

LETTERS

Distinguishing random environmental fluctuations from ecological catastrophes for the North Pacific Ocean

Chih-hao Hsieh¹, Sarah M. Glaser¹, Andrew J. Lucas¹ & George Sugihara¹

The prospect of rapid dynamic changes in the environment is a pressing concern that has profound management and public policy implications^{1,2}. Worries over sudden climate change and irreversible changes in ecosystems are rooted in the potential that nonlinear systems have for complex and 'pathological' behaviours^{1,2}. Nonlinear behaviours have been shown in model systems³ and in some natural systems^{1,4–8}, but their occurrence in large-scale marine environments remains controversial^{9,10}. Here we show that time series observations of key physical variables^{11–14} for the North Pacific Ocean that seem to show these behaviours are not deterministically nonlinear, and are best described as linear stochastic. In contrast, we find that time series for biological variables^{5,15–17} having similar properties exhibit a low-dimensional nonlinear signature. To our knowledge, this is the first direct test for nonlinearity in large-scale physical and biological data for the marine environment. These results address a continuing debate over the origin of rapid shifts in certain key marine observations as coming from essentially stochastic processes or from dominant nonlinear mechanisms^{1,9,10,18–20}. Our measurements suggest that large-scale marine ecosystems are dynamically nonlinear, and as such have the capacity for dramatic change in response to stochastic fluctuations in basin-scale physical states.

Recent effort to characterize the decadal-scale behaviour of North Pacific physical and biological phenomena has centred on the concept of 'regime shifts'^{18–21}. These regime shifts appear as quasi-stationary states in measured parameters, separated by periods of rapid transition²⁰. Although attention has been focused on the qualitative phenomenology of these shifts (that is, documenting the appearance of distinct regimes with rapid shifts between them), nowhere in the discussion has their dynamical origin been directly assessed. True regime shifts are not random features of the time series, but are formally associated with the ideas of nonlinear amplification⁷, alternative basins of attraction^{20,22}, multiple stable states², hysteresis and fold catastrophe^{1,23}, all of which require the underlying dynamics to be nonlinear in origin. For example, while it is quite clear that major changes occurred in the commonly measured North Pacific abiotic and biotic indices around 1976–77 (for example, patterns of sea surface temperature (SST), fisheries landings data, zooplankton abundance and community composition)^{18,21}, the nature of such changes remains elusive. Are such changes indicative of the operation of nonlinear dynamics or are they features of the data that might arise stochastically?

Some researchers (predominantly physical oceanographers) have suggested that apparent shifts observed in key physical variables are not singular (nonlinear transitional) events but instead represent normal statistical deviations^{9,10}. Insofar as similar features in marine physical observations can be reproduced stochastically as random

events¹⁰, it is not necessary to invoke complicated nonlinear mechanisms. In contrast, others (predominantly biologists) have been inclined to see rapid environmental shifts as a fundamentally nonlinear phenomenon with important ecological implications^{1,18,19}. They view the changes in populations and community structure that occur across putative regimes as being more than passive linear tracking of environmental variability. Rather, they see the rapid shifts in biological variables as an amplified response to environmental change pushing the system into different local basins of attraction or alternative states^{7,8,20}. Fold catastrophes are a special case for achieving alternative states that raise the possibility of hysteresis or non-symmetrical reversibility of ecosystem states (for example, where population crashes are easier to attain than recoveries)¹. Such instability and irreversibility have become a cautionary tale for environmental management and policy makers, bringing nonlinear phenomena to the fore.

A major weakness of the current debate is its focus on the statistical phenomenology of regime shifts. This approach examines the timing and magnitude of hypothesized shifts in the time series to see if they represent statistically distinct states separated by rapid transitions²⁰. Identifying these plateaus and transitions usually involves subjectivity at some level that is difficult to overcome (for example, specifying the timing of shifts). Techniques that promise solutions for this require too much data for the biological time series involved²⁰, and many of the approaches assume the existence of only two states—a simple but arbitrary assertion. It seems curious that although the phenomenon being debated is a nonlinear one, nowhere in the methodological debate is the question of nonlinearity explicitly examined. Insofar as it is the nonlinear basis of the putative shifts that give them their meaning, it should be illuminating to directly measure the observations to determine if they are in fact consistent with the necessary hypothesis of nonlinearity.

