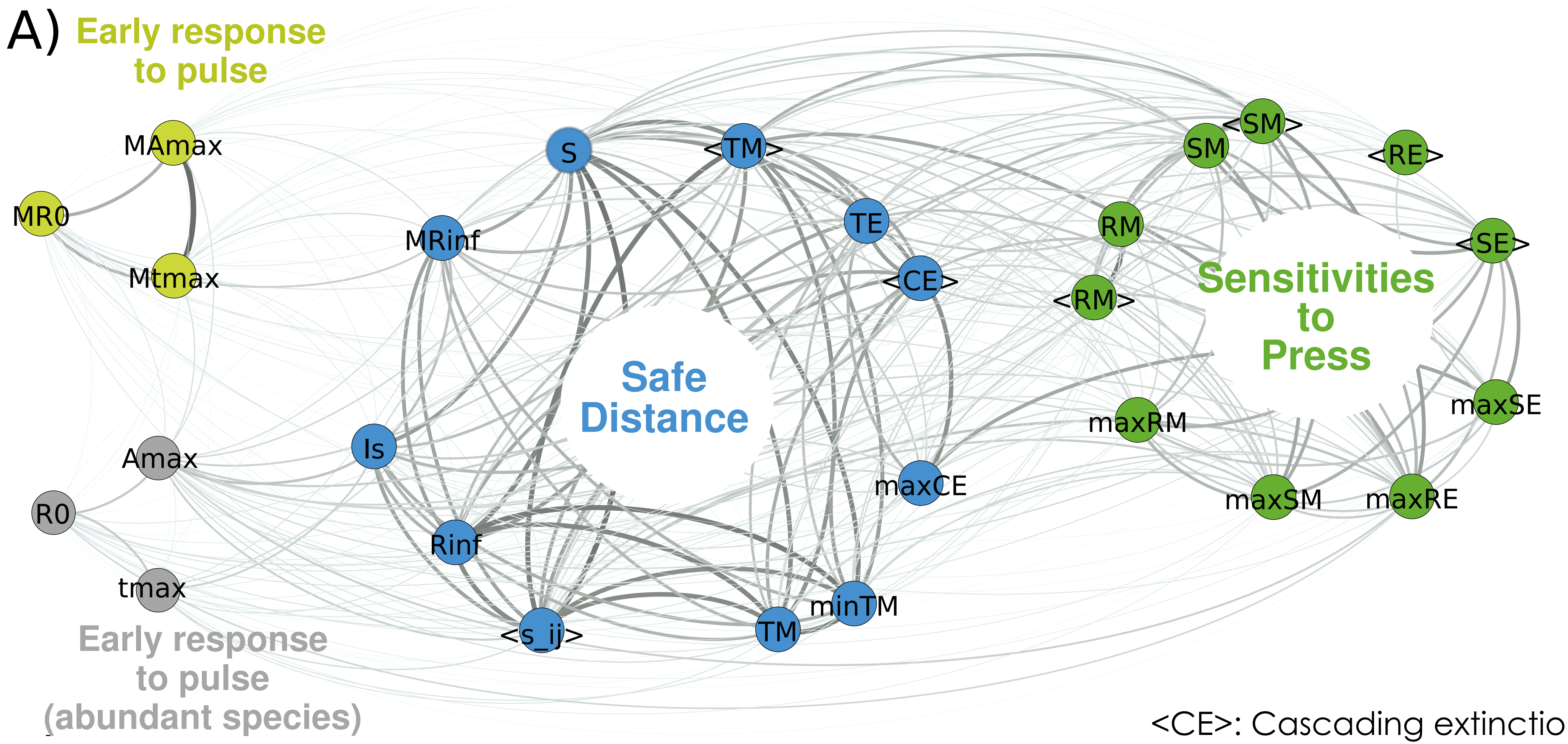
- biggest difference few species networks

Dominguez-Garcia, Dakos, Kefi (in revision)

three groups based on modularity algorithm

Dominguez-Garcia, Dakos, Kefi (in revision)

three groups based on modularity algorithm



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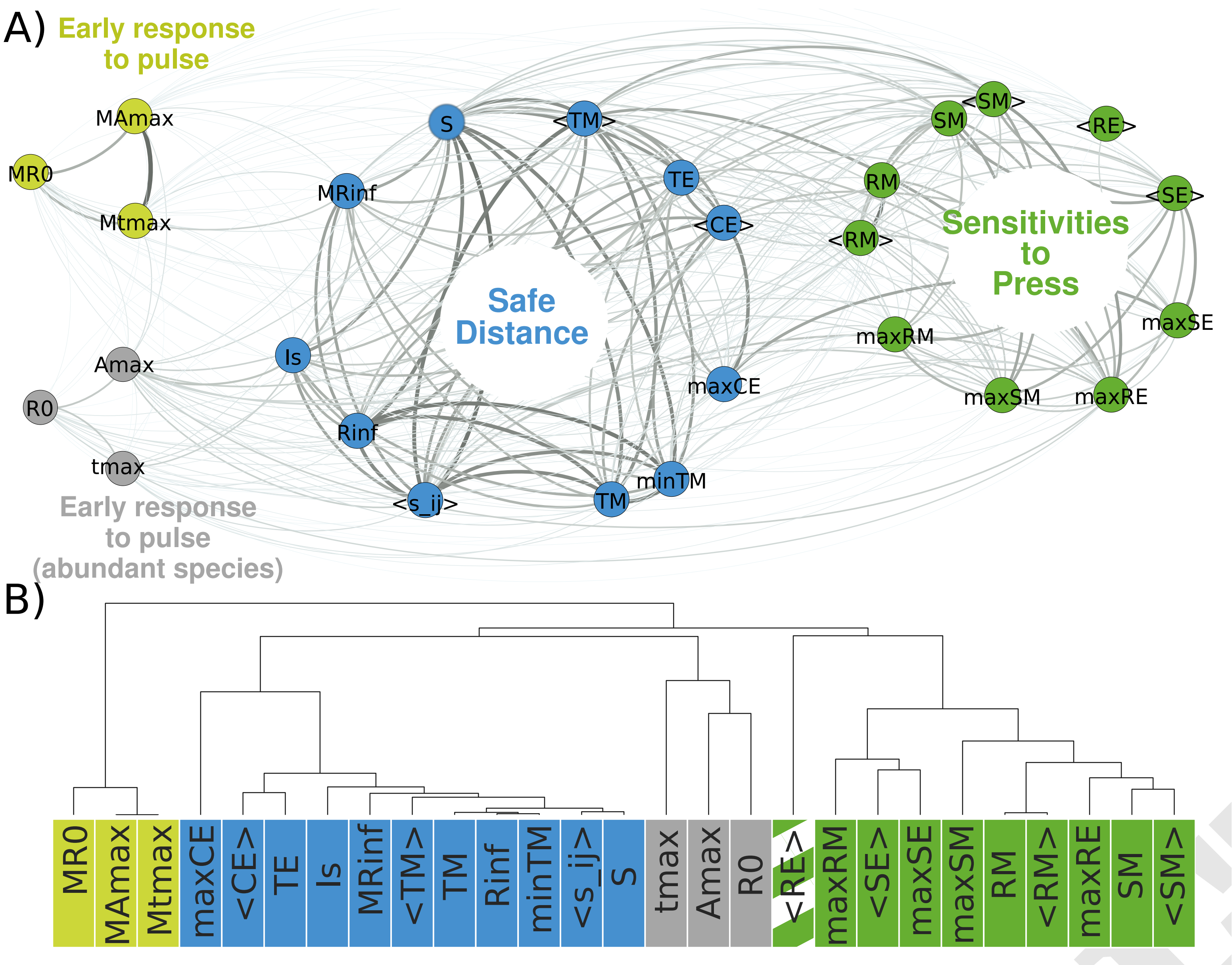
Dominguez-Garcia, Dakos, Kefi (in revision)

(dis)-similarity between metrics



Dominguez-Garcia, Dakos, Kefi (in revision)

so, which metric(s) to use?

Dominguez-Garcia, Dakos, Kefi (in revision)

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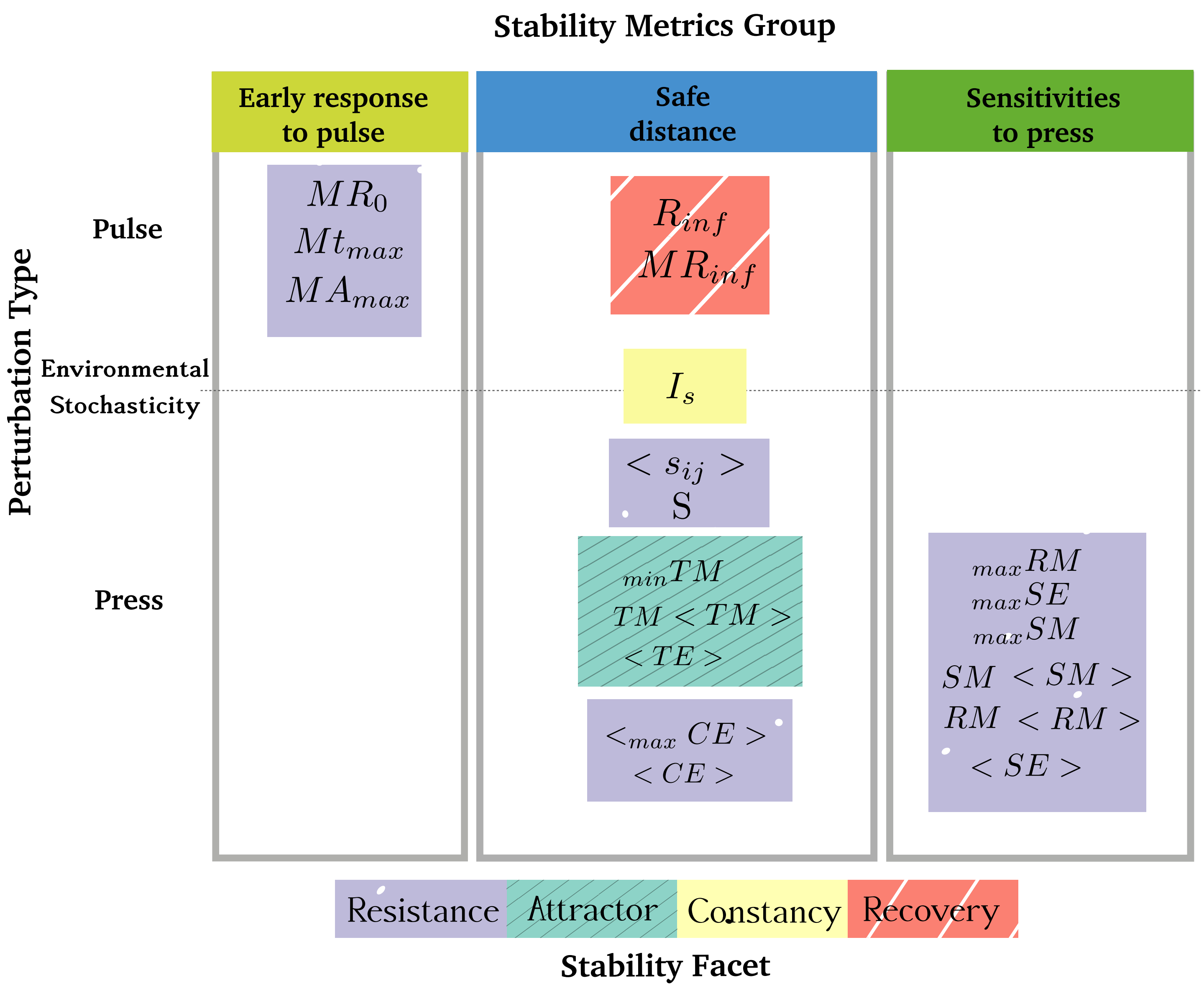


