

Environmental Context Dependency in Species Interactions

Owen Liu

18 July, 2018

Primary target journal: Nature Ecology and Evolution

Journal Guidelines:

- Maximum 3500 words main text (excluding introductory paragraph/abstract)
- Maximum 6 display items (figures/tables)
- The introductory paragraph is typically 150 words and is unreferenced; it contains a brief account of the background and rationale of the work, followed by a statement of the main conclusions introduced by the phrase “Here we show” or some equivalent. An introduction (without heading) of up to 500 words of referenced text expands on the background of the work (some overlap with the summary is acceptable), and is followed by a concise, focused account of the findings (headed ‘Results’), and one or two short paragraphs of discussion (headed ‘Discussion’).

Work confirmed/supported/debates:

- Tegner et al 1997, Dayton et al 1999
- Bottom-up vs. top-down forcing? Disturbance or herbivory?
- Competition between urchin species?
- Physical drivers increase predictability of algae models!

Suggested future research

- Predominance of mutualism- why the positive interactions of Pterygophora and Macro-cystis?
- Urchin grazing pressure as most important??
- Multiple stressors (e.g. herbivory, sst, wave height)

FIGURES

Time series of study species Example attractor? CCM results Empirical interaction web, in “normal”, “high disturbance”, and “high nutrient stress” environments??

Introductory paragraph (abstract)

Ecological interactions are not uniform across time, and instead vary with environmental conditions. Interactions among species are often measured with short-term controlled ex-

periments, but these experiments are subject to the particular environmental conditions under which they are performed. As an alternative, we utilize empirical dynamic modeling applied to a 30-year time series to estimate species interaction strengths across a wide range of environmental conditions in a coastal marine ecosystem. By including large-scale climate indices, sea surface temperature, and a measure of physical disturbance in analyses, we show that environmental context influences the strength and direction of species interactions. In so doing, we are able to confirm and extend results from previous studies, as well as identify potentially important but understudied interactions. The significant context dependency in species interactions found in this study argues for a greater utilization of long-term data and empirical dynamic modeling in studies of ecosystem dynamics.

43 Introduction

Interactions between species drive patterns of diversity, stability, resilience, and productivity in nature¹⁻⁴. In any ecosystem, the collection of species interactions determines community dynamics. Until recently, most studies viewed these dynamics—e.g., the bleaching and recovery of a coral reef, or the assembly and disassembly of terrestrial plant communities—as processes resulting from static, predictable species interactions. However, the observation that species interactions are not spatiotemporally uniform⁵⁻⁸ calls into question assumptions of interaction stability.

Ecologists recognize now that important species interactions may vary over time, but this context dependency remains difficult to measure and describe. Experiments that measure interactions are generally performed over a limited spatiotemporal range, and are therefore subject to a specific environmental context that may not encompass the range of conditions experienced by that ecosystem over longer time scales⁹. This is worrying, since environmental context can profoundly influence the outcome of species interactions ranging anywhere from keystone predation⁷ to competition^{5,10,11}, to protective symbioses¹²⁻¹⁴.

Moreover, the focus of the search for context dependency has been on mean interaction strengths, at the expense of specific examinations of interaction variance⁸. This focus may be misguided, as it has been shown that interactions that are variable in magnitude and direction—and therefore “weak” when averaged—may actually be some of the most important in driving community dynamics⁴. If key species interactions are variable in this way across environmental gradients, then many studies may be attributing important ecological phenomena to observational noise.

