Beyond singular driver-response tipping points & thresholds

recent examples and emerging approaches

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“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).

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Coastal and marine organisms

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.

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Ecosystem services and sectors

Confidence level for transition: L=Low, M=Medium, H=High and VH=Very high
“knowledge and culture construct societal limits to adaptation, but these limits are mutable”
- 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
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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?
Defining ecosystem thresholds for human activities and environmental pressures in the California Current

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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 multi-model 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 (n = 10) pressures. Through this, we identified the influence of thresholds on the downstream ecosystem.
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.


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

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

What should we monitor to predict tipping points?
“both simulation and marine empirical studies suggest that within-year sampling increases the likelihood of detecting approaching tipping points”
Asynchrony among local communities stabilises ecosystem function of metacommunities

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 database, patchiness, plant communities, primary productivity, species synchrony.

“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?

Changes in variance

• Increased variance as indicator of approaching tipping point
Predicting tipping points in complex environmental systems

John C. Moore

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 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...
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
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
Predicting tipping points in mutualistic networks through dimension reduction

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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 certain generic features. With respect to the current dynamics...
Complex dimension model

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

Change in plant

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

Change in pollinator
Reduced dimension model

\[ \frac{dP_{\text{eff}}}{dt} = \alpha P_{\text{eff}} - \beta P_{\text{eff}}^2 + \frac{\langle \gamma P \rangle A_{\text{eff}}}{1 + h\langle \gamma P \rangle A_{\text{eff}}} P_{\text{eff}} + \mu, \]

\[ \frac{dA_{\text{eff}}}{dt} = \alpha A_{\text{eff}} - \beta A_{\text{eff}}^2 - \kappa A_{\text{eff}} + \frac{\langle \gamma A \rangle P_{\text{eff}}}{1 + h\langle \gamma A \rangle P_{\text{eff}}} A_{\text{eff}} + \mu, \quad [3] \]
Fig. 5. Predicting tipping point triggered by an increase in pollinator mortality (decay) rate. For networks A (A and B) and B (C and D), resilience functions exhibit a tipping point as the pollinator decay rate $\kappa$ 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 $h = 0.6$, $t = 0.5$, $g_{i}^{(A)} = g_{i}^{(P)} = 1$, $\alpha_{i}^{(A)} = \alpha_{i}^{(P)} = 0.3$, $\mu_{A} = \mu_{P} = 0.0001$, 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 hysteretic behavior (predicted by our mathematical analysis).

$k =$ pollinator mort. rate

$f_{n} =$ Fraction of removed pollinators (e.g., prey)

$f_{l} =$ Fraction of removed mutualistic links (facilitation)
How can we build on this?
Trophic Interactions, Management Trade-Offs and Climate Change: The Need for Adaptive Thresholds to Operationalize Ecosystem Indicators

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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