Dominguez-Garcia, Dakos, Kefi (in revision)

so, which metric(s) to use?

- at least 1 metric per group

- depends on:

-type of disturbance
-level of correlation
-feasible to measure

- not all correlations clear mathematical link:

need for assessing latent links (if they exist)
for clarifying which metric to use

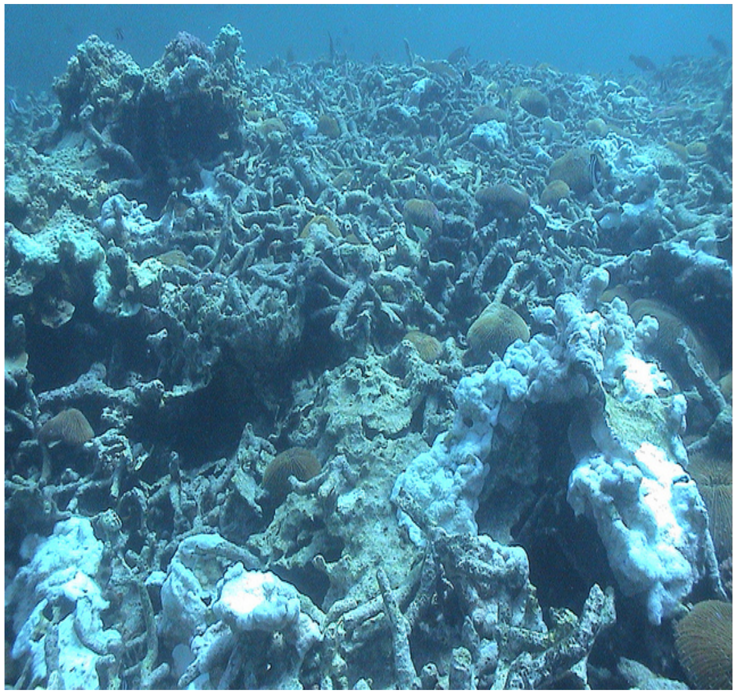
Dominguez-Garcia, Dakos, Kefi (in revision)