Here we test a suite of key physical and biological time series observations for the North Pacific basin. Our aim is not to examine particular events to see if they satisfy the statistical description of a regime; rather, we look at complete time series to see if the variations contained in the whole data series were nonlinear in origin.

We examine these data using established methods from nonlinear time series analysis that involve state space reconstruction with lagged coordinate embeddings (Takens' theorem)^{5,7,8,24}. To determine whether a time series reflects linear or nonlinear processes, we compare the out-of-sample forecast skill of a linear model versus an equivalent nonlinear model. This involves a two-step procedure: (1) we use simplex-projection⁵ to identify the best embedding dimension (the number of independent variables required to model the process)⁵ (Fig. 1), and (2) we use this embedding in the S-map procedure^{7,8,25,26} to assess the nonlinearity of the time series (Fig. 2). The method of S-maps relies on fitting a series of models

¹Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California 92093-0202, USA.

(from linear to nonlinear) where the degree of nonlinearity is controlled by a local weighting parameter θ . Improved out-of-sample forecast skill with increasingly nonlinear models (larger θ) indicates that the underlying dynamics were themselves nonlinear²⁵. The forecast protocol, which involves a blind evaluation of forecast skill, is a rigorous standard that avoids model over-fitting or arbitrary fits to the data (see Methods and Supplementary Information).

We analyse the key time series commonly associated with the North Pacific regime shift debate that have sufficient length for the methods to apply. Physical measurements include indices that collapse North Pacific basin-wide phenomena into single time series (for example, via empirical orthogonal functions), and coastal SST time series (Table 1). The Southern Oscillation Index (SOI)¹³ is widely used for tracking the state of the El Niño/Southern Oscillation, which is the leading source of North Pacific interannual climate variations. The North Pacific Index (NPI)¹² and the Pacific Decadal Oscillation Index (PDO)¹¹ track the leading patterns of North Pacific sea-level pressure and SST variability, respectively. We chose the three longest daily coastal SST time series in the eastern Pacific (Scripps Pier, Pacific Grove and Farallones Islands)¹⁴. These time series are highly correlated with basin scale indices while also reflecting strong local dynamics. This collection of data is broadly representative of the large-scale physical state of the North Pacific basin over the twentieth century (Table 1).

Biological data analysed include annual commercial landings for Pacific salmon and trout (1938–2000)¹⁷, the weekly Scripps Pier diatom record (1920–39)⁵ and the California Cooperative Oceanic Fisheries Investigation (CalCOFI) time series for copepods¹⁶ and larval fishes¹⁵ (Table 2). In order to generate time series of sufficient length, composite CalCOFI series were created and then analysed (see Methods). These data have been part of the regime-shift literature, and form a representative collection for this analysis.

All of the major physical indices in Table 1 possess characteristics consistent with high dimensional or stochastic processes (for example, Fig. 1c). This simple characterization is true from weekly to annual timescales. They are well modelled as linear autoregressive (AR) processes of high order, showing no significant forecast

improvement as the S-maps are tuned towards nonlinear solutions (for example, Fig. 2c).

In contrast, all of the biological data in Table 2 (both simple and composites) consistently exhibit nonlinear signatures. These series were best rendered in relatively low embedding dimensions (for example, Fig. 1d), and without exception showed improvement in out-of-sample forecast skill as the S-maps were tuned towards increasingly nonlinear solutions (for example, Fig. 2d). Although not all $\Delta\rho$ (change in forecast skill measured as a difference in the correlation coefficients) in Table 2 are significant, all show improvement, which is significant for the biological ensemble (binomial probability <0.001).