A solution to these difficulties is to a) utilize ecological observations collected over a long time period, across a large range of environmental contexts, with b) an analytical method to directly estimate context-dependent species interactions from those observations. Such an approach could help to characterize environmental contingencies in species interactions and explicitly examine interaction variability. Here, we use empirical dynamic modelling (EDM,¹⁵) to estimate a varying species interaction network and establish environmental context dependency in interaction strength and direction. Empirical dynamic modelling uses information from single or multiple time series to empirically model relationships between variables through

the reconstruction of dynamic attractors (<https://youtu.be/8DikuwwPWsY>). The general modelling framework for all EDM methods is readily adaptable to many different sorts of time series variables, including environmental variables manifesting at different scales^{16–18}. Because the methods are specifically designed for nonlinear dynamic systems, EDM—in theory—should be able to illuminate context-dependent patterns in species interactions.

Recently-developed EDM methods exist for uncovering dynamic species interactions from time series data¹⁵, but these methods have insofar been applied only to simulated and planktonic communities, and their utility to the study of other ecological systems remains untested. We focus here instead on giant kelp forests in southern California, a diverse and temporally dynamic ecosystem in which many important species interactions are well-documented^{19–21}. The study of kelp forests has been foundational to ecological theory, especially regarding the relative influence of top-down and bottom-up structuring forces^{22–26}. Recently, however, findings from long-term kelp forest research programs have begun to challenge many long-held beliefs about the drivers of kelp forest ecosystem dynamics²⁷. In particular, a longer-term perspective has led to a recognition of the critical importance of environmental context—such as level of physical disturbance or the current state of El Niño conditions—for understanding kelp forest processes^{28–31}.

In this study, we utilize monitoring data from one such effort at San Nicolas Island, a small, remote member of the California Channel Islands in the northeast Pacific³². Our analyses focus on the dynamics of five common southern California kelp forest species, whose interactions are thought to be important in structuring kelp forest ecosystems^{19,21,33}. The giant kelp *Macrocystis pyrifera* is the eponymous foundation species, the primary canopy- and habitat-forming kelp along most of the central and southern coast of California²⁰. We explore its dynamics and interactions with two presumptive competitors and two abundant herbivores. The understory kelp species *Laminaria farlowii* and *Pterygophora californica* compete with *Macrocystis* for space, light, and nutrients^{34–36}. The two herbivores—the purple sea urchin *Strongylocentrotus purpuratus* and the red sea urchin *Mesocentrotus franciscanus*—are thought in many places to control *Macrocystis* density and can sometimes wipe out entire giant kelp forests, leading to the alternative ecosystem state known as an urchin barren³⁷.

To characterize environmental context dependency in kelp forest interactions between these five species, we take three general steps (see Methods). First, we use empirical dynamic modeling causality tests called convergent cross-mapping³⁸ to construct a kelp forest species interaction network directly from time series data. Even though these common kelp forest species are all thought to interact, we tested that assumption with convergent cross mapping, which can separate correlation from causation³⁸.

Second, we use multivariate S-maps (sequential locally weighted global linear maps)^{15,39} to reconstruct the interactions between species for all of the causal links established in the previous step. S-maps reconstructs dynamic “attractors” by casting the abundances of causally-related species into state space. That is, for a set of causally-related species A , B , and C , a point in multivariate space $\{A_t, B_t, C_t\}$ can be plotted, using each species’ abundance at time t . The attractor is then created by tracing this multivariate trajectory forward in time for all t (FIG?). S-maps then computes sequential Jacobian matrices for each point along the attractor, where the elements of each matrix are the partial derivatives

116 between species. These estimated partial derivatives are our measure of species interactions.
 117 The last step is to investigate if and how species interactions varies with environmental context.
 118 Because multivariate S-maps are computed for every point along reconstructed attractors, we
 119 can extract distributions of interactions that can be related back to environmental context.
 120 We explore patterns of species interactions in relation to sea surface temperature, physical
 121 disturbance (measured by wave height), and three indices of low-frequency climate modes:
 122 the Multivariate ENSO Index, the Pacific Decadal Oscillation, and the North Pacific Gyre
 123 Oscillation^{40–42}.

