Beyond singular driver-response tipping points & thresholds

recent examples and emerging approaches

Kirstin Holsman

NOAA AFSC

WK13 PICES 2019

Kirstin.Holsman@noaa.gov

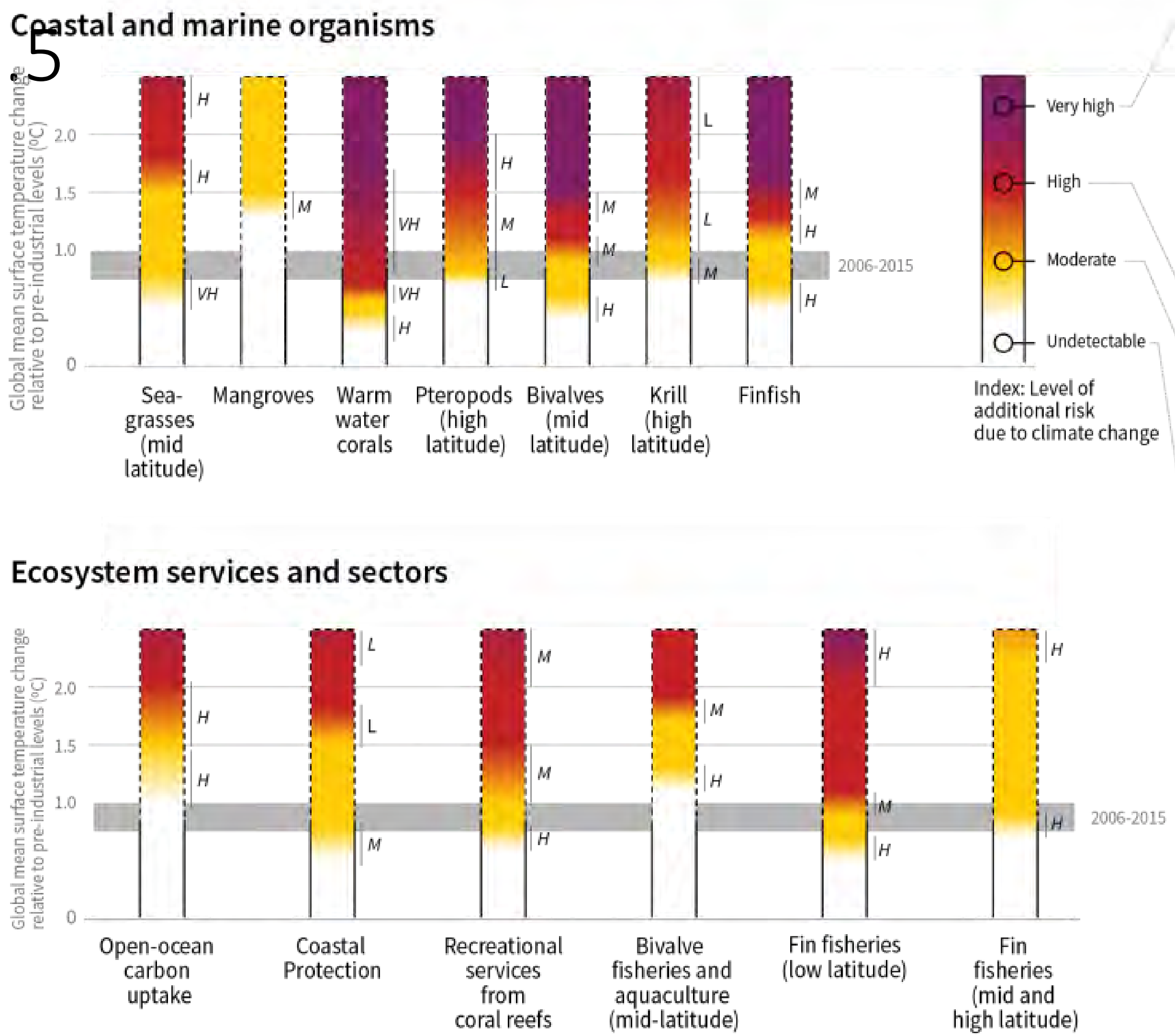
IPCC SR1.5

"Tipping points refer to **critical thresholds in a system that, when exceeded, can lead to a significant change in the state of the system**, often with an understanding that the change is **irreversible**. An understanding of the sensitivities of tipping points in the physical climate system, as well as in ecosystems and human systems, is essential for understanding the **risks** associated with different degrees of global warming. This subsection reviews tipping points across these three areas **within the context of the different sensitivities** to 1.5°C versus 2°C of global warming."

Risks for specific marine and coastal organisms, ecosystems and sectors

The key elements are presented here as a function of the risk level assessed between 1.5 and 2°C (Average global sea surface temperature).

IPCC SR1.5



Purple indicates very high risks of severe impacts and the presence of significant irreversibility or the persistence of climate-related hazards, combined with limited ability to adapt due to the nature of the hazard or impacts/risks.

Red indicates severe and widespread impacts.

Yellow indicates that impacts/risks are detectable and attributable to climate change with at least medium confidence.

White indicates that no impacts are detectable and attributable to climate change.

Confidence level for transition: *L*=Low, *M*=Medium, *H*=High and *VH*=Very high *"knowledge and culture construct societal limits to adaptation, but these <u>limits are mutable</u>"*

- Adger et al. (2009).