measuring changes in stability for
detecting abrupt ecosystem responses

catastrophic shifts in ecosystems

Shallow lakes

Coral reefs

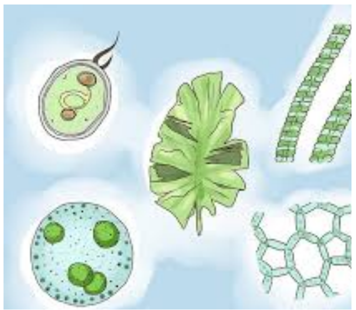


shallow lake tipping points to eutrophication

macrophytes

- ↓ ↑ -

algae



Uhlmann 1980, Developments in Hydrobiology

shallow lake tipping points to eutrophication

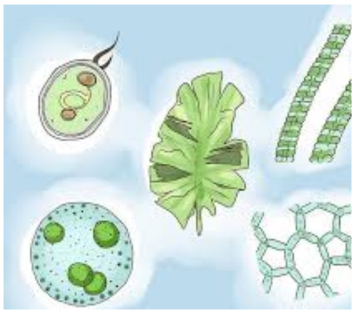
nutrient loading

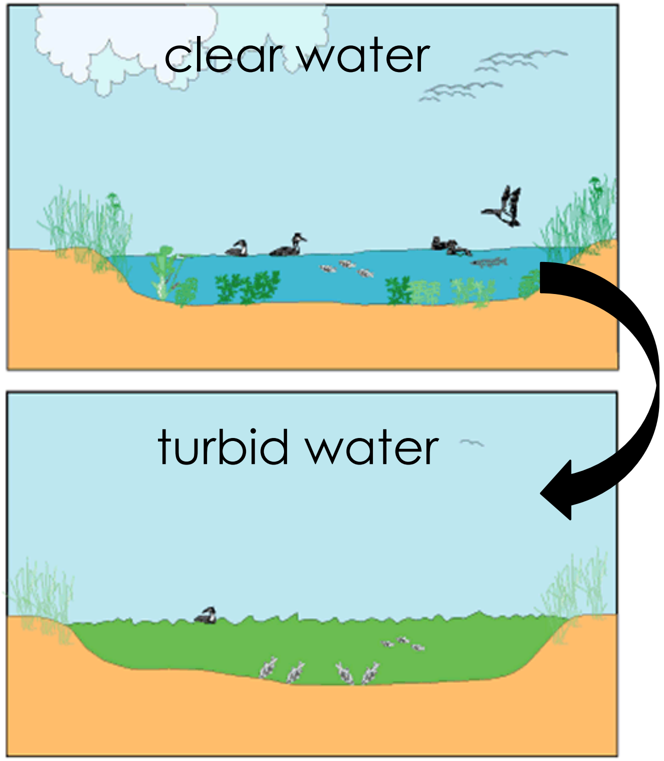
macrophytes

-

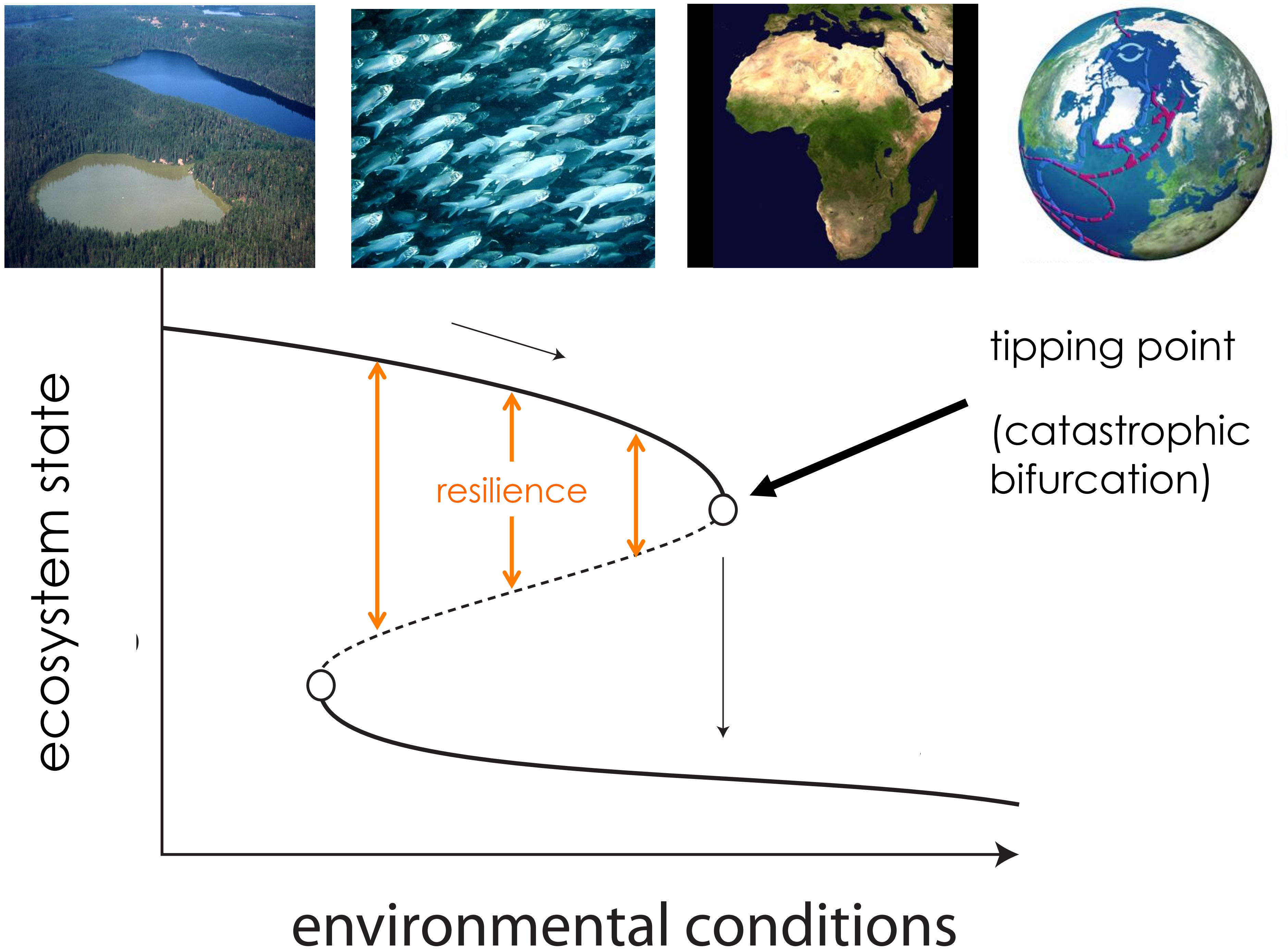
-

algae



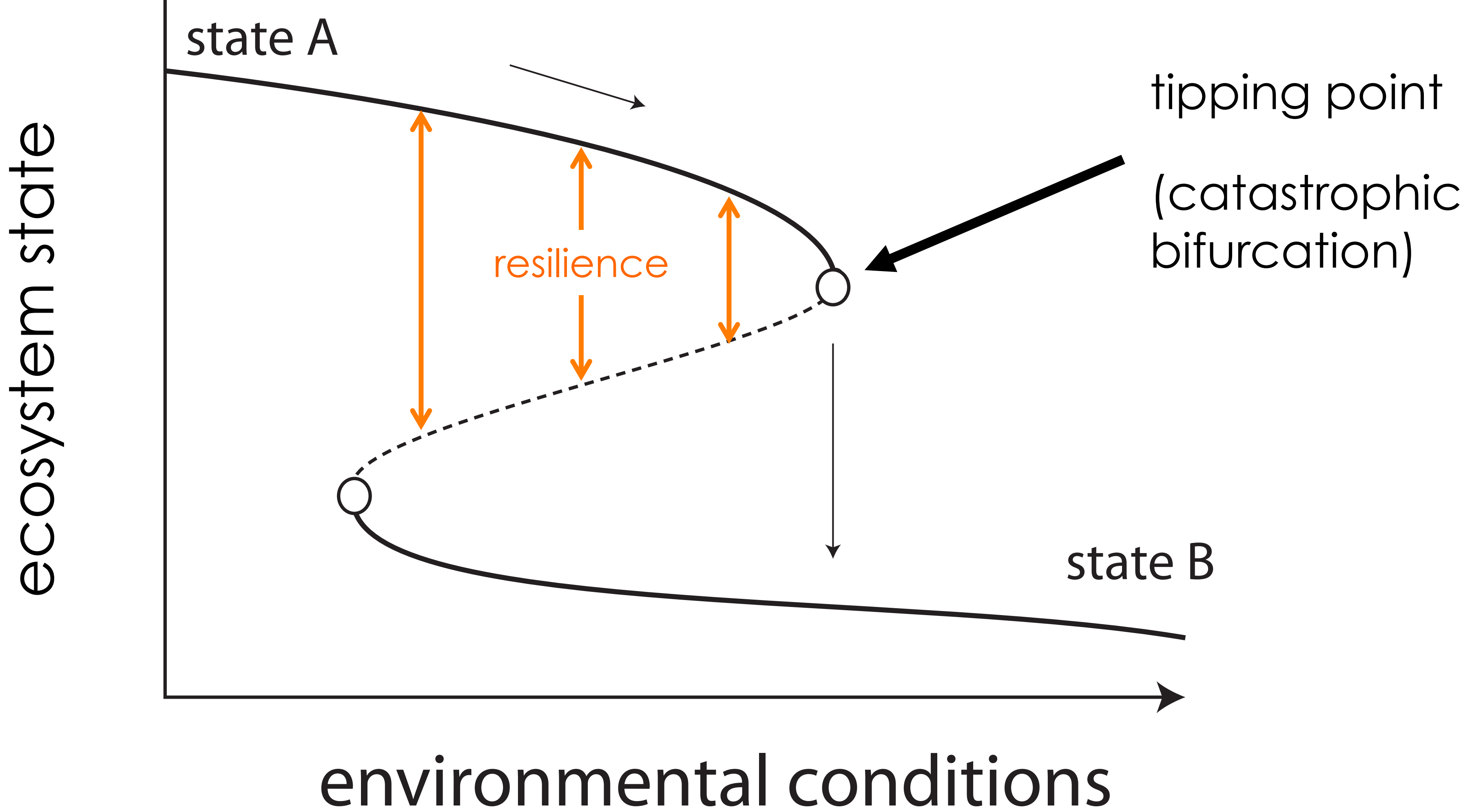


Uhlmann 1980, Developments in Hydrobiology


tipping point
(catastrophic bifurcation)
resilience
ecosystem state
environmental conditions

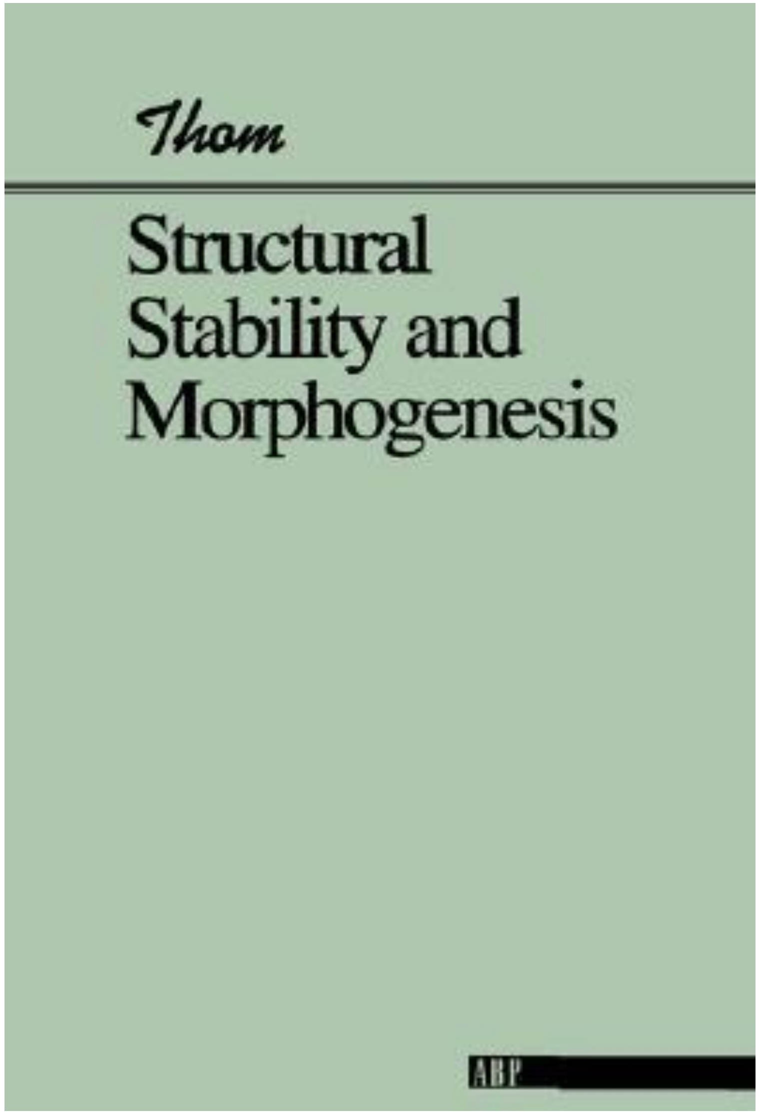



Can we detect tipping points in advance?

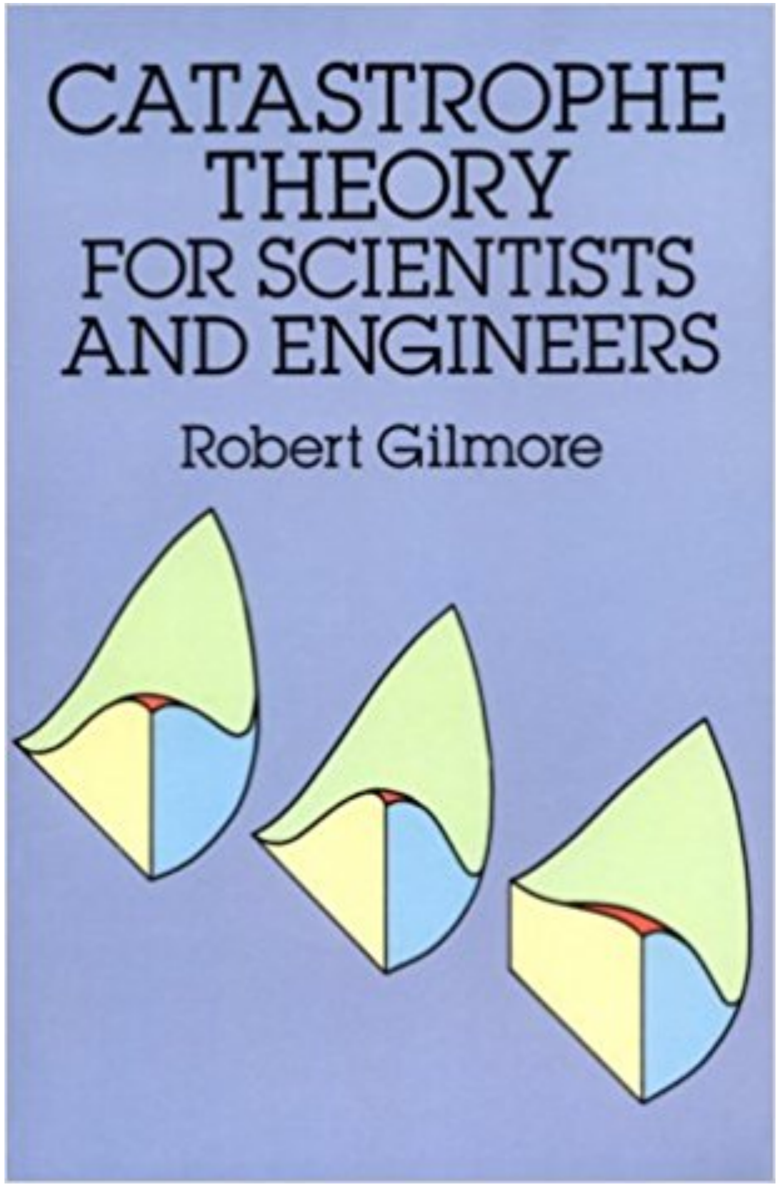


systems prior to tipping points slow down

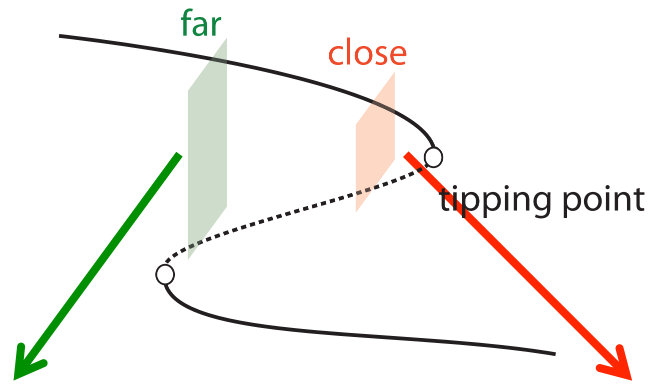
catastrophe theory and catastrophe flags