124 Results and discussion

- 125 • CCM results and variable interaction network- centrality of *Macrocystis*
- 126 • Mean vs. variance in certain algal interactions?
- 127 • Bidirectional mean interactions (across two dimensions, A on B and B on A)?
- 128 • Frequency of positive vs. negative interactions? Across environmental gradients?

129 References

- 130 1. Connell, J. H. Diversity in Tropical Rain Forests and Coral Reefs. *Science* **199**, 1302–1310
 131 (1978).
- 132 2. Suttle, K. B., Thomsen, M. A. & Power, M. E. Species Interactions Reverse Grassland
 133 Responses to Changing Climate. *Science* **315**, 640–642 (2007).
- 134 3. Tilman, D. The ecological consequences of changes in biodiversity: a search for general
 135 principles. *Ecology* **80**, 1455–1474 (1999).
- 136 4. Berlow, E. L. Strong effects of weak interactions in ecological communities. *Nature* **398**,
 137 330–334 (1999).
- 138 5. Odadi, W. O., Karachi, M. K., Abdulrazak, S. A. & Young, T. P. African wild ungulates
 139 compete with or facilitate cattle depending on season. *Science* **333**, 1753–1755 (2011).
- 140 6. Pennings, S. C. & Silliman, B. R. Linking Biogeography and Community Ecology :
 141 Latitudinal Variation in Plant-Herbivore Interaction Strength. *Ecology* **86**, 2310–2319 (2005).
- 142 7. Menge, B. A., Berlow, E. L., Blanchette, C. A., Navarrete, S. A. & Yamada, B. The
 143 Keystone Species Concept : Variation in Interaction Strength in a Rocky Intertidal Habitat.
 144 **64**, 249–286 (1994).
- 145 8. Chamberlain, S. A., Bronstein, J. L. & Rudgers, J. A. How context dependent are species
 146 interactions? *Ecology Letters* **17**, 881–890 (2014).
- 147 9. Vaughn, K. J. & Young, T. P. Contingent Conclusions: Year of Initiation Influences
 148 Ecological Field Experiments, but Temporal Replication is Rare. *Restoration Ecology* **18**,