IPCC : pathways of resilience

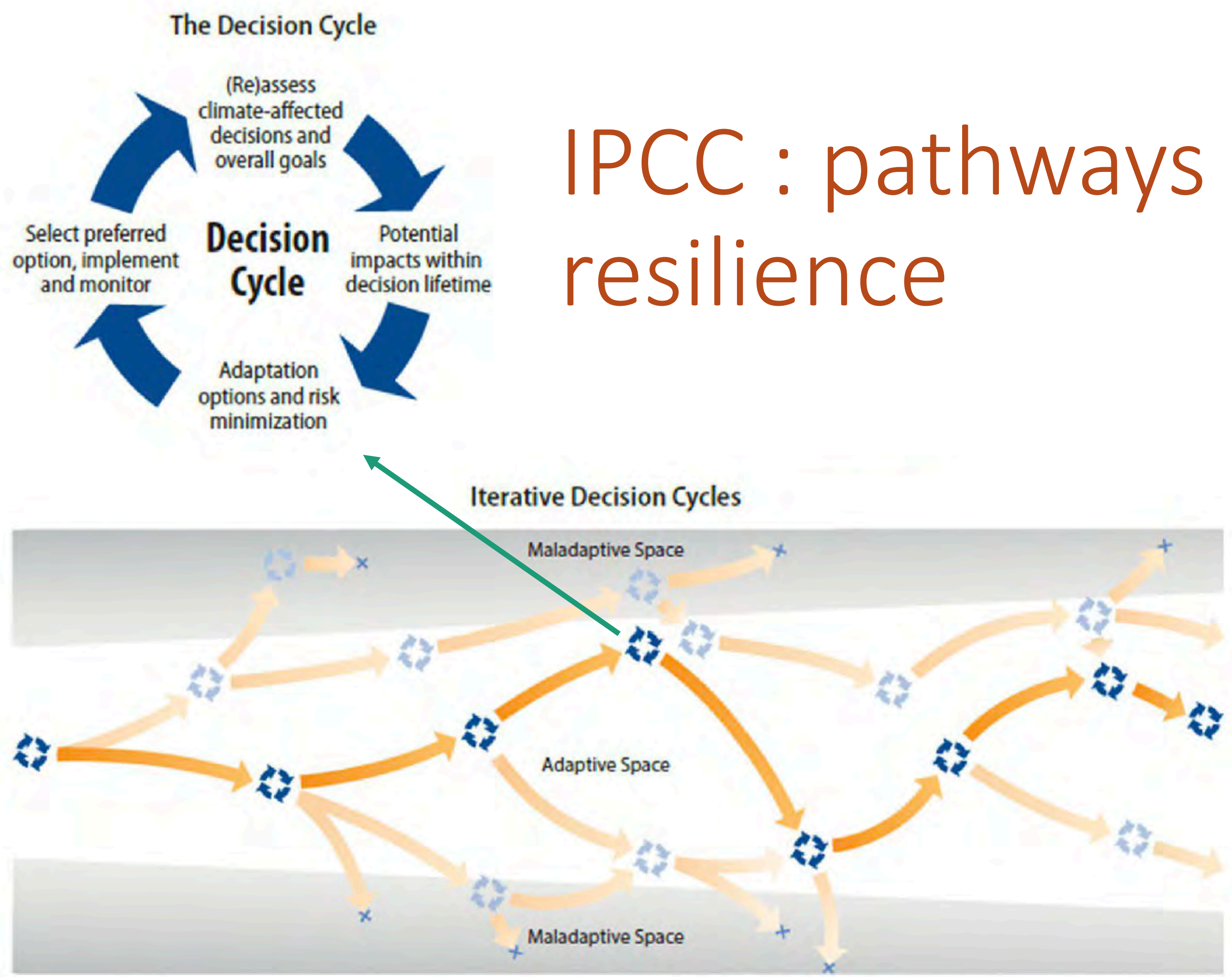


Fig. 1 from Wise et al. 2014. Reconceptualising adaptation to climate change as part of pathways of change and response. Global Environmental Change 28: 325–336

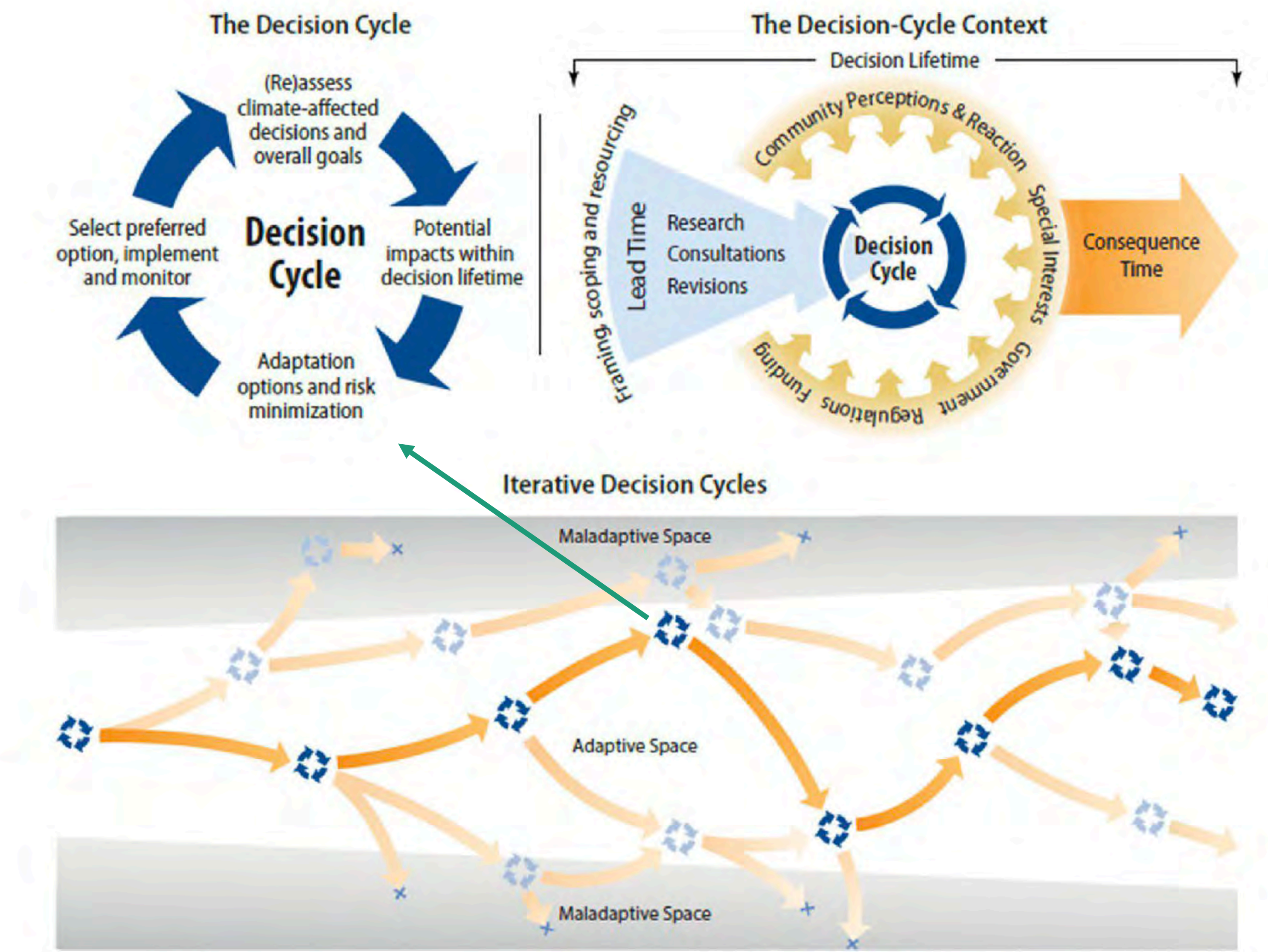


Fig. 1 from Wise et al. 2014. Reconceptualising adaptation to climate change as part of pathways of change and response. Global Environmental Change 28: 325–336

- ✓ Risk inherently depends on values
- ✓ Include a “plurality of perspectives” *
- ✓ Consider interacting (non-linear) pressures

“Interconnections among risks can span sectors and regions with multiple climatic and non-climatic influences, including societal responses to climate change and other issues (Helbing 2013; Moser and Hart 2015; Oppenheimer 2013).”
- Mach et al. 2016

How do we define thresholds?

esa ECOSPHERE

Defining ecosystem thresholds for human activities and environmental pressures in the California Current

Jameal F. Samhouri,[1,†] Kelly S. Andrews,[1] Gavin Fay,[2] Chris J. Harvey,[1] Elliott L. Hazen,[3] Shannon M. Hennessey,[4] Kirstin Holsman,[5] Mary E. Hunsicker,[6] Scott I. Large,[7] Kristin N. Marshall,[1] Adrian C. Stier,[8,9] Jamie C. Tam,[10] and Stephani G. Zador[5]

[1]*Conservation Biology Division, Northwest Fisheries Science Center, National Marine Fisheries Service, National Oceanic & Atmospheric Administration, 2725 Montlake Boulevard, Seattle, Washington 98112 USA*
[2]*Department of Fisheries Oceanography, School for Marine Science and Technology, University of Massachusetts Dartmouth, 200 Mill Road, Fairhaven, Massachusetts 02719 USA*
[3]*Environmental Research Division, Southwest Fisheries Science Center, National Marine Fisheries Service, National Oceanic & Atmospheric Administration, 99 Pacific Street, Suite 255A, Monterey, California 93940 USA*
[4]*Department of Integrative Biology, Oregon State University, 3029 Cordley Hall, Corvallis, Oregon 97331 USA*
[5]*Resource Ecology & Fisheries Management Division, Alaska Fisheries Science Center, National Marine Fisheries Service, National Oceanic & Atmospheric Administration, 7600 Sand Point Way N.E., Seattle, Washington 98115 USA*
[6]*Fish Ecology Division, Northwest Fisheries Science Center, National Marine Fisheries Service, National Oceanic & Atmospheric Administration, 2032 SE OSU Drive, Newport, Oregon 97365 USA*
[7]*International Council for the Exploration of the Sea (ICES), H.C. Andersens Boulevard 44-46, 1553 Copenhagen V, Denmark*
[8]*National Center for Ecological Analysis and Synthesis, 735 State Street, Santa Barbara, California 93101 USA*
[9]*Department of Ecology, Evolution, and Marine Biology, University of California, Santa Barbara, California 93106 USA*
[10]*Northeast Fisheries Science Center, National Marine Fisheries Service, National Oceanic & Atmospheric Administration, 166 Water Street, Woods Hole, Massachusetts 02543 USA*