Thom 1976



Gilmore 1981



tipping point indicators

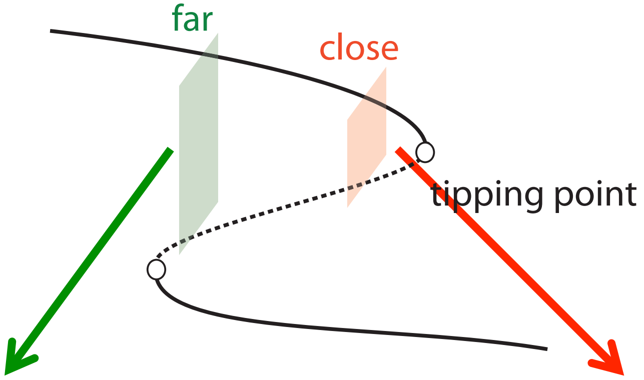
far from tipping

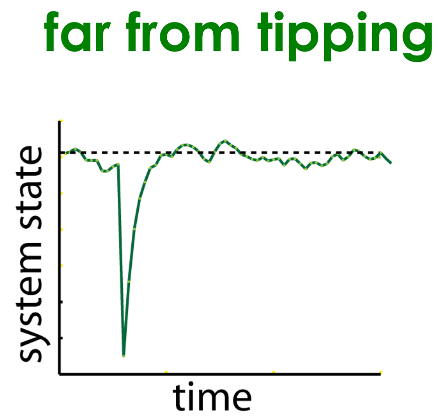
close to tipping

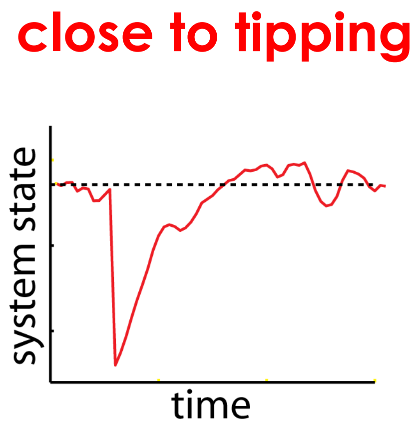
leading indicators
(Early Warnings)

Scheffer et al 2009, Nature

tipping point indicators







leading indicators
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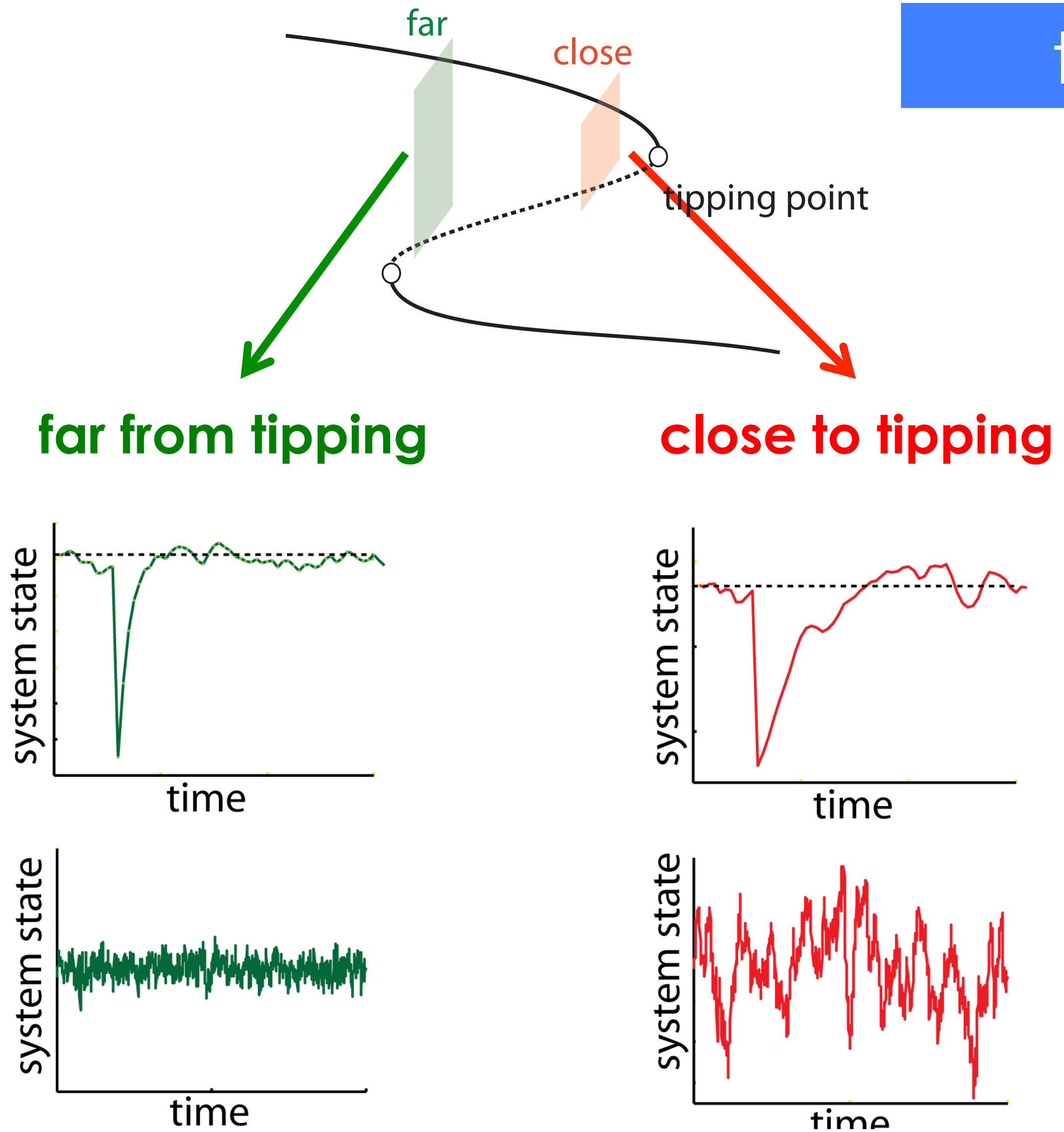
recovery time increases

Scheffer et al 2009, Nature

tipping point indicators



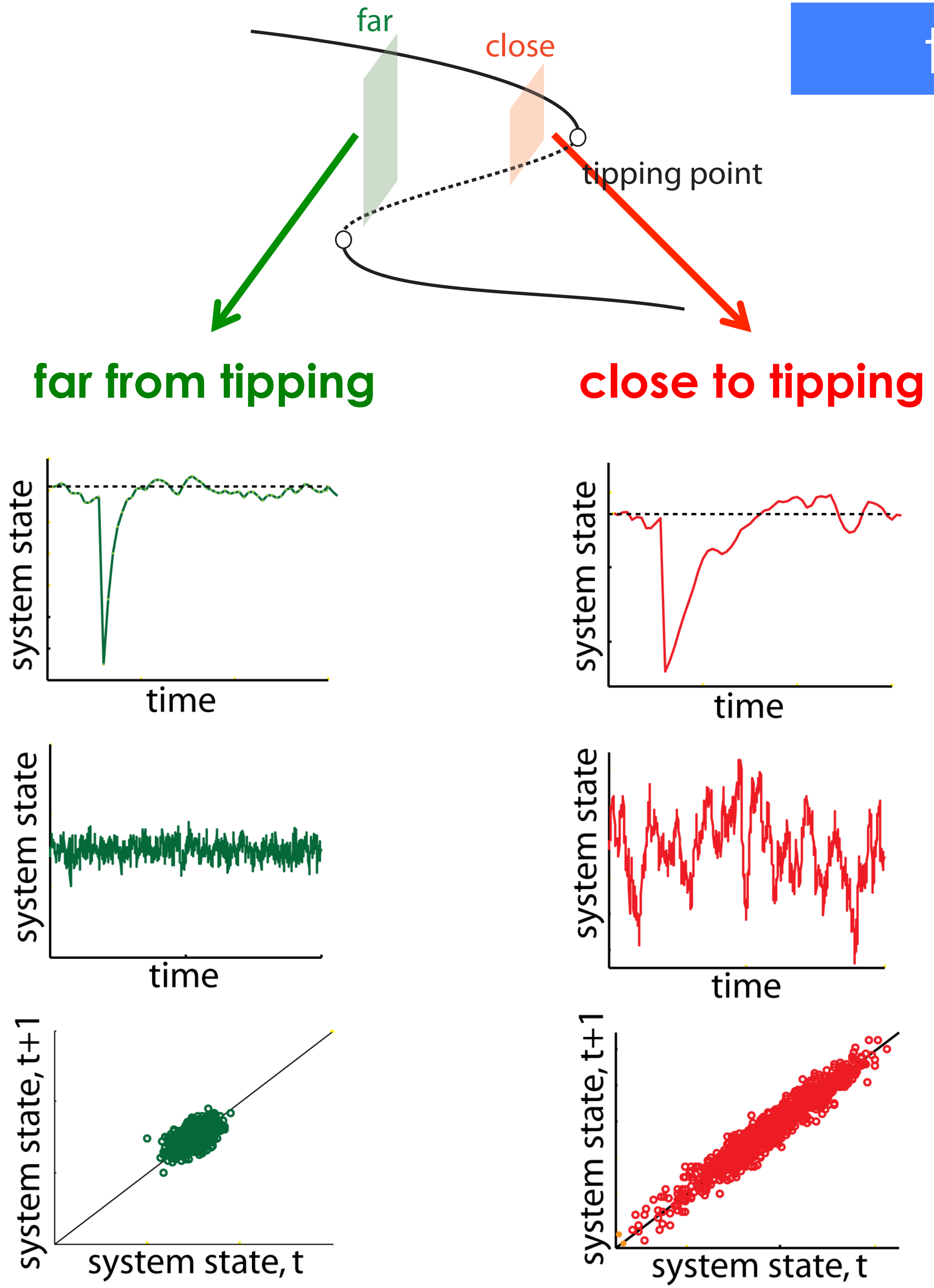
leading indicators (Early Warnings)

recovery time increases

variance increases

Scheffer et al 2009, Nature

tipping point indicators



leading indicators
(Early Warnings)

recovery time increases

variance increases

autocorrelation rises

Scheffer et al 2009, Nature

tools for tipping point detection – in time and space

Method
Metric-based
Autocorrelation at-lag-1
Autoregressive coefficient of AR(1) model
Return rate (inverse of AR(1) coefficient)
Detrended fluctuation analysis
Spectral density
Spectral ratio (of low to high frequencies)
Spectral exponent
Standard deviation
Coefficient of variation
Skewness
Kurtosis
Conditional heteroskedasticity
BDS test
Model-based
Time-varying AR(p) models
Nonparametric drift-diffusion-jump models
Threshold AR(p) models
Potential analysis (potential wells estimator)