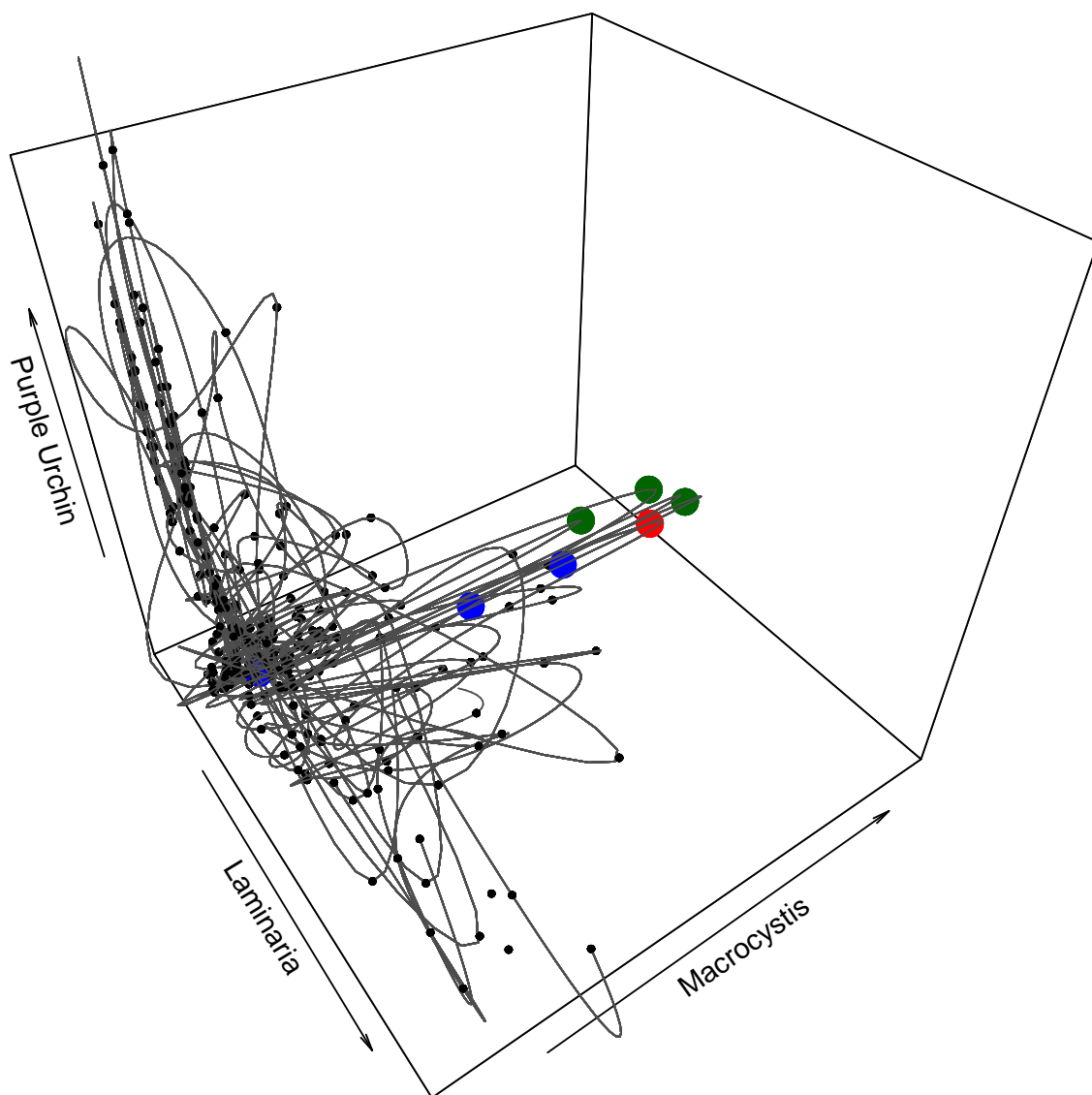


Figure 1: Example reconstructed dynamic attractor