Citation: Samhouri, J. F., K. S. Andrews, G. Fay, C. J. Harvey, E. L. Hazen, S. M. Hennessey, K. Holsman, M. E. Hunsicker, S. I. Large, K. N. Marshall, A. C. Stier, J. C. Tam, and S. G. Zador. 2017. Defining ecosystem thresholds for human activities and environmental pressures in the California Current. Ecosphere 8(6):e01860. 10.1002/ecs2.1860

Abstract. The oceans are changing more rapidly than ever before. Unprecedented climatic variability is interacting with unmistakable long-term trends, all against a backdrop of intensifying human activities. What remains unclear, however, is how to evaluate whether conditions have changed sufficiently to provoke major responses of species, habitats, and communities. We developed a framework based on multimodel inference to define ecosystem-based thresholds for human and environmental pressures in the California Current marine ecosystem. To demonstrate how to apply the framework, we explored two decades of data using gradient forest and generalized additive model analyses, screening for nonlinearities and potential threshold responses of ecosystem states (n = 9) across environmental (n = 6) and human

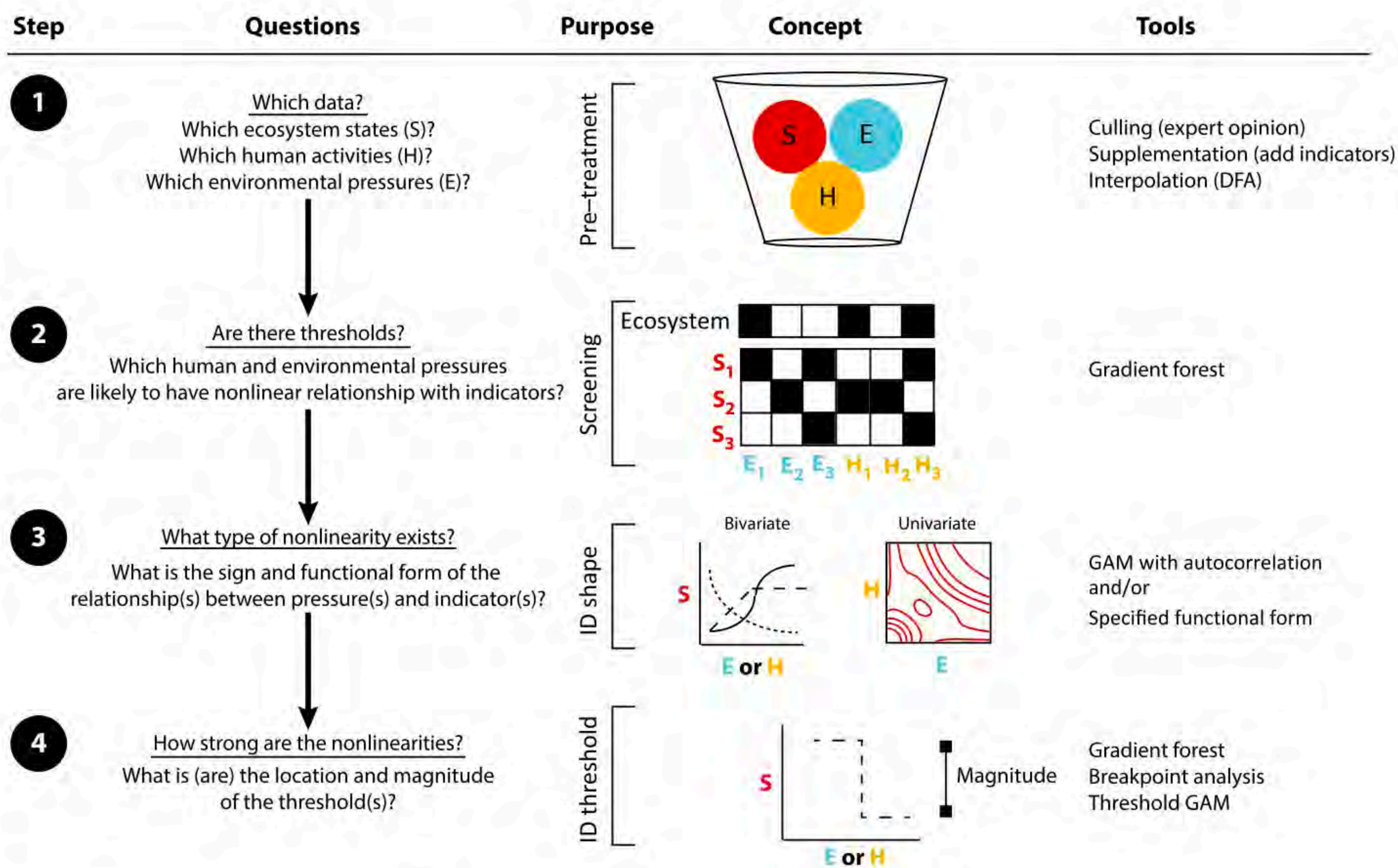
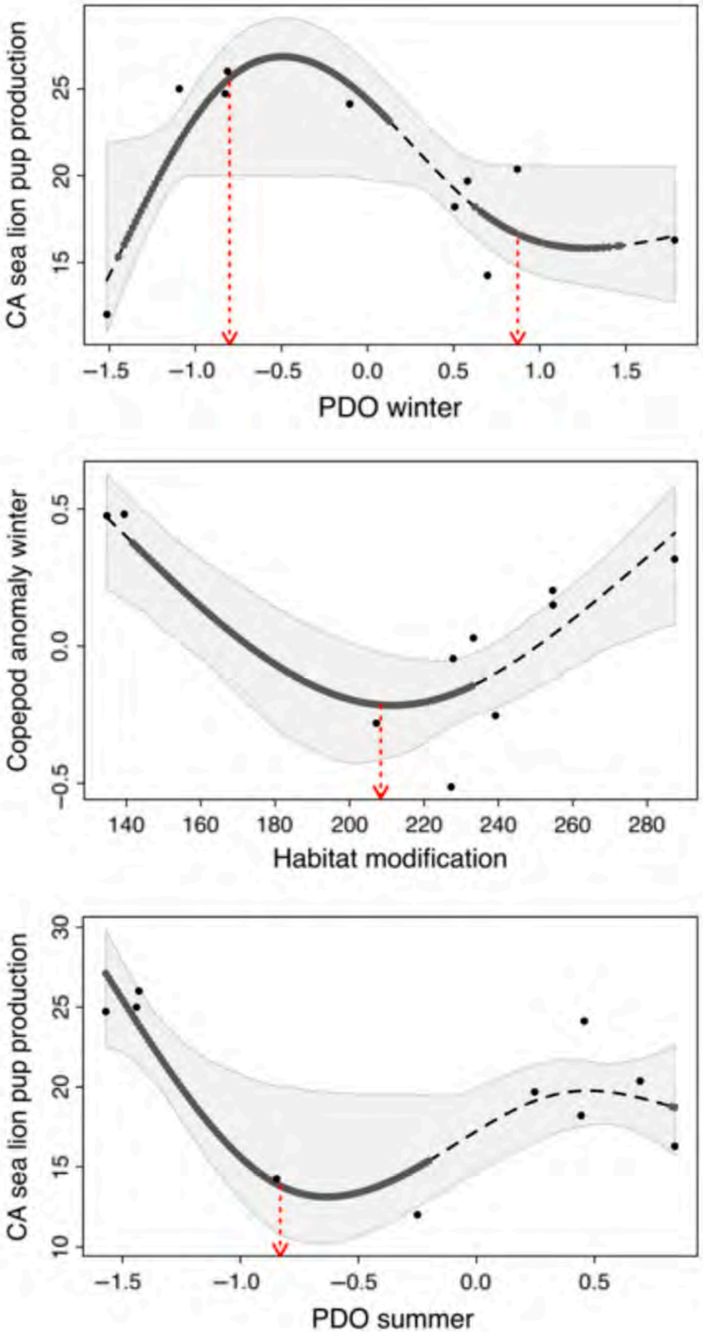