Early Warning Signals Toolbox

early-warning-signals.org

earlywarnings

github.com/earlywarningtoolbox
github.com/spatial-ews/spatialwarnings

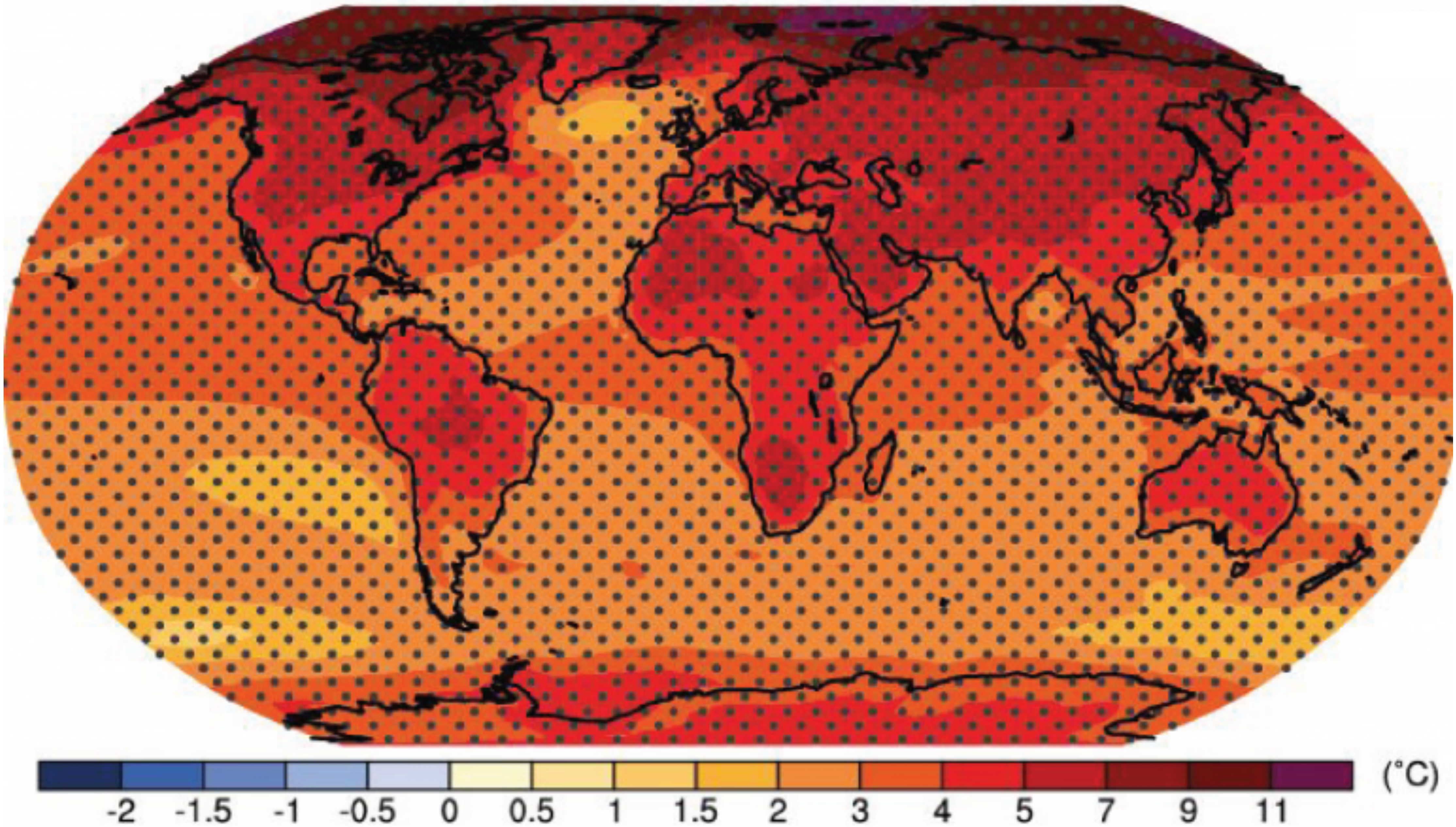
Dakos et al 2012, PLoS One
Ives & Dakos 2012, Ecosphere
Boettiger & Hastings 2013, J R Soc Int
Kéfi et al 2014, PLoS One
Seekel & Dakos 2015, Ecology & Evolution




Ultimate aims:

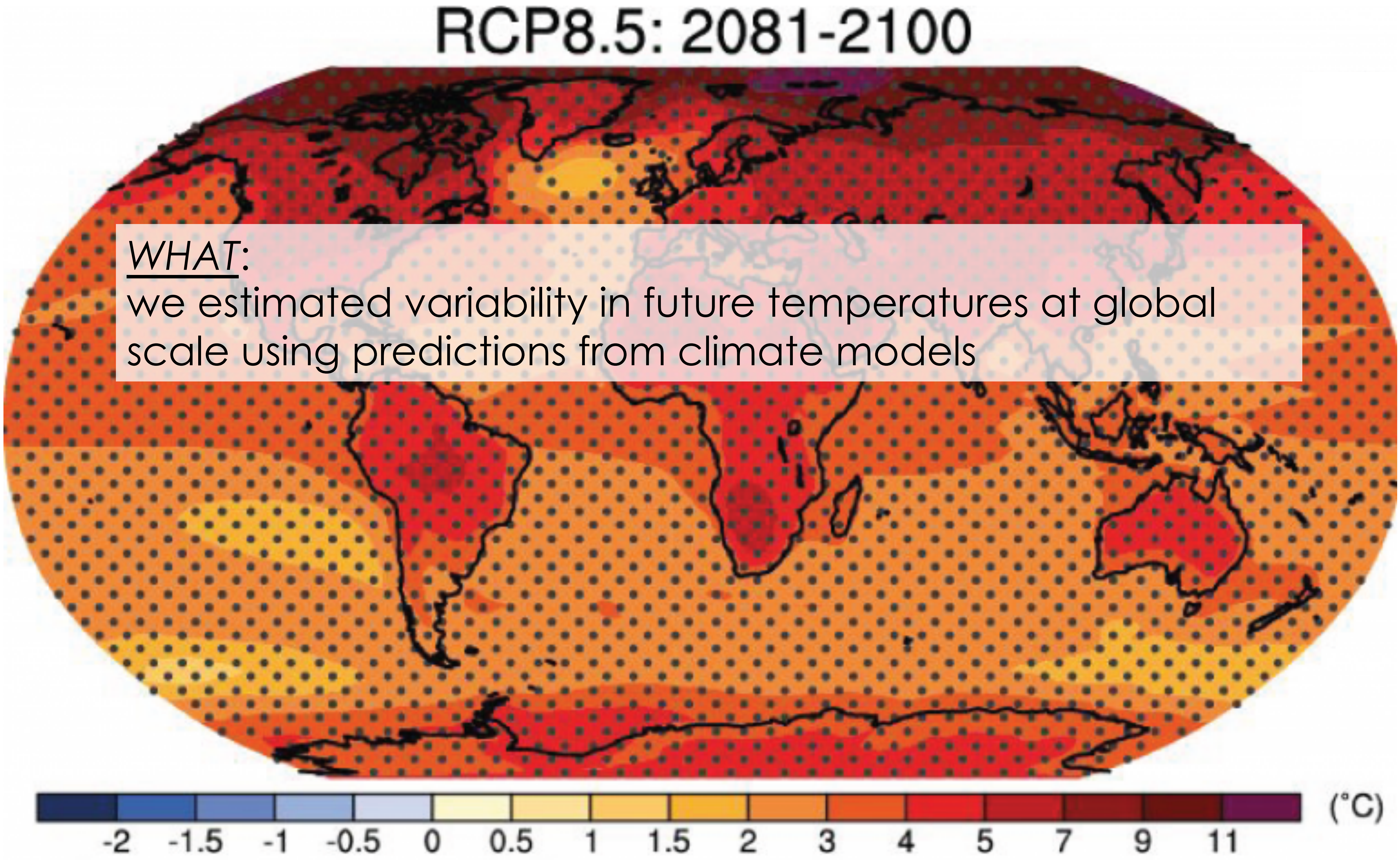
1. Rank resilience across systems/sites/species (hotspots)
2. Monitor changes in resilience within a system (warnings)