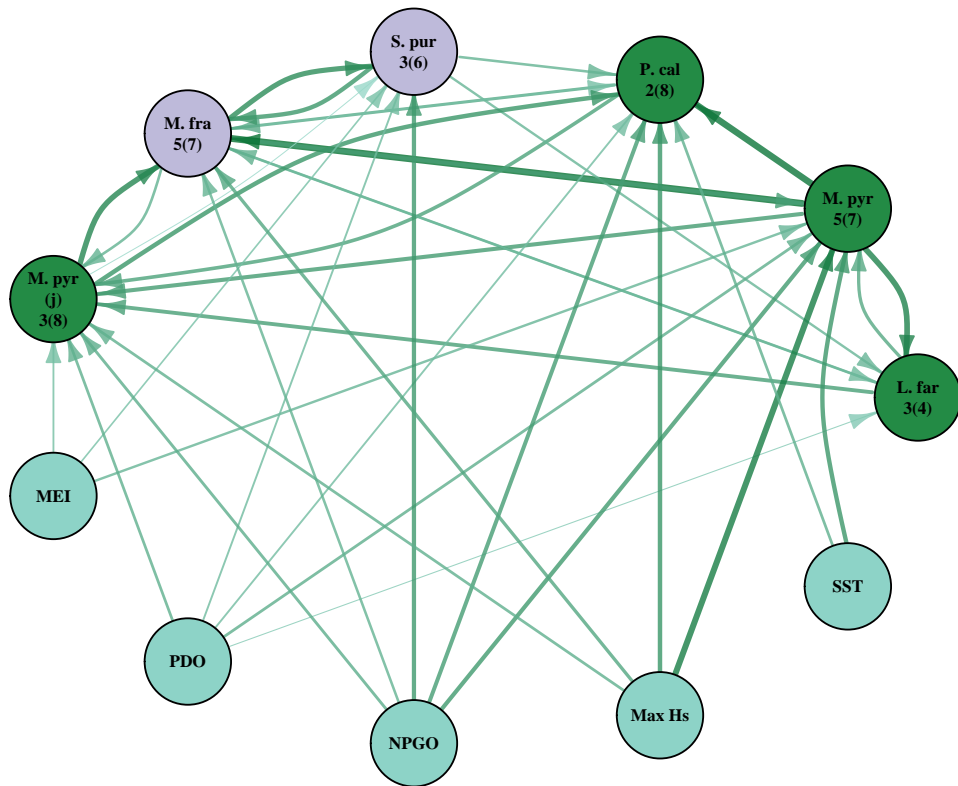


Figure 2: Reconstructed interaction web using results of convergent cross mapping