Fig. 1. Analytical framework for defining ecosystem-based thresholds for environmental and human pressures. S = ecosystem state indicator(s); E = environmental pressure indicator(s); H = human pressure indicator(s); DFA = dynamic factor analysis; mag = magnitude of ecosystem response across a threshold. Note that the tools listed here are intended as examples, rather than an exhaustive list. GAM, generalized additive model.



Samhouri, J. F., K. S. Andrews, G. Fay, C. J. Harvey, E. L. Hazen, S. M. Hennessey, K. Holsman, M. E. Hunsicker, S. I. Large, K. N. Marshall, A. C. Stier, J. C. Tam, and S. G. Zador. 2017. Defining ecosystem thresholds for human activities and environmental pressures in the California Current. Ecosphere 8.

Large, S. I., G. Fay, K. D. Friedland, and J. S. Link. 2013. Defining trends and thresholds in responses of ecological indicators to fishing and environmental pressures. ICES Journal of Marine Science 70:755–767.

Tam, J. C., J. S. Link, S. I. Large, K. Andrews, K. D. Friedland, J. Gove, E. Hazen, K. Holsman, M. Karnauskas, J. F. Samhouri, R. Shuford, N. Tomilieri, and S. Zador. 2017. Comparing Apples to Oranges: Common Trends and Thresholds in Anthropogenic and Environmental Pressures across Multiple Marine Ecosystems. Frontiers in Marine Science 4.

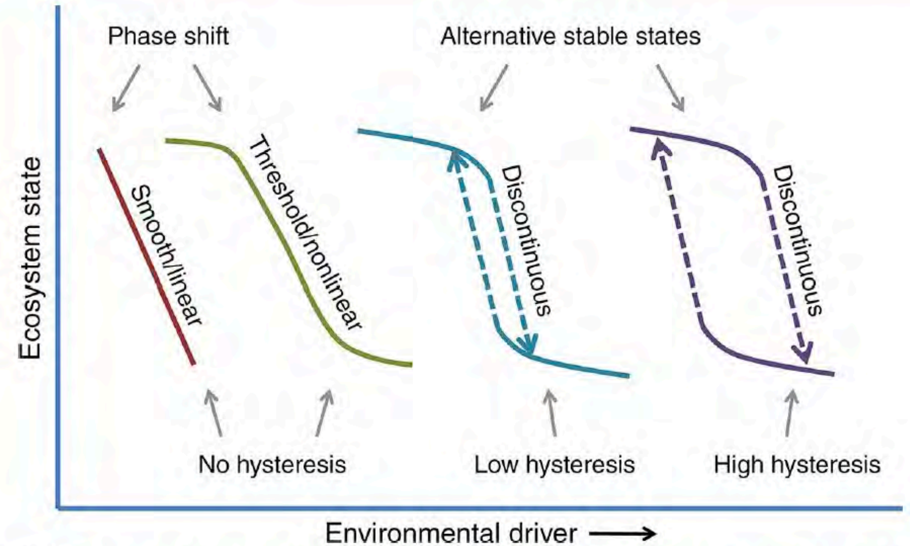


Fig. 1. Types of regime shifts. Phase shifts can be smooth or nonlinear, whereas alternative stable states show discontinuous change with some level of hysteresis. Modified from Dudgeon et al. (2010).

Selkoe, K. A., et al. 2015. Principles for managing marine ecosystems prone to tipping points. Ecosystem Health and Sustainability 1(5):17. http://dx.doi.org/10.1890/EHS14-0024.1

SELKOE ET AL. Managing ocean tipping points

Table 3. Summary of principles for managing ecosystems prone to tipping points.

Social-ecological observation	Management principle
1. Tipping points are common.	1. In the absence of evidence to the contrary, assume nonlinearity.
2. Intense human use may cause a tipping point by radically altering ecological structure and function.	2. Address stressor intensity and interactive, cross-scale effects of human uses to avoid tipping points.
3. Early-warning indicators of tipping points enable proactive responses.	3. Work toward identifying and monitoring leading indicators of tipping points.
4. Crossing a tipping point may redistribute ecosystem benefits.	4. Work to make transparent the effects of tipping points on benefits, burdens, and preferences.
5. Tipping points change the balance between costs of action and inaction.	5. Tipping points warrant increased precaution.
6. Thresholds can guide target-setting for management.	6. Tie management targets to ecosystem thresholds.
7. Tiered management can reduce monitoring costs while managing risk.	7. Increase monitoring and intervention as risk of a tipping point increases.

Selkoe, K. A., et al. 2015. Principles for managing marine ecosystems prone to tipping points. Ecosystem Health and Sustainability 1(5):17. http://dx.doi.org/10.1890/EHS14-0024.1

What should we monitor to predict tipping points?

Journal of Environmental Management 234 (2019) 131–137

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

ELSEVIER

Research article

Monitoring for tipping points in the marine environment

Judi E. Hewitt[a,b,*], Simon F. Thrush[b]

[a] NIWA, Gate 10 Silverdale Rd, Hamilton, New Zealand
[b] University of Auckland, Auckland, New Zealand

ARTICLE INFO

Keywords:
Threshold responses
Management
Design
Early warning signals
Detection
Methods

ABSTRACT

Increasingly studies are reporting sudden and dramatic changes in the structure and function of communities or ecosystems. The prevalence of these reports demonstrates the importance for management of being able to detect whether these have happened and, preferably, whether they are likely to occur. Ecological theory provides the rationale for why such changes occur and a variety of statistical indicators of approach that have generic properties have been developed. However, whether the theory has successfully translated into monitoring programmes is unknown. We searched the literature for guidelines that would drive design of monitoring programmes able to detect past and approaching tipping points and analysed marine monitoring programmes in New Zealand. We found very few guidelines in the ecological, environmental or monitoring literature, although both simulation and marine empirical studies suggest that within-year sampling increases the likelihood of detecting approaching tipping points. The combination of the need to monitor both small and medium scale temporal dynamics of multiple variables to detect tipping points meant that few marine monitoring programmes in New Zealand were fit for that purpose. Interestingly, we found many marine examples of studies detecting past and approaching TP with fewer data than was common in the theoretical literature. We, therefore, suggest that utilizing ecological knowledge is of paramount importance in designing and analyzing time-series monitoring for tipping points and increasing the certainty for short-term or infrequent datasets of whether a tipping point has occurred. As monitoring plays an important role in management of tipping points by providing supporting information for other locations about when and why a tipping point may occur, we believe that monitoring for tipping points should be promoted.

"both simulation and marine empirical studies suggest that within-year sampling increases the likelihood of detecting approaching tipping points"

What should we monitor?