RCP8.5: 2081-2100



mean temperature

IPCC 2013

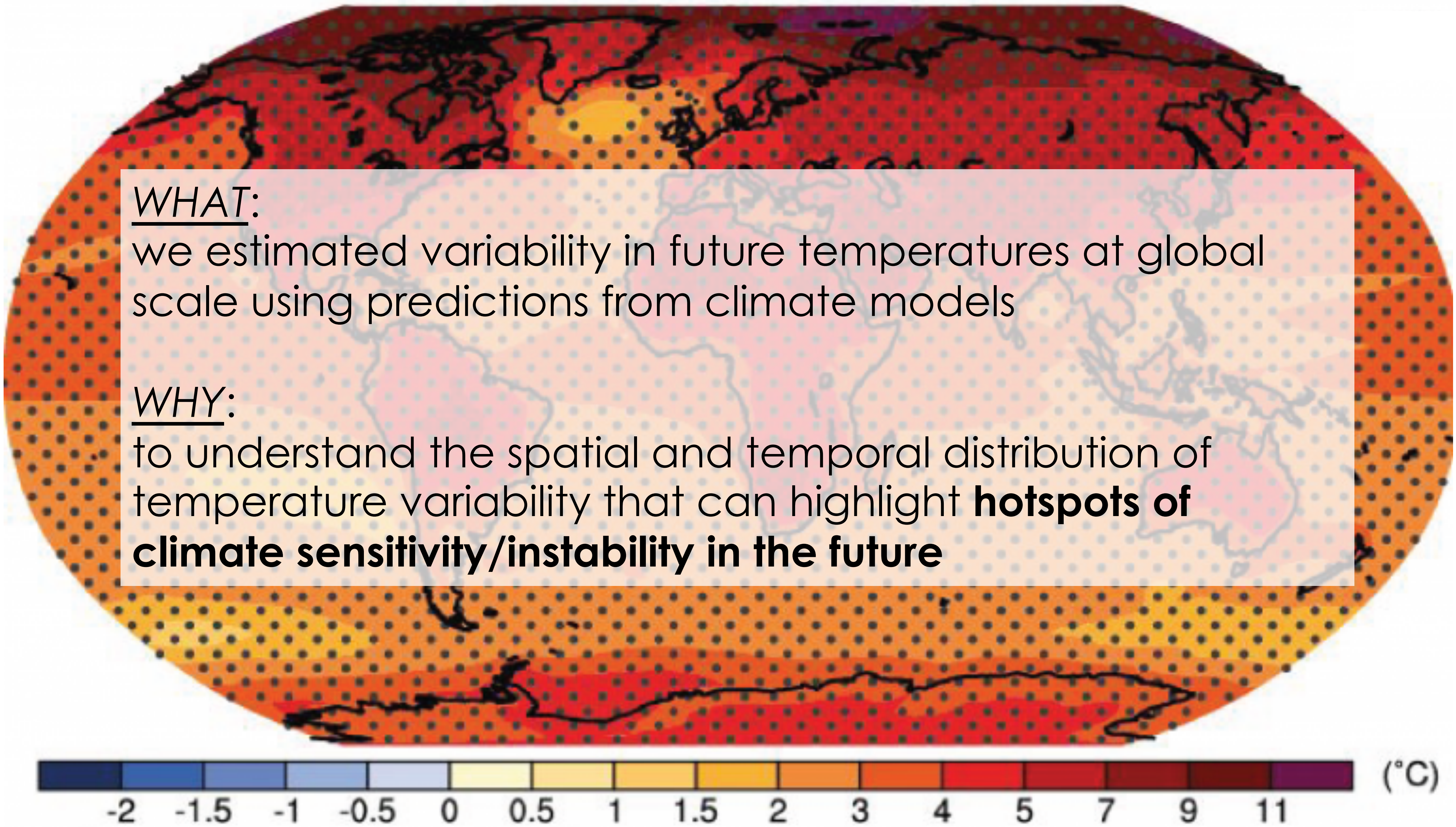


<u>WHAT</u>:
we estimated variability in future temperatures at global scale using predictions from climate models

mean temperature

IPCC 2013

RCP8.5: 2081-2100



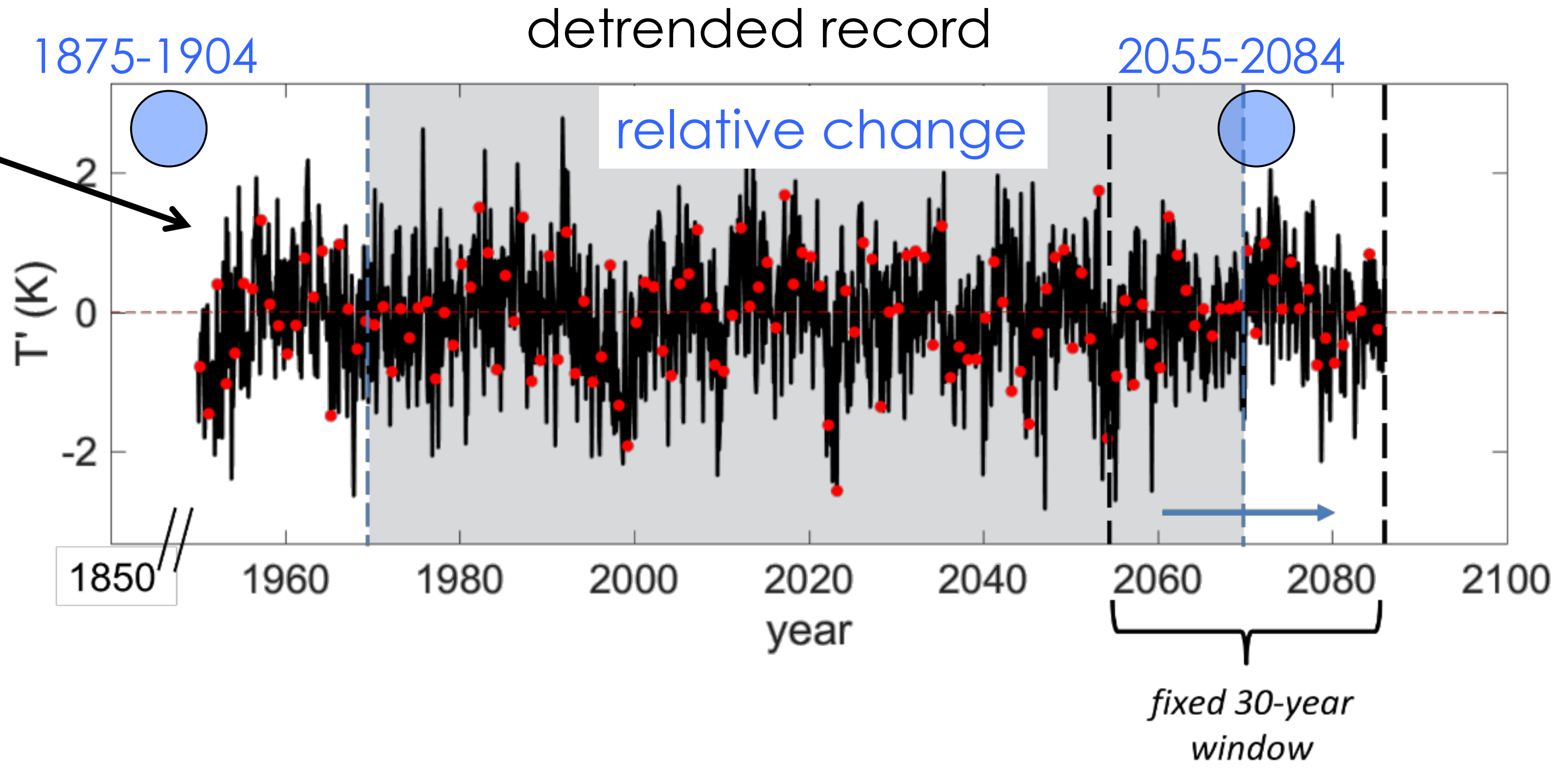
WHAT:
we estimated variability in future temperatures at global scale using predictions from climate models

WHY:
to understand the spatial and temporal distribution of temperature variability that can highlight **hotspots of climate sensitivity/instability in the future**

mean temperature

IPCC 2013

increased temperature variability as proxy for hotspots of climate sensitivity



Bathiany, Dakos, Scheffer, Lenton 2018, Science Advances

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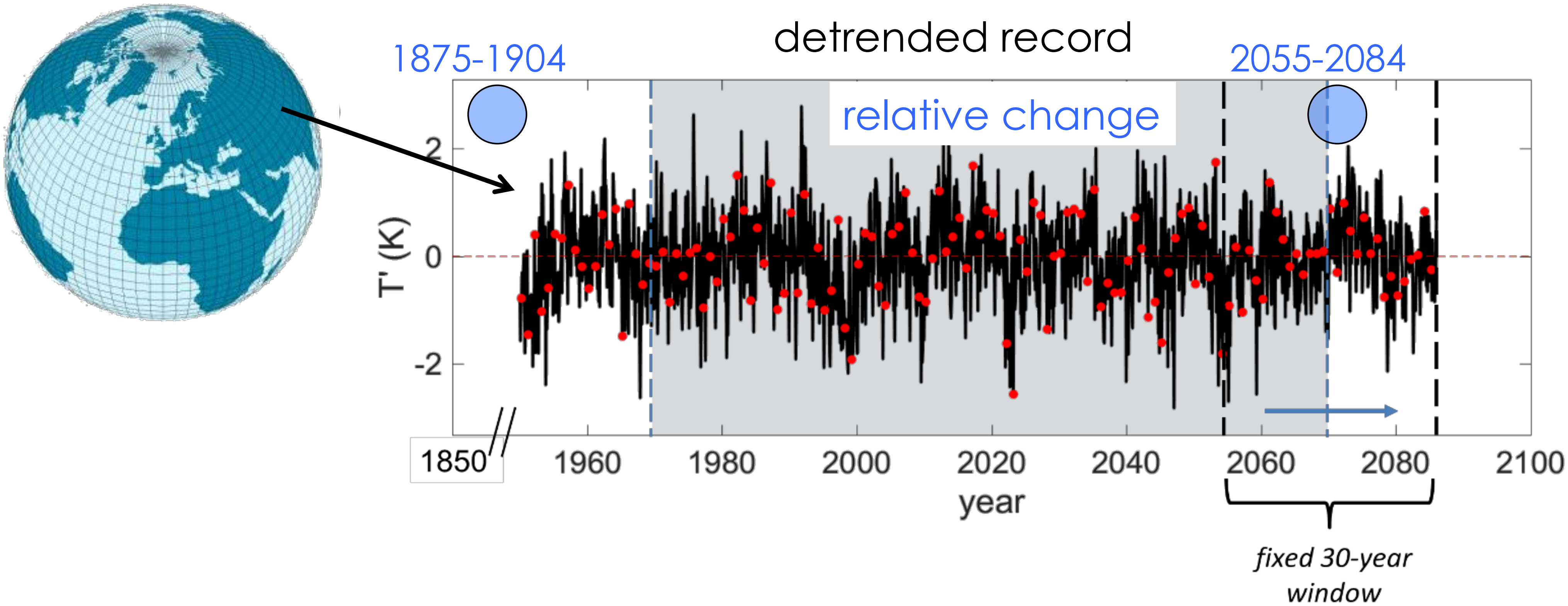