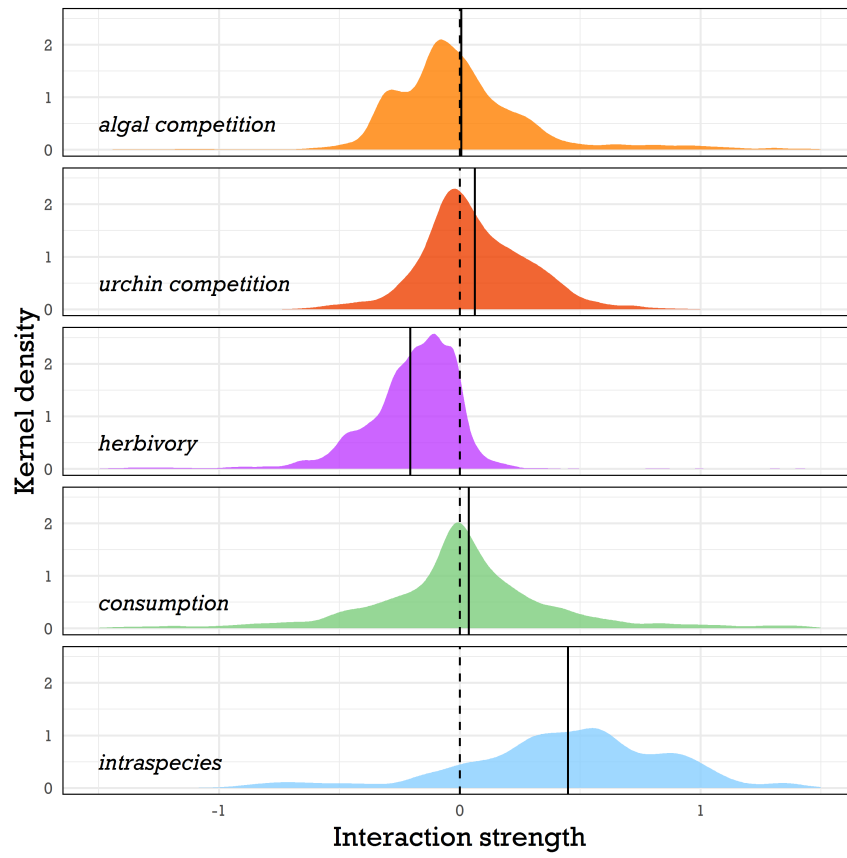


Figure 3: Distribution of estimated interaction by type

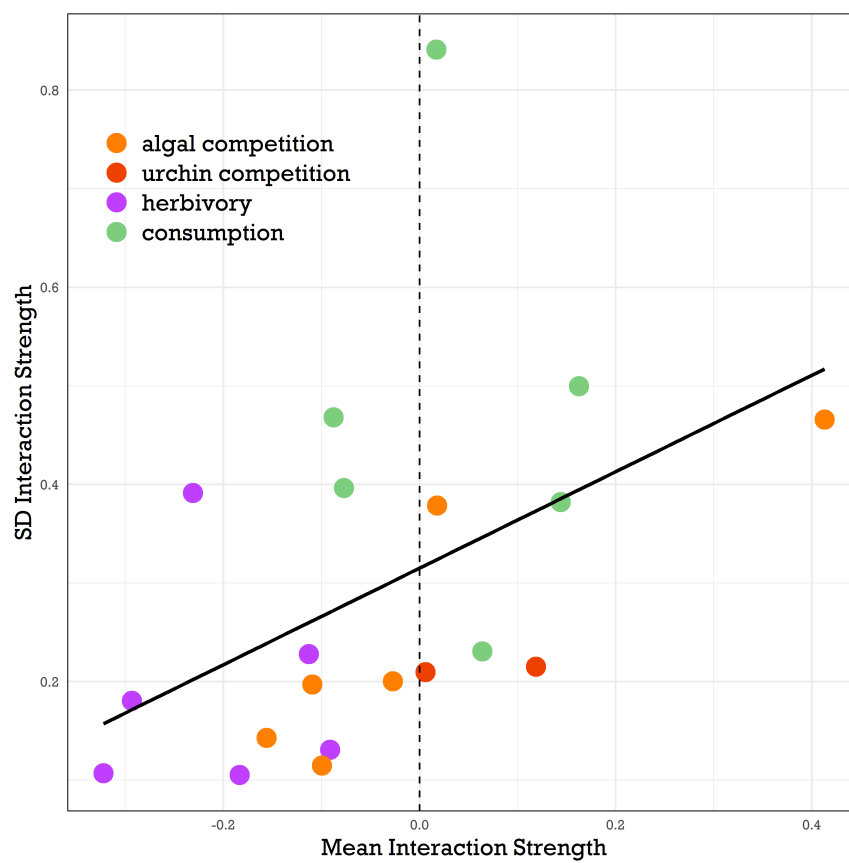


Figure 4: Mean and standard deviation of each estimated unidirectional species interaction