The fundamentally different way that regime shifts in the North Pacific have been viewed by physical oceanographers and biological oceanographers coincides with the different character of their respective time series. The physical time series do not appear to arise from low dimensional nonlinear processes, and the irregular features that have been hypothesized to indicate nonlinear deterministic regimes are better characterized as stochastic. At first sight, they do not show the required nonlinearity to allow the interpretation that the shift-like features are more than random events.

It is perhaps not surprising that some of the physical indices appear to be linear-stochastic insofar as they are constructed from linear combinations of observations. As linear aggregates (that is, averages or linear orthogonal functions), these indices may mask possible nonlinearities in individual physical measurements. For example, although station-based barometric pressures in temperate latitudes are highly nonlinear, it has been shown that this nonlinearity can vanish in larger spatial aggregates⁶. The dynamics of measles in Great Britain also exhibit this behaviour: individual cities display highly nonlinear infection rates, but these deterministic nonlinear effects appear as noise when the individual cities are aggregated into a single time series for the country as a whole²⁴. Thus, simply because the PDO, NPI and SOI do not show nonlinear characteristics does

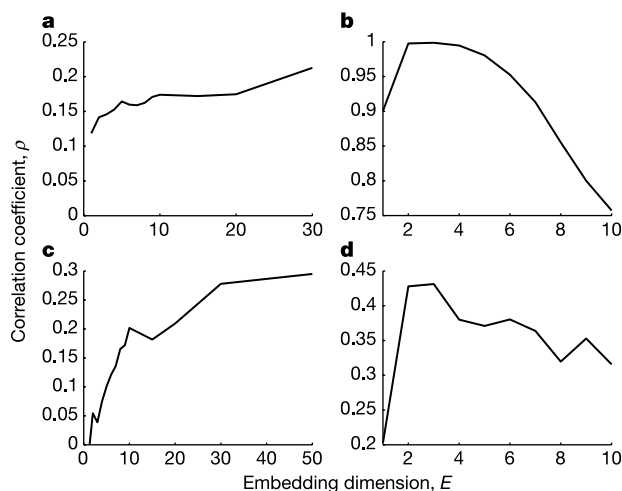


Figure 1 | Examples of the simplex projection method. **a, b**, Model time series; red noise³⁰ (**a**) and the nonlinear tent map⁵ (**b**). **c, d**, Natural time series; Scripps Pier SST (**c**) and Scripps Pier diatoms (**d**). Panels **b** and **c** both show increasing skill (higher correlation coefficients, ρ) at higher embedding dimensions (E), which indicates that the underlying processes are high-dimensional (random for all practical purposes). In contrast, the chaotic tent map (**b**) and the Scripps Pier diatom time series (**d**) both show optimal skill (best ρ) with low-dimensional embeddings.

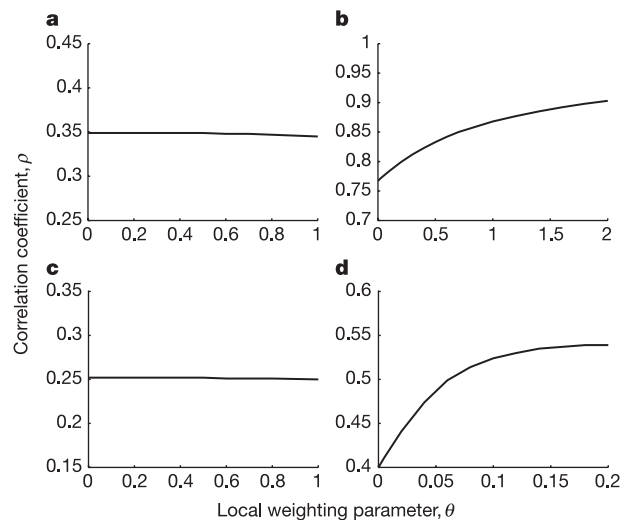


Figure 2 | Examples of the S-map method for the four time series from Fig. 1. The model generated red noise (**a**) and the Scripps Pier SST time series (**c**) show no improvement in forecast skill as S-maps are tuned towards increasingly local or nonlinear solutions (by increasing θ). Consequently, these time series do not show any indication of nonlinearity, and display all the hallmarks of a stochastic (high dimensional) linear generating mechanism. In contrast, the chaotic tent map (**b**) and the Scripps Pier diatom time series (**d**) both show increased skill as the S-map is tuned towards nonlinear solutions.