- temperature output from 37 models from the Coupled Model Intercomparison Project 5 (CMIP5)

Bathiany, Dakos, Scheffer, Lenton 2018, Science Advances

Relative changes in variability of monthly temperature until 2100

Bathiany, Dakos, Scheffer, Lenton 2018, Science Advances

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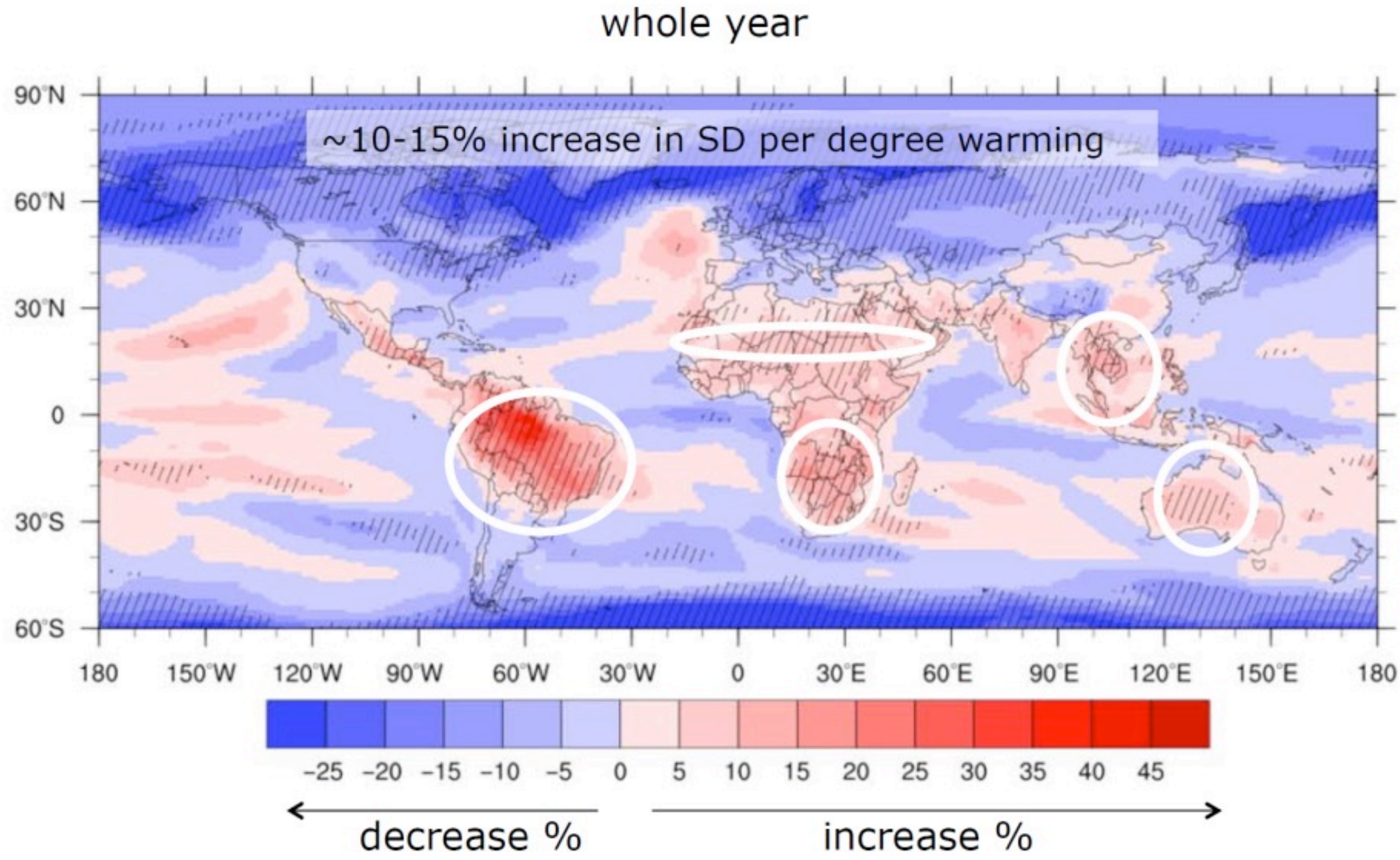
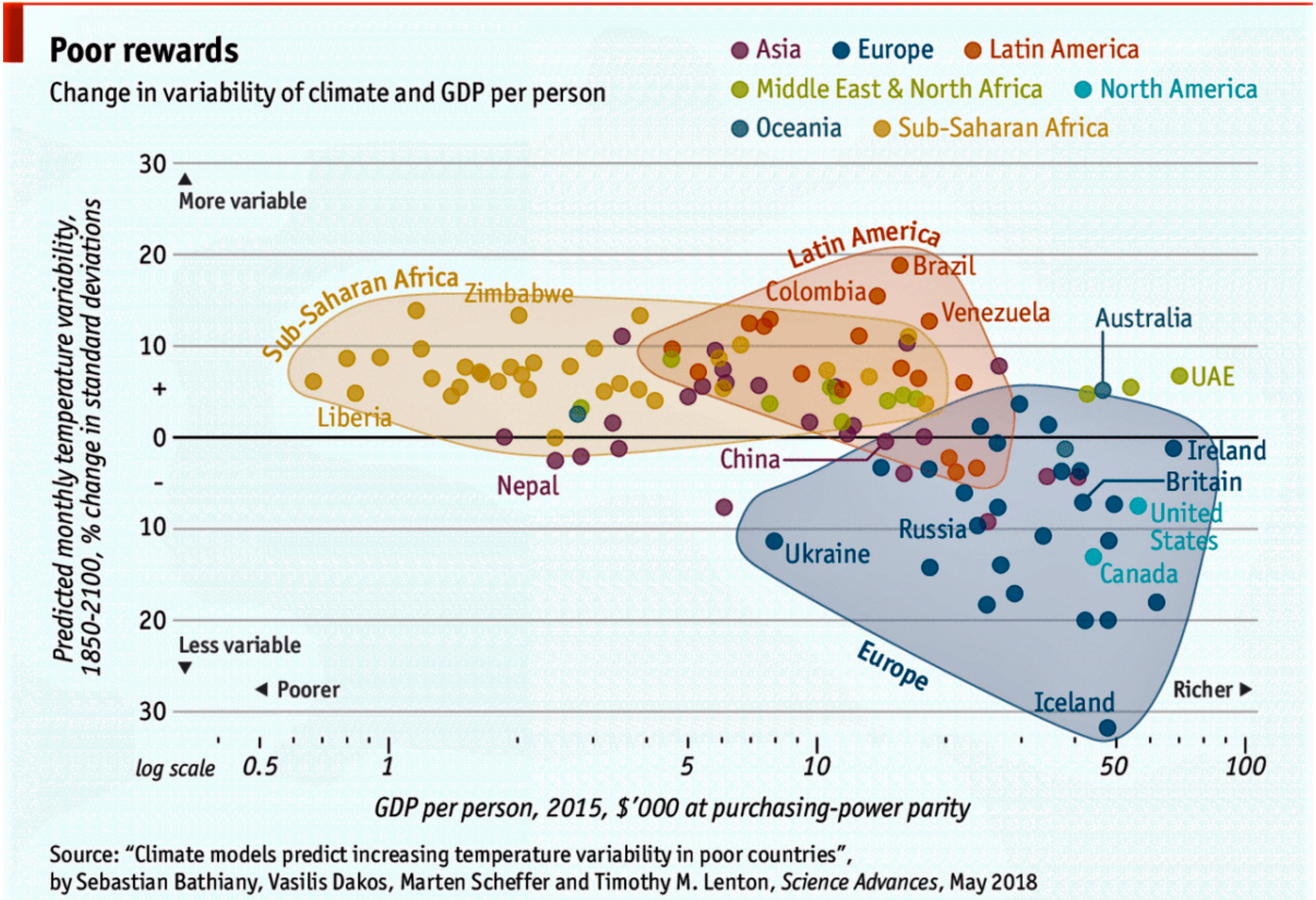