ECOLOGY LETTERS
Ecology Letters, (2017) 20: 1534–1545 doi: 10.1111/ele.12861

LETTER

Asynchrony among local communities stabilises ecosystem function of metacommunities

Kevin R. Wilcox,[1*,a,c] Andrew T. Tredennick,[2*,a] Sally E. Koerner,[3,c] Emily Grman,[4,c] Lauren M. Hallett,[5] Meghan L. Avolio,[6,b] Kimberly J. La Pierre,[7,b] Gregory R. Houseman,[8,c] Forest Isbell,[9,c] David Samuel Johnson,[10,c] Juha M. Alatalo,[11] Andrew H. Baldwin,[12] Edward W. Bork,[13] Elizabeth H. Boughton,[14] William D. Bowman,[15] Andrea J. Britton,[16] James F. Cahill Jr.,[17] Scott L. Collins,[18] Guozhen Du,[19] Anu Eskelinen,[20,21,22] Laura Gough,[23] Anke Jentsch,[24] Christel Kern,[25] Kari Klanderud,[26] Alan K. Knapp,[27] Juergen Kreyling,[28] Yiqi Luo,[1,29,30] Jennie R. McLaren,[31] Patrick Megonigal,[32] Vladimir Onipchenko,[33] Janet Prevéy,[34] Jodi N. Price,[35] Clare H. Robinson,[36] Osvaldo E. Sala,[37] Melinda D. Smith,[27] Nadejda A. Soudzilovskaia,[38] Lara Souza,[1,39] David Tilman,[40] Shannon R. White,[41] Zhuwen Xu,[42] Laura Yahdjian,[43] Qiang Yu,[44] Pengfei Zhang,[19] and Yunhai Zhang[45,46]

Abstract

Temporal stability of ecosystem functioning increases the predictability and reliability of ecosystem services, and understanding the drivers of stability across spatial scales is important for land management and policy decisions. We used species-level abundance data from 62 plant communities across five continents to assess mechanisms of temporal stability across spatial scales. We assessed how asynchrony (i.e. different units responding dissimilarly through time) of species and local communities stabilised metacommunity ecosystem function. Asynchrony of species increased stability of local communities, and asynchrony among local communities enhanced metacommunity stability by a wide range of magnitudes (1–315%); this range was positively correlated with the size of the metacommunity. Additionally, asynchronous responses among local communities were linked with species' populations fluctuating asynchronously across space, perhaps stemming from physical and/or competitive differences among local communities. Accordingly, we suggest spatial heterogeneity should be a major focus for maintaining the stability of ecosystem services at larger spatial scales.

Keywords

Alpha diversity, alpha variability, beta diversity, biodiversity, CoRRE data base, patchiness, plant communities, primary productivity, species synchrony.

Ecology Letters (2017) **20**: 1534–1545

Can emergent synchrony indicate approaching tipping point?

"asynchrony among local communities enhanced metacommunity stability by a wide range of magnitudes"

Limits are context dependent and change through time (Adger et al. 2009)

- How do we capture temporal autocorrelation in tipping points?
- Can deterioration in AR indicate approaching tipping point?
- Can emergent synergies indicate approaching tipping point?

Adger et al. (2009). Are there social limits to adaptation to climate change? Climatic Change, 93(3–4), 335–354. https://doi.org/10.1007/s10584-008-9520-z

Changes in variance

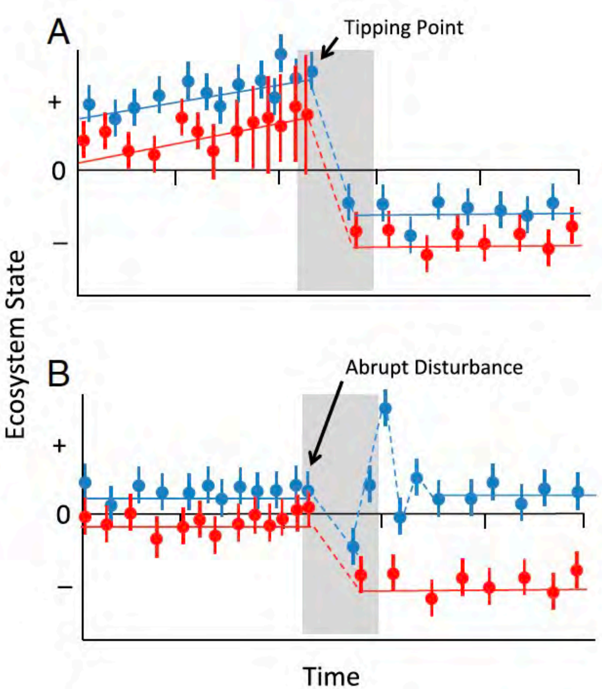
- Increased variance as indicator of approaching tipping point

COMMENTARY

Predicting tipping points in complex environmental systems

John C. Moore[a,b,1]

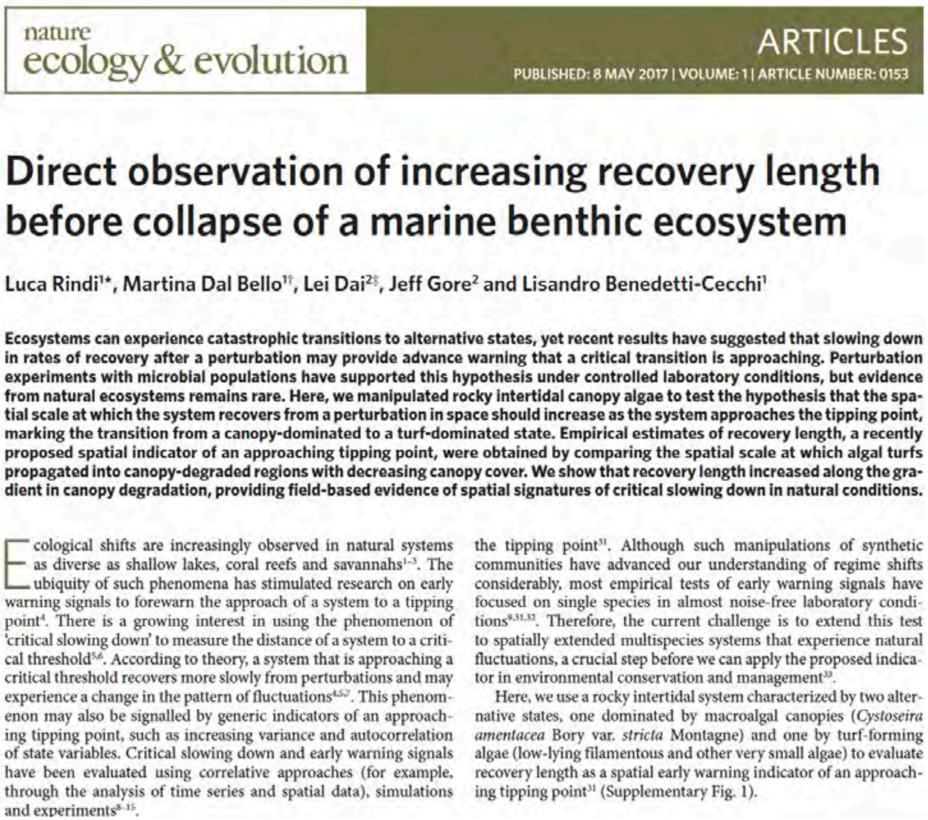
Ecologists have long recognized that ecosystems can exist and function in one state within predictable bounds for extended periods of time and then abruptly shift to an alternate state (1–5). Desertification of grasslands, shrub expansion in the Arctic, the eutrophication of lakes, ocean acidification, the formation of marine dead zones, and the degradation of coral reefs represent real and potential ecological regime shifts marked by a tipping point or threshold in one or more external drivers or controlling variables within the system that when breached causes a major change in the system's structure, function, or dynamics (6–9). Large or incremental alterations in climate, land use, biodiversity (invasive species or the overexploitation of species), and biogeochemical cycles represent external and internal drivers that when pushed too far cross thresholds that can could lead to regime shifts (Fig. 1). Seeing the tipping point after the fact and ascribing mechanisms to the change is one thing; predicting them using empirical data has been a challenge. The difficulty in predicting tipping points stems