Table 1 | Analyses of key North Pacific physical time series

Timescale	Physical data	Best E	Best θ	Best ρ	$\Delta\rho$	Nonlinear?	N	P -value
Weekly	SIO SST	20 +	0	0.252	0	No	4,226	1
Monthly	SIO SST	20 +	0	0.787	0	No	984	1
Monthly	Pacific Grove SST	20 +	0	0.524	0	No	945	1
Monthly	Farallones SST	20 +	0	0.486	0	No	764	1
Monthly	PDO	20 +	0	0.255	0	No	1,248	1
Monthly	NPI	20 +	0	0.636	0	No	1,260	1
Monthly	SOI	20 +	0	0.380	0	No	852	1
Quarterly	SIO SST	20 +	0	0.958	0	No	328	1
Quarterly	PDO	20 +	0	0.376	0	No	416	1
Quarterly	NPI	20 +	0	0.497	0	No	420	1
Quarterly	SOI	20 +	0	0.328	0	No	284	1
Annual	SIO SST, composite	20	0	0.770	0	No	984	1
Annual	PDO, composite	10	0	0.547	0	No	1,248	1
Annual	NPI, composite	16	0	0.674	0	No	1,260	1
Annual	SOI, composite	13	0	0.640	0	No	852	1

E , embedding dimension; θ , nonlinear tuning parameter. Best ρ (θ_{best}) indicates forecast skill (correlation coefficient), obtained using $\Delta\rho = (\rho \text{ at } \theta_{\text{best}}) - (\rho \text{ at } \theta_0)$. A positive $\Delta\rho$ measures the difference in forecasting skill of the best nonlinear model (that is, where $\theta > 0$) as compared to the global linear model (that is, where $\theta = 0$). Thus, $\Delta\rho = \rho_{\text{best}} - \rho_0$. Data were analysed at various decimations (resolution in time scale). The PDO, NPI and SOI indices have monthly resolution. Quarterly data are averages of those monthly values. Daily coastal SST anomalies (daily data minus the year-day average over the entire record) were averaged to form weekly, monthly and quarterly time series. Owing to the paucity of data at the annual scale, we constructed composite time series by concatenating monthly values (all Januaries, all Februaries, ... all Decembers). These data are best embedded in high dimensions and show no improvement in forecast skill as the S-maps are tuned towards nonlinear solutions. As such, on timescales relevant to the regime shift debate, these physical oceanographic time series are unanimous in showing the hallmarks of linear stochastic generating mechanisms.

not preclude the possibility of nonlinear dynamics operating on finer scales. Nonetheless, these indices have been at the heart of the regime-shift debate, and we show their features to be stochastic.

More significantly, the various SST records, which are primary (non-aggregated) measurements, show the temperature shift phenomenon to be stochastic. That is, even simple SST measurements, which are emblematic of the physical regime shift phenomenon²¹, do not indicate that temperature shifts have low dimensional nonlinear modes. Rather, they are high dimensional, and consequently they will be more difficult to model mechanistically in a way that replicates the phenomenological forecasting skill of a high degree AR model. This is a fundamental constraint on modelling efforts that we demonstrate empirically here. These findings resonate with the conception of the ocean as a linear red-noise integrator of atmospheric phenomena, a hypothesis first advanced in the 1970s²⁷. However, it is clear that not all physical environmental time series are, by definition, high dimensional and stochastic; for example, analysis of meteorological observations shows strong low dimensional non-linearity in the atmosphere, indicative of the potential for catastrophic climate change^{6,28}. Furthermore, although true regime shift

behaviour did not appear in the North Pacific physical oceanographic data that we tested, this obviously does not preclude the possibility of such behaviour having occurred further into the past or arising in the future. It simply did not occur in the last century, where the alleged shifts are indistinguishable from random events.