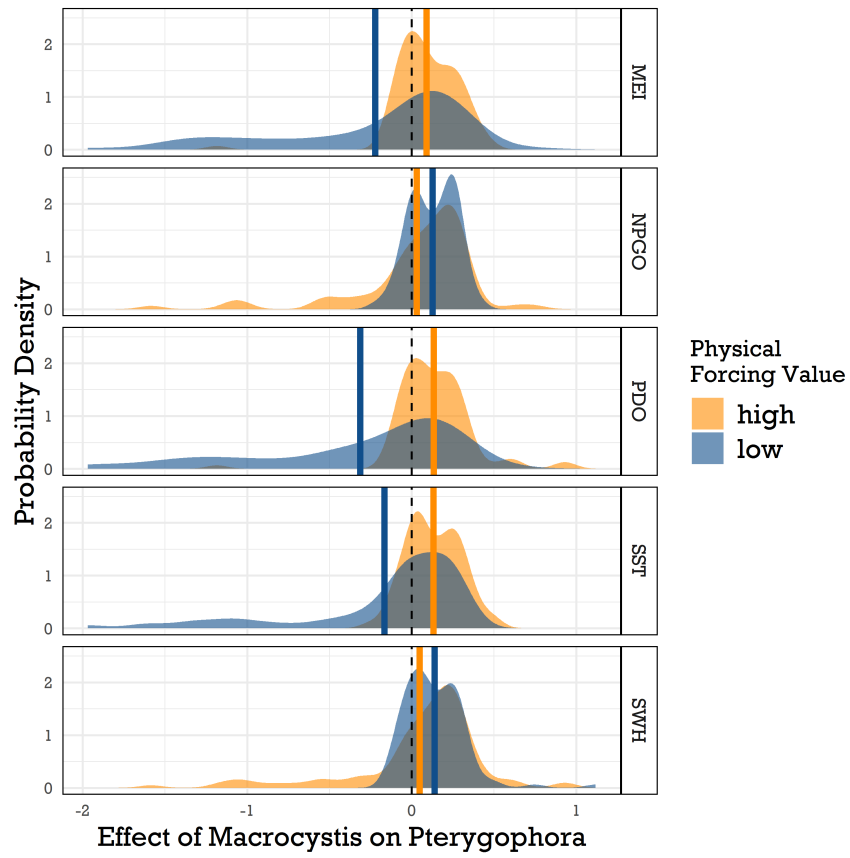


Figure 5: Macrocyctis effect on Pterygophora

149 59–64 (2010).

150 10. Lima, M., Ernest, S. K. M., Brown, J. H., Belgrano, A. & Stenseth, N. C. Chihuahuan
151 Desert Kangaroo Rats: Nonlinear Effects of Population Dynamics, Competition, and Rainfall.
152 *Ecology* **89**, 2594–2603 (2008).

153 11. Holzapfel, C. & Mahall, B. E. Bidirectional Facilitation and Interference between Shrubs
154 and Annuals in the Mojave Desert. *Ecology* **80**, 1747–1761 (1999).

155 12. Daskin, J. H. & Alford, R. A. Context-dependent symbioses and their potential roles
156 in wildlife diseases. *Proceedings of the Royal Society B: Biological Sciences* **279**, 1457–1465
157 (2012).

158 13. Glynn, P. W. Coral reef bleaching: Facts, hypotheses and implications. *Global Change*
159 *Biology* **2**, 495–509 (1996).

160 14. White, J. D., Sarnelle, O. & Hamilton, S. K. Unexpected population response to increasing
161 temperature in the context of a strong species interaction. *Ecological Applications* (2017).
162 doi:10.1002/eap.1558

163 15. Deyle, E. R., May, R. M., Munch, S. B. & Sugihara, G. Tracking and forecasting
164 ecosystem interactions in real time. *Proceedings of the Royal Society B: Biological Sciences*
165 **283**, 20152258 (2016).

166 16. Deyle, E. R. *et al.* Predicting climate effects on Pacific sardine. *Proceedings of the*
167 *National Academy of Sciences of the United States of America* **110**, 6430–6435 (2013).

168 17. Chang, C. W., Ushio, M. & Hsieh, C. hao. Empirical dynamic modeling for beginners.
169 *Ecological Research* 1–12 (2017). doi:10.1007/s11284-017-1469-9

170 18. Ye, H., Deyle, E. R., Gilarranz, L. J. & Sugihara, G. Distinguishing time-delayed causal
171 interactions using convergent cross mapping. *Scientific reports* **5**, 14750 (2015).

172 19. Foster, M. S. & Schiel, D. R. Ecology of giant kelp forests in California: a community
173 profile. *United States Fish and Wildlife Service Biological Report* **85**, 1–152 (1985).

174 20. Graham, M. H., Vásquez, J. A. & Buschmann, A. H. Global Ecology of the Giant Kelp
175 *Macrocystis* : From Ecotypes To Ecosystems. *Oceanography and Marine Biology* **45**, 39–88
176 (2007).

177 21. Teagle, H., Hawkins, S. J., Moore, P. J. & Smale, D. A. The role of kelp species as
178 biogenic habitat formers in coastal marine ecosystems. *Journal of Experimental Marine*
179 *Biology and Ecology* **492**, 81–98 (2017).

180 22. Estes, J. A. & Palmisano, J. F. Sea otters: their role in structuring nearshore communities.
181 **185**, 1058–1060 (1974).

182 23. Graham, M. *et al.* Population dynamics of giant kelp *Macrocystis pyrifera* along a wave
183 exposure gradient. *Marine Ecology Progress Series* **148**, 269–279 (1997).