COMMENTARY

Changes in variance

- Increased variance as indicator of approaching tipping point
- Decrease in variance increase in approaching tipping point?
  - More synchrony = less variance within a year but increased variance between years
  - Declines in spatial heterogeneity indicate instability



nature ecology & evolution

ARTICLES

PUBLISHED: 8 MAY 2017 | VOLUME: 1 | ARTICLE NUMBER: 0153

Direct observation of increasing recovery length before collapse of a marine benthic ecosystem

Luca Rindi[1*], Martina Dal Bello[1†], Lei Dai[2‡], Jeff Gore[2] and Lisandro Benedetti-Cecchi[1]

Ecosystems can experience catastrophic transitions to alternative states, yet recent results have suggested that slowing down in rates of recovery after a perturbation may provide advance warning that a critical transition is approaching. Perturbation experiments with microbial populations have supported this hypothesis under controlled laboratory conditions, but evidence from natural ecosystems remains rare. Here, we manipulated rocky intertidal canopy algae to test the hypothesis that the spatial scale at which the system recovers from a perturbation in space should increase as the system approaches the tipping point, marking the transition from a canopy-dominated to a turf-dominated state. Empirical estimates of recovery length, a recently proposed spatial indicator of an approaching tipping point, were obtained by comparing the spatial scale at which algal turfs propagated into canopy-degraded regions with decreasing canopy cover. We show that recovery length increased along the gradient in canopy degradation, providing field-based evidence of spatial signatures of critical slowing down in natural conditions.

Ecological shifts are increasingly observed in natural systems as diverse as shallow lakes, coral reefs and savannahs[1–3]. The ubiquity of such phenomena has stimulated research on early warning signals to forewarn the approach of a system to a tipping point[4]. There is a growing interest in using the phenomenon of 'critical slowing down' to measure the distance of a system to a critical threshold[5,6]. According to theory, a system that is approaching a critical threshold recovers more slowly from perturbations and may experience a change in the pattern of fluctuations[4,5,7]. This phenomenon may also be signalled by generic indicators of an approaching tipping point, such as increasing variance and autocorrelation of state variables. Critical slowing down and early warning signals have been evaluated using correlative approaches (for example, through the analysis of time series and spatial data), simulations and experiments[8–15].

the tipping point[31]. Although such manipulations of synthetic communities have advanced our understanding of regime shifts considerably, most empirical tests of early warning signals have focused on single species in almost noise-free laboratory conditions[9,31,32]. Therefore, the current challenge is to extend this test to spatially extended multispecies systems that experience natural fluctuations, a crucial step before we can apply the proposed indicator in environmental conservation and management[33].

Here, we use a rocky intertidal system characterized by two alternative states, one dominated by macroalgal canopies (*Cystoseira amentacea* Bory var. *stricta* Montagne) and one by turf-forming algae (low-lying filamentous and other very small algae) to evaluate recovery length as a spatial early warning indicator of an approaching tipping point[31] (Supplementary Fig. 1).

Recovery time

slowing down in rates of recovery after a perturbation may provide advance warning that a critical transition is approaching

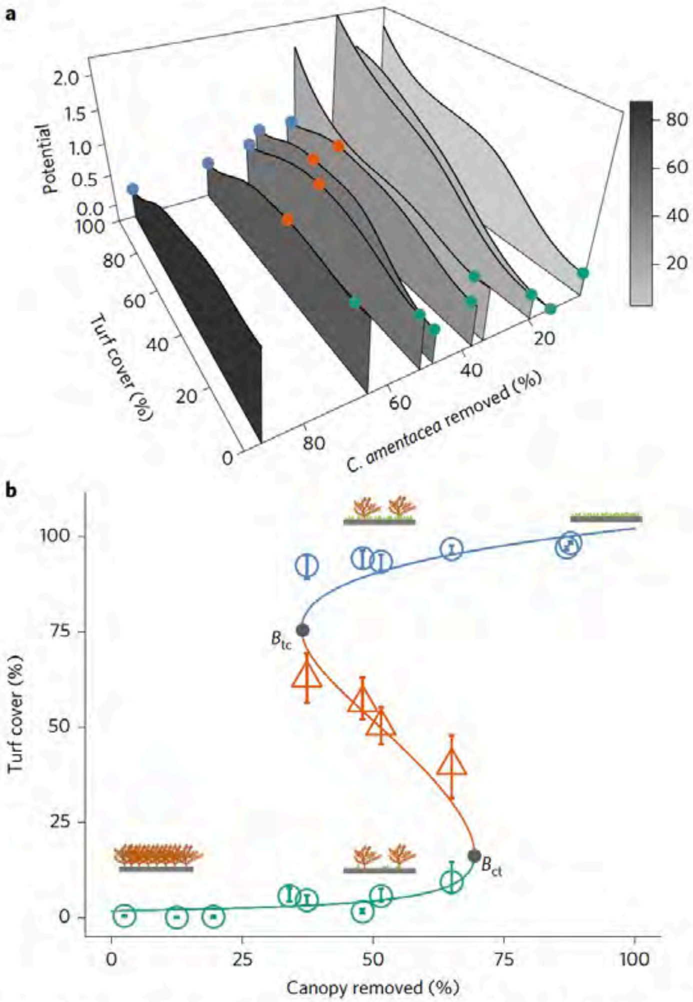


Figure 1 | Canopy degradation leads to a regime shift from a canopy- to a turf-dominated state. a, Potential landscapes inferred from experimental

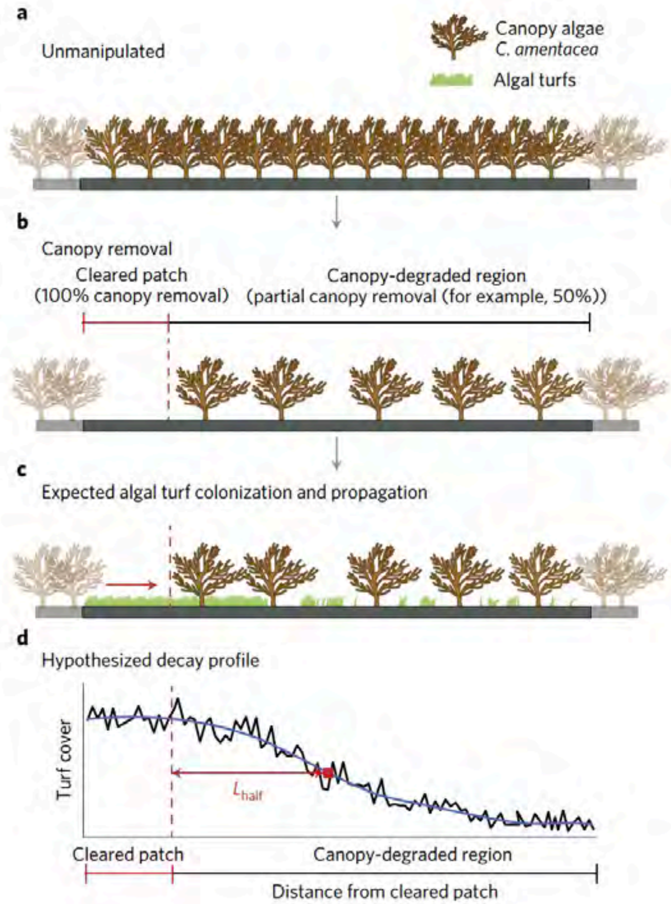


Figure 2 | Schematic illustration of the experiment and measurement of the recovery length. a, Horizontal view of an unmanipulated transect with full cover of *C. amentacea* (semi-transparent plants indicate that the canopy extended off the first two quadrats; approximately 90 cm). A cleared patch where all erect organisms were cleared from the substratum was produced