Biological time series appear to have dynamics that are fundamentally different from those of the physical variables associated with regime shifts. The relatively skilful out-of-sample forecasts at low embedding dimensions (even in composites) are consistent with the view that biological populations are nonlinear stochastic²⁵. The full set of dynamics consists of a low dimensional, nonlinear, noise-free skeleton convolved with stochastic events acting on that skeleton to define the invariant measure²⁵. Thus, the biological populations are not simply tracking the environment. Rather, our results support the hypothesis that ecological dynamics in the oceans can be characterized by nonlinear amplification of stochastic physical forcing by biological processes^{7,8}. Regardless of interpretation, the biological time series for the North Pacific basin have the necessary signature for regimes to be actual nonlinear features of the data as opposed to randomly generated ones. This result for landings data and larval fish

Table 2 | Analyses of key North Pacific biological time series

Timescale	Biological data	Best E	Best θ	Best ρ	$\Delta\rho$	Nonlinear?	N	P -value
Weekly	Scripps Pier diatom	3	0.3	0.539	0.139*	Yes	830	<0.01
Monthly	Scripps Pier diatom	4	0.05	0.542	0.083	Yes	206	0.134
Quarterly	CalCOFI coastal larval fish	7	1.6	0.715	0.031*	Yes	3,220	<0.01
Quarterly	CalCOFI coastal-oceanic larval fish	8	0.6	0.744	0.017	Yes	1,400	0.164
Quarterly	CalCOFI oceanic larval fish	8	1.4	0.678	0.020*	Yes	4,760	0.040
Biannual	CalCOFI copepod	6	1.2	0.677	0.027	Yes	1,736	0.078
Annual	CalCOFI copepod	5	0.4	0.566	0.015	Yes	868	0.322
Annual	CalCOFI coastal larval fish	5	0.6	0.603	0.060*	Yes	805	0.038
Annual	CalCOFI coastal-oceanic larval fish	4	0.2	0.502	0.092	Yes	350	0.063
Annual	CalCOFI oceanic larval fish	7	0.6	0.576	0.017	Yes	1,190	0.273
Annual	Chinook salmon	3	0.4	0.448	0.440*	Yes	63	<0.01
Annual	Coho salmon	7	0.3	0.656	0.117	Yes	63	0.213
Annual	Chum salmon	4	0.18	0.634	0.767*	Yes	63	<0.01
Annual	Steelhead trout	3	0.2	0.281	0.272	Yes	63	0.118
Annual	Sockeye salmon	4	0.7	0.484	0.168	Yes	63	0.168
Annual	Composite salmon and trout	4	0.3	0.464	0.078	Yes	315	0.148

Parameters as in Table 1. Monthly diatom data are averages of weekly samples. Quarterly larval fish data represent four cruises per year, and biannual copepod data represent two cruises per year. Annual larval fish data are averages of the quarterly samples, and annual copepod data are averages of biannual samples. Commercial fisheries landing data are annual totals. These population data (described in text) are best embedded in low dimensions, and show improvement in forecast skill as the S-maps are tuned towards increasingly nonlinear solutions. Even where $\Delta\rho$ is not significant (asterisk indicates significant at the 0.05 level), the nonlinear model ($\theta > 0$) still outperforms the global linear model ($\theta = 0$). As such, these biological time series all show the hallmarks of nonlinear generating mechanisms.

abundance should call into question static conceptions of maximum sustainable yield and the use of fixed exploitation quotas for managing commercial fisheries². The potential for rapid and unpredictable shifts in response to environmental stochasticity and human impact supports a precautionary management approach for marine ecosystems¹.