Bathiany, Dakos, Scheffer, Lenton 2018, Science Advances

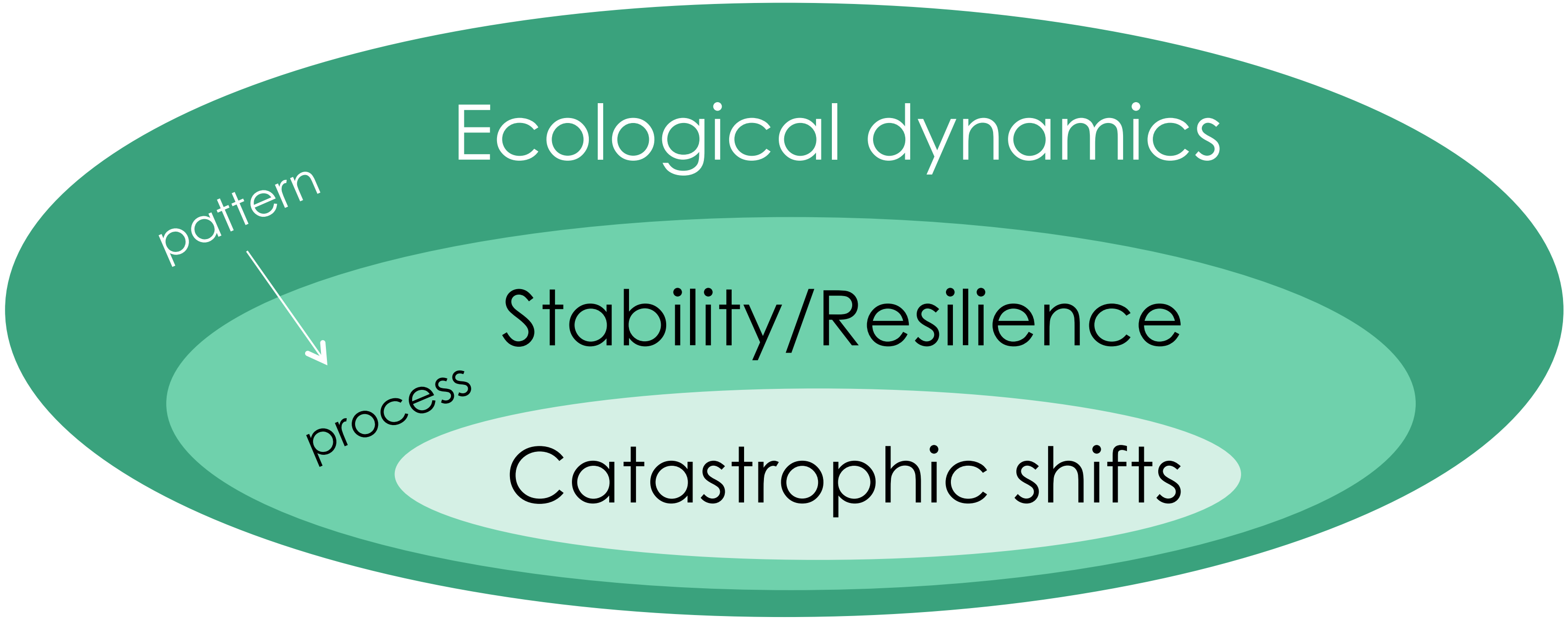
Climate injustice

- Strong CO_2 emitters least affected
- Poorest countries face highest variability



(redrawn by the Economist)

summing up



- Stability metrics strongly correlated but unclear their mathematical link: (if they exist) this will help clarifying which metric to use
- Well-developed toolbox for using temporal (and spatial) fluctuations to detect tipping points: challenge to apply them in practice

Acknowledgements

Sonia Kefi
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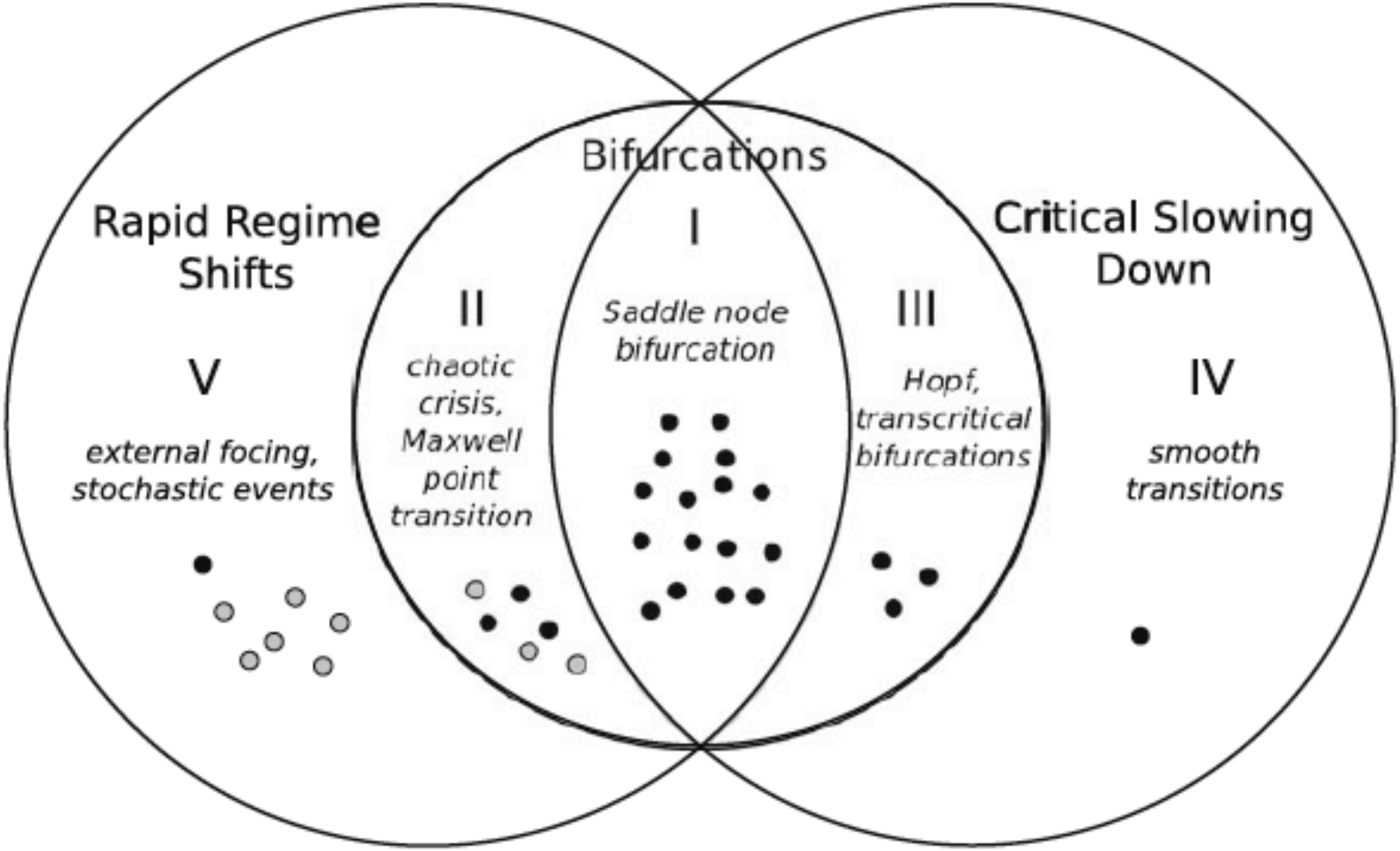
Kéfi, S, Dominguez-Garcia V, Donohue I, Fontaine C, Thébault E, Dakos V, *Ecology Letters*. In press.

Bathiany S, Dakos V, Scheffer M, Lenton T M (2018). *Science Advances* 4, eaar5809.

early-warning-signals.org
github.com/earlywarningtoolbox

theoretical challenge - too generic?



There can be tipping points without EWS

There can be EWS without tipping points

Boettiger et al. 2013

Method	Data	Details	References
Trends in statistical signals	Abundance or spatial	Strong temporal trends – typically estimated using a sliding window approach – in a variety of generic warning signals in the direction predicted by theory (e.g. increasing variance and autocorrelation) indicate an approaching collapse. In spatial contexts, trends may be in spatial variance, spatial skewness or spatial correlations	(Guttal & Jayaprakash 2008; Dakos *et al*. 2012; Dai *et al*. 2013; Kéfi *et al*. 2014)
Model selection using likelihood ratio tests	Abundance	Models representing deteriorating and stable conditions are fit to data, with model selection used to determine which (deteriorating or stable) best describes the observed data	Boettiger & Hastings (2012b)
Across sample variance	Abundance across multiple sites	Estimates the between-survey sample variance across multiple sampling sites within the same population. Appears to be robust to significant sampling errors	Hefley *et al*. (2013)
Conditional heteroskedasticity	Abundance	Conditional heteroskedasticity implies that variance at one time step is highly related to variance in the proceeding time steps. Thus, as a tipping point is approached the portion of the time series in the vicinity of the bifurcation will appear as a cluster of high variability when compared to areas of the time series away from the bifurcation point	Seekell *et al*. (2011)
Measures of reduced complexity	Abundance or spatial	Changes in the randomness of the system are inferred through changes in the Kolmogorov algorithmic complexity, with reduced randomness (increased complexity) indicating less white noise in the system and hence a looming bifurcation	Dakos & Soler-Toscano (2016)
Spectral density ratio	Abundance	Spectral density ratio measures the ratio of high- to low-frequency processes in a time series, with a shift to low frequency-dominated processes (spectral 'reddening) indicating an approaching collapse	Biggs *et al*. (2009)
Fisher information	Spatial or abundance	Captures patterns in the dynamics of a system from trends in variables that characterise its condition. Multiple variables are combined into a single index that can track changes in the dynamic order of the system	Sundstrom *et al*. (2017)
Quickset change points	Abundance	Employs two models [collapse vs. no collapse, as in Boettiger & Hastings (2012b)] which are updated with each input of new data. A signal is generated when the likelihood ratio exceeds a predefined threshold based on the user's tolerance for false alarms	Carpenter *et al*. (2014)
Pattern-based spatial signals	Spatial	Changes in the organisation and patchiness of strongly spatial ecosystems can be indicative of regime shifts, in particular shifts in patch-size distributions, occurrence of self-organising patterns based on 'Turing instability' and deviation from observed power law distribution of patch sizes	(Rietkerk 2004; Kéfi *et al*. 2007, 2014; Deblauwe *et al*. 2011)
Generalised modelling	Abundance and structural information	A generalised model is constructed of the system which describes the structure of the system without specifying specific functional forms, typically this entails identifying critical system variables (e.g. abundance) along with processes (e.g. birth rate) or other information (e.g. mortality is likely to be linear)	Lade & Gross (2012)
Trends in statistical signals of BDI models	Rate information	Extensions of trend-based signals developed by Dakos *et al*. (2012) and others, whereby emergent diseases can by forecast by looking for trends in signals such as the coefficient of variance from the moment generating function of a stationary birth–death–immigration process	Brett *et al*. (2017)
Network-based	Abundance and spatial	Based on the connectivity and clustering coefficient of nodes in a network, with higher connectivity suggesting an impending regime shift	(Tirabassi *et al*. 2014; Yin *et al*. 2016) (Yin *et al*. 2016)
Trends in fitness-related traits	Trait	Shifts in fitness-related traits – specifically declines in body size at either the population or community level – are used to infer approaching collapse.	(Clements & Ozgul 2016a; Spanbauer *et al*. 2016)
Combined signals	Abundance and spatial, abundance and trait	Abundance-based measures of stability (e.g. increased variance) and either spatial or trait-based measures are combined into a single metric by normalising the trend in each indicator and summing in across the time series. Thus, producing a composite metric which should reduce Type I and II error	(Drake & Griffen 2010; Clements & Ozgul 2016a)

Clements & Ozgul 2018