PNAS PLUS
SEE COMMENTARY
ECOLOGY

Predicting tipping points in mutualistic networks through dimension reduction

Junjie Jiang[a], Zi-Gang Huang[b,c], Thomas P. Seager[d], Wei Lin[e], Celso Grebogi[f], Alan Hastings[g,1], and Ying-Cheng Lai[a,h,1]

[a]School of Electrical, Computer, and Energy Engineering, Arizona State University, Tempe, AZ 85287; [b]School of Physical Science and Technology, Lanzhou University, Lanzhou 730000, China; [c]School of Life Science and Technology, Xi'an Jiaotong University, Xi'an 710049, China; [d]School of Sustainable Engineering and Built Environment, Arizona State University, Tempe, AZ 85287; [e]School of Mathematical Sciences, Center for Computational Systems Biology, Fudan University, Shanghai 200433, China; [f]Institute for Complex Systems and Mathematical Biology, King's College, University of Aberdeen, Aberdeen AB24 3UE, United Kingdom; [g]Department of Environmental Science and Policy, University of California, Davis, CA 95616; and [h]Department of Physics, Arizona State University, Tempe, AZ 85287

Edited by Nils Chr. Stenseth, University of Oslo, Oslo, Norway, and approved November 27, 2017 (received for review August 23, 2017)

Complex networked systems ranging from ecosystems and the climate to economic, social, and infrastructure systems can exhibit a tipping point (a "point of no return") at which a total collapse of the system occurs. To understand the dynamical mechanism of a tipping point and to predict its occurrence as a system parameter varies are of uttermost importance, tasks that are hindered by the often extremely high dimensionality of the underlying system. Using complex mutualistic networks in ecology as a prototype class of systems, we carry out a dimension reduction process to arrive at an effective 2D system with the two dynamical variables corresponding to the average pollinator and plant abundances. We show, using 59 empirical mutualistic networks extracted from real data, that our 2D model can accurately predict the occurrence of a tipping point, even in the presence of stochastic disturbances. We also find that, because of the lack of sufficient randomness in the structure of the real networks, weighted averaging is necessary in the dimension reduction process. Our reduced model can serve as a paradigm for understanding and predicting the tipping point dynamics in real world mutualistic networks for safeguarding pollinators, and the general principle can be extended to a broad range of disciplines to address the issues of resilience and sustainability.

within the groups or aggregates. For a networked system with a large number of mutually interacting components and many independent parameters, the corresponding phase space dimensionality can be prohibitively high for any direct analysis that aims to gain theoretical insights into the dynamical underpinnings of the tipping point. In such a case, the approach of dimension reduction can turn out to be useful. The purpose of this paper is to apply dimension reduction to a class of bipartite mutualistic networked systems in ecology to arrive at a 2D system that captures the essential mutualistic interactions in the original system. More importantly, it can be used to assess the likelihood of the occurrence of a catastrophic tipping point in the system as the environment continues to deteriorate.

In the development of nonlinear dynamics, dimension reduction has played a fundamental role. For example, the classic Lorenz system (17), a system described by three ordinary differential equations (ODEs) with a simple kind of nonlinearity, is the result of drastic reduction in dimension from the Rayleigh–Bénard convection equations with an infinite phase space dimension. Study of the reduced model can lead to insights into dynamical phenomena not only in the original system but also, beyond. In this sense, the reduced model may be said to possess cer-

Complex dimension model

(predation)
competition term

intrinsic growth rate

mutualism term

immigration rate

Change in plant

$$\frac{dP_i}{dt} = P_i \left(\alpha_i^{(P)} - \sum_{j=1}^{S_P} \beta_{ij}^{(P)} P_j + \frac{\sum_{k=1}^{S_A} \gamma_{ik}^{(P)} A_k}{1 + h \sum_{k=1}^{S_A} \gamma_{ik}^{(P)} A_k} \right) + \mu_P,$$

1/2 saturation coef

# of pollinators

Change in pollinator

$$\frac{dA_i}{dt} = A_i \left(\alpha_i^{(A)} - \kappa_i - \sum_{j=1}^{S_A} \beta_{ij}^{(A)} A_j + \frac{\sum_{k=1}^{S_P} \gamma_{ik}^{(A)} P_k}{1 + h \sum_{k=1}^{S_P} \gamma_{ik}^{(A)} P_k} \right) + \mu_A,$$

species decay rate

Pollinator Abundance

Reduced dimension model

Reduced dimension model

network growth rate

Combined effects of inter/intra specific comp

$$\frac{dP_{\text{eff}}}{dt} = \alpha P_{\text{eff}} - \beta P_{\text{eff}}^2 + \frac{\langle \gamma_P \rangle A_{\text{eff}}}{1 + h\langle \gamma_P \rangle A_{\text{eff}}} P_{\text{eff}} + \mu,$$

$$\frac{dA_{\text{eff}}}{dt} = \alpha A_{\text{eff}} - \beta A_{\text{eff}}^2 - \kappa A_{\text{eff}} + \frac{\langle \gamma_A \rangle P_{\text{eff}}}{1 + h\langle \gamma_A \rangle P_{\text{eff}}} A_{\text{eff}} + \mu, \quad \textbf{[3]}$$

