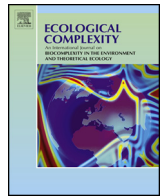




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Original Research Article

# Measuring complexity to infer changes in the dynamics of ecological systems under stress

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### ABSTRACT

Despite advances in our mechanistic understanding of ecological processes, the inherent complexity of real-world ecosystems still limits our ability in predicting ecological dynamics especially in the face of on-going environmental stress. Developing a model is frequently challenged by structure uncertainty, unknown parameters, and limited data for exploring out-of-sample predictions. One way to address this challenge is to look for patterns in the data themselves in order to infer the underlying processes of an ecological system rather than to build system-specific models. For example, it has been recently suggested that statistical changes in ecological dynamics can be used to infer changes in the stability of ecosystems as they approach tipping points. For computer scientists such inference is similar to the notion of a Turing machine: a computational device that could execute a program (the process) to produce the observed data (the pattern). Here, we make use of such basic computational ideas introduced by Alan Turing to recognize changing patterns in ecological dynamics in ecosystems under stress. To do this, we use the concept of Kolmogorov algorithmic complexity that is a measure of randomness. In particular, we estimate an approximation to Kolmogorov complexity based on the Block Decomposition Method (BDM). We apply BDM to identify changes in complexity in simulated time-series and spatial datasets from ecosystems that experience different types of ecological transitions. We find that in all cases,  $K_{BDM}$  complexity decreased before all ecological transitions both in time-series and spatial datasets. These trends indicate that loss of stability in the ecological models we explored is characterized by loss of complexity and the emergence of a regular and computable underlying structure. Our results suggest that Kolmogorov complexity may serve as tool for revealing changes in the dynamics of ecosystems close to ecological transitions.

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## 1. Introduction

When Alan Turing was cracking intercepted coded messages from the Nazis during World War II (Copeland, 2004), he probably could not imagine that his computational breakthroughs could be used for identifying changes in patterns of ecological data. Turing was trying to recognize regularities in the coded messages of Nazi Germans and come up with a “program” that would back-transform the messages to their decoded content. This “program” is similar to what Turing developed after the war into what is called a *Turing machine*. Turing machines are abstract computational

devices that can execute simple rules that represent a program. Once applied to some data (like the coded messages of Nazi Germans), Turing machines will reveal their real (computed) content. Indeed, the idea that there exists a program that can produce an observed pattern is powerful and is central in the science of algorithms and computational problems (Kolmogorov, 1965).

In a somewhat similar way, ecologists have been attempting to link pattern (the “data”) to process (the “program”) when studying ecological systems. A classical example is distinguishing stochasticity from deterministic chaos in population dynamics. Are the patterns in the dynamics of fish stock populations a stochastic trajectory around an equilibrium state, or do the patterns hold the signature of a well-defined chaotic attractor that looks random but in fact it is completely deterministic? Are the boom and bust dynamics of sardine and anchovies populations off the coast of

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Chile (Luch-Belda et al., 1989) driven by external environmental forces or by inherent feedbacks between populations and their competitors? Of course, such divides are oversimplifications. Ecologists have considerably improved their understanding in explaining such observed patterns by recognizing that it is a mix of dynamical processes and environmental stochasticity that shapes the trajectories of populations and ecological systems in general. However, our mechanistic understanding is still incomplete (Beckage et al., 2011), uncertainty in the parameters or in the functional relationships used in the models we develop remains high (Evans et al., 2013), and our ability in predicting ecological dynamics in the face of environmental stress is limited (Schindler and Hilborn, 2015).

Still, there is an increasing need in developing a more predictive ecological science that moves from explanatory to anticipatory predictions (Mouquet et al., 2015). This perspective appears to be facilitated by a rise in the availability and collection of data (Evans et al., 2013), together with the development