METHODS

Forecasting techniques. To determine whether a time series reflects linear or nonlinear processes, we compare the out-of-sample forecast skill of a linear model versus an equivalent nonlinear model. This involves using lag coordinate embeddings in a two-step procedure: (1) we use simplex-projection³ to identify the best embedding dimension, and (2) we use this embedding in the S-map procedure^{7,8,25} to assess the nonlinearity of the time series. In both cases, model performance is evaluated out-of-sample with the time series divided into equal halves. The first half (library set) is used to build the model, while the second half (prediction set) is reserved to judge the out-of-sample performance of model forecasts.

Simplex projection is a nearest-neighbour forecasting algorithm that involves tracking the forward evolution of nearby points in a lag coordinate embedding⁵. For this study, an exploratory series of embedding dimensions (E) ranging from 1 to 20 (or higher) are used to evaluate the prediction, and the best E is chosen on the basis of prediction skill (Fig. 1). This embedding is then used in the S-map procedure. S-maps are an extension of standard linear autoregressive models in which the coefficients depend on the location of the predictee in an E -dimensional embedding^{5,7,8,25,26}. (The predictee is the current state of the system from which the prediction is being made.) New coefficients are recalculated by singular value decomposition for each new prediction. In this calculation, the weight given to each vector in the library depends on how close that vector is to the predictee. The extent of this weighting is determined by the parameter θ . When $\theta = 0$ we obtain a global (single) linear map, and increasing values of θ in the S-map give increasingly local or nonlinear mappings²⁶ (Fig. 2). A detailed account of these methods is given in Supplementary Information.

All analyses were done both on raw values and on first differenced data to minimize the possibility of masking the nonlinear signal by trivial autocorrelation and to account for possible non-stationary trends in the data⁵. As no qualitative difference was found between analyses, we report here only the more conservative first differenced results.

Composite technique. The CalCOFI data represent one of the most comprehensive oceanographic monitoring programmes in the Pacific. Although hundreds of individual species are sampled, each time series alone is too short to apply the forecasting methods directly, particularly on the annual scale. For example, each larval fish time series contained only 35 annual data points (140 quarterly observations from 1951–2002, with a gap in quarterly collection and identification between 1967 and 1983). To accommodate the individual paucity of points due to these gaps, we generate composite time series²⁶ based on the known principal distributions of fish species^{15,29}: coastal (23 taxa), coastal-oceanic (10 taxa), and oceanic groups (34 taxa). To minimize the number of gaps in the copepod data, only time series from 1951–66 and 1985–99 were used (for a total of 31 annual data points). Thus, we could only use copepod time series for the 28 taxa that occurred most frequently during the sampling period (at least 20 of 31 years). The copepods are treated as a single equivalence class, given the lack of an unambiguous separation of species by region. However, the results are unaffected when predominantly northern and predominantly southern species are treated provisionally as separate groups.

Individual time series are normalized to have unit mean and variance, and combined by equivalence class to produce composite time series²⁶. This composite S-map procedure involves random combination of time series within each equivalence class (connecting individual time series end-to-end in different order to give different library/predictee combinations). The procedure is repeated 100 times or until all combinations are exhausted, and the average of these results for the CalCOFI data are reported in Table 2. The gaps and seams between time series are accounted for by discarding all vectors that traverse a gap or seam²⁶. As a null test for the CalCOFI composites, we applied the procedure to null versions of each of the composite equivalence classes (composite time series with phases randomized) and as expected, obtained consistent linear signatures. By contrast, nonlinear signatures are obtained for the CalCOFI data even when the library and prediction halves are no longer randomly assigned, but are systematically chosen to be most different from each other (that is, with library and prediction sets each consisting of individual species whose time series covary most positively). This yields library sets of similar species that are most dissimilar to the prediction sets. In addition to the fact that all of the data in this study are normalized and first differenced, this additional test eliminates the remote

possibility of producing a nonlinear artefact by combining heterogeneous data sets symmetrically into the library and prediction sets.

Physical variables required compositing at the annual scale only. The library vector comprises all January values from the first half of the time series (here ~1900–50) and so forth until December. The prediction vector is likewise constructed from the second half of the time series (here ~1951–2000).

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Supplementary Information is linked to the online version of the paper at www.nature.com/nature.

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