average spp decay rate

general migrate rate

Average pollinator Abundance

mutualistic interaction strengths

- unweighted Avg
- degree weighted Avg
- eigenvector avg

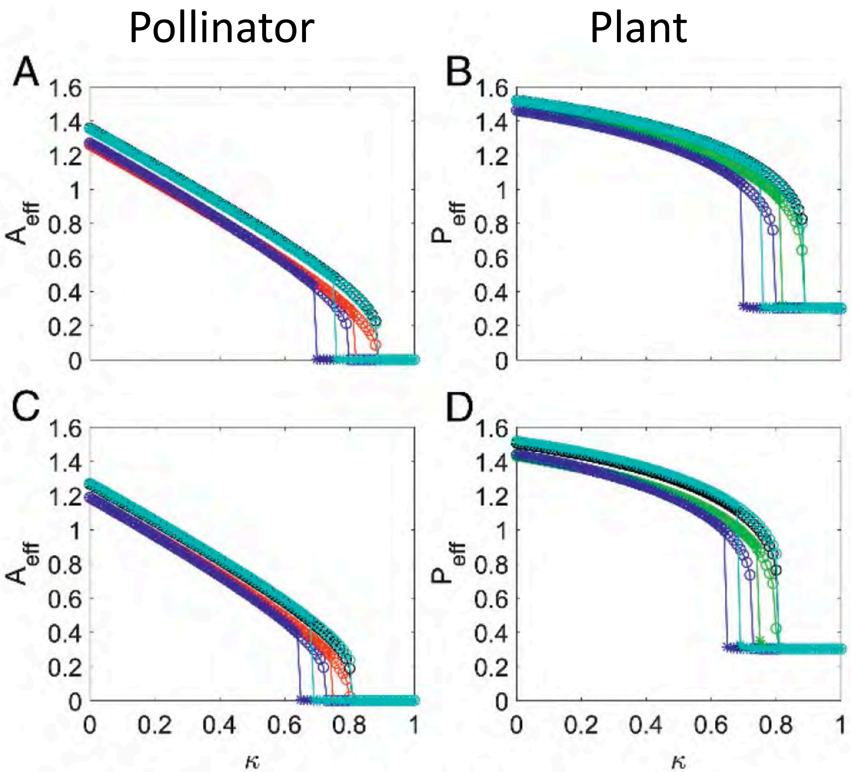


Fig. 5. Predicting tipping point triggered by an increase in pollinator mortal (decay) rate. For networks *A* (*A* and *B*) and *B* (*C* and *D*), resilience functions exhibit a tipping point as the pollinator decay rate κ is continuously increased. The red and green curves are the average pollinator (*A* and *C*) and plant (*B* and *D*) abundances from the original networks, while the blue, black, and cyan curves in all of the panels are the results from the reduced system using averaging methods *i–iii*, respectively. The parameters are $h=0.6$, $t=0.5$, $\beta_{ii}^{(A)}=\beta_{ii}^{(P)}=1$, $\alpha_i^{(A)}=\alpha_i^{(P)}=0.3$, $\mu_A=\mu_P=0.0001$, and $\gamma_0=1$. Note that the network structure remains intact, as no pollinator is removed. As for the case of removing pollinators, the reduced system with averaging method *ii* or *iii* is able to predict the onset of the tipping point correctly. Note the occurrence of a hysteresis behavior (predicted by our mathematical analysis).

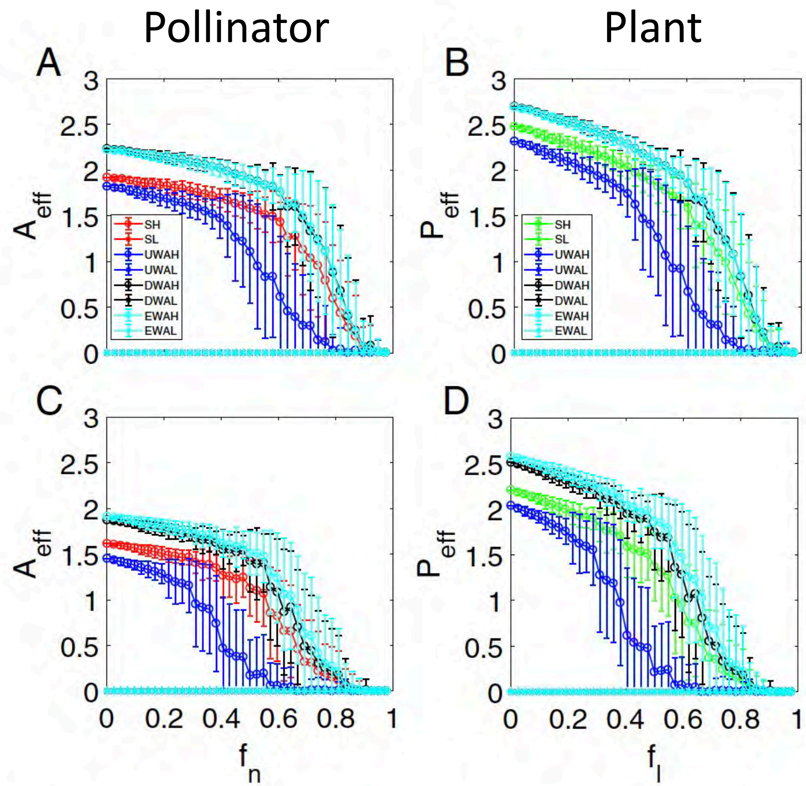


Fig. 4. Resilient functions with a tipping point. For networks *A* (*A* and *B*) and *B* (*C* and *D*), ensemble-averaged pollinator abundance (*A* and *C*) vs. f_n, the fraction of removed pollinators, and ensemble-averaged plant abundance (*B* and *D*) vs. f_l, the fraction of removed mutualistic links corresponding to the value of f_n in *A* and *C*. The legends are the same as in Fig. 3. The notations SH and SL stand for the high and low initial values of the original average species abundance, respectively. UWAH, UWAL, DWAH, DWAL, EWAH, and EWAL denote unweighted average high, unweighted average low, degree-weighted average high, degree-weighted average low, eigenvalue-weighted average high, and eigenvalue-weighted average low, respectively. The parameters are $h=0.2$, $t=0.5$, $\beta_{ii}^{(A)}=\beta_{ii}^{(P)}=1$, $\alpha_i^{(A)}=\alpha_i^{(P)}=-0.3$, $\mu_A=\mu_P=0.0001$, $\gamma_0=1$, and $\kappa=0$. Before f_n (or f_l for plants) reaches unity, a tipping point associated with total collapse of the system occurs at which the species abundances are diminished.

f_n= Fraction of removed pollinators (e.g., prey)

k = pollinator mort. rate

f_l= Fraction of removed mutualistic links (facilitation)

How can we build on this?

frontiers in Marine Science

ORIGINAL RESEARCH
published: 21 May 2019
doi: 10.3389/fmars.2019.00249

Check for updates

Trophic Interactions, Management Trade-Offs and Climate Change: The Need for Adaptive Thresholds to Operationalize Ecosystem Indicators

Martina Kadin[1*†], Thorsten Blenckner[1‡], Michele Casini[2§], Anna Gårdmark[3||], Maria Angeles Torres[3†¶] and Saskia A. Otto[1,4#]

[1] Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden, [2] Institute of Marine Research, Department of Aquatic Resources, Swedish University of Agricultural Sciences, Lysekil, Sweden, [3] Department of Aquatic Resources, Swedish University of Agricultural Sciences, Öregrund, Sweden, [4] Institute of Marine Ecosystem and Fishery Science, Center for Earth System Research and Sustainability, University of Hamburg, Hamburg, Germany

OPEN ACCESS

Edited by:
Dorte Krause-Jensen,
Aarhus University, Denmark

Reviewed by:
Henrique Cabral,
Irstea Centre de Bordeaux, France
Kevin David Friedland,
National Oceanic and Atmospheric Administration (NOAA), United States

****Correspondence:***
Martina Kadin
martina.kadin@nrm.se;
mkadin@uw.edu
orcid.org/0000-0002-4706-7267

†Present address:
Martina Kadin,
Swedish Museum of Natural History, Stockholm, Sweden
Maria Angeles Torres,
Instituto Español de Oceanografía, Centro Oceanográfico de Cádiz, Cádiz, Spain

‡orcid.org/0000-0002-6991-7680
§orcid.org/0000-0003-4910-5236
||orcid.org/0000-0003-1803-0622
¶orcid.org/0000-0003-4922-1894
#orcid.org/0000-0001-7780-1322

Ecosystem-based management (EBM) is commonly applied to achieve sustainable use of marine resources. For EBM, regular ecosystem-wide assessments of changes in environmental or ecological status are essential components, as well as assessments of the effects of management measures. Assessments are typically carried out using indicators. A major challenge for the usage of indicators in EBM is trophic interactions as these may influence indicator responses. Trophic interactions can also shape trade-offs between management targets, because they modify and mediate the effects of pressures on ecosystems. Characterization of such interactions is in turn a challenge when testing the usability of indicators. Climate variability and climate change may also impact indicators directly, as well as indirectly through trophic interactions. Together, these effects may alter interpretation of indicators in assessments and evaluation of management measures. We developed indicator networks – statistical models of coupled indicators – to identify links representing trophic interactions

Potential approaches

- Add dynamics and stochasticity to tipping point analyses
- Add spatial and/or temporal autocorrelation to reduced dimension approach
- Use s”(x) approach to ID tipping points based on interactions
- Simulations? From indicator sets or existing data repos (RAM legacy, etc).
- Map these thresholds to climate change deg

- Functional redundancy
- Amplification/attenuation
- Species interactions
- Recovery time
- Spatial autocorrelation
- Reduced dimensionality approaches