184 24. Kvitek, R. G., Iampietro, P. J. & Bowlby, C. E. Sea Otters and Benthic Prey Communities
185 : a Direct Test of the Sea Otter As Keystone Predator in Washington State. *Marine Mammal*

- 186 *Science* **14**, 895–902 (1998).
- 187 25. Foster, M. S. & Schiel, D. R. Loss of predators and the collapse of southern California
188 kelp forests (?): Alternatives, explanations and generalizations. *Journal of Experimental*
189 *Marine Biology and Ecology* **393**, 59–70 (2010).
- 190 26. Reed, D. C. *et al.* Wave disturbance overwhelms top-down and bottom-up control of
191 primary production in California kelp forests. *Ecology* **92**, 2108–2116 (2011).
- 192 27. Reed, D. *et al.* Extreme warming challenges sentinel status of kelp forests as indicators
193 of climate change. *Nature Communications* **7**, 13757 (2016).
- 194 28. Parnell, P. E. *et al.* The response of giant kelp (*Macrocystis pyrifera*) in southern
195 California to low-frequency climate forcing. *Limnology and Oceanography* **55**, 2686–2702
196 (2010).
- 197 29. Byrnes, J. E. *et al.* Climate-driven increases in storm frequency simplify kelp forest food
198 webs. *Global Change Biology* **17**, 2513–2524 (2011).
- 199 30. Bell, T. W., Cavanaugh, K. C., Reed, D. C. & Siegel, D. A. Geographical variability in
200 the controls of giant kelp biomass dynamics. *Journal of Biogeography* **42**, 2010–2021 (2015).
- 201 31. Young, M. A. *et al.* Environmental controls on spatial patterns in the long-term
202 persistence of giant kelp in central California. *Ecology* **86**, 45–60 (2015).
- 203 32. Kenner, M. C. *et al.* A multi-decade time series of kelp forest community structure at
204 San Nicolas Island, California (USA). *Ecology* **94**, 2654–2654 (2013).
- 205 33. Foster, M. S. Organization of macroalgal assemblages in the Northeast Pacific: the
206 assumption of homogeneity and the illusion of generality. *Hydrobiologia* **192**, 21–33 (1990).
- 207 34. Dayton, P. K. *et al.* Patch dynamics and stability of some California USA kelp
208 communities. *Ecological Monographs* **54**, 253–290 (1984).
- 209 35. Dayton, P. K., Tegner, M. J., Edwards, P. B. & Riser, K. L. Temporal and spatial scales
210 of kelp demography: the role of oceanographic climate. *Ecological Monographs* **69**, 219–250
211 (1999).
- 212 36. Reed, D. C. & Foster, M. S. The effects of canopy shadings on algal recruitment and
213 growth in a giant kelp forest. *Ecology* **65**, 937–948 (1984).
- 214 37. Ling, S. *et al.* Global regime shift dynamics of catastrophic sea urchin overgrazing. *Phil.*
215 *Trans. R. Soc. B* **370**, 20130269 (2014).
- 216 38. Sugihara, G. *et al.* Detecting causality in complex ecosystems. *Science* **338**, 496–500
217 (2012).
- 218 39. Sugihara, G. Nonlinear forecasting for the classification of natural time series. *Philo-*
219 *sophical Transactions of the Royal Society of London Series A-Mathematical Physical and*
220 *Engineering Sciences* **348**, 477–495 (1994).
- 221 40. Wolter, K. & Timlin, M. S. El Niño/Southern Oscillation behaviour since 1871 as
222 diagnosed in an extended multivariate ENSO index (MEI.ext). *International Journal of*

- 223** *Climatology* **31**, 1074–1087 (2011).
- 224** 41. Mantua, N. J. & Hare, S. R. The Pacific Decadal Oscillation. **58**, 35–44 (2002).
- 225** 42. Di Lorenzo, E. *et al.* North Pacific Gyre Oscillation links ocean climate and ecosystem
- 226** change. *Geophysical Research Letters* **35**, 2–7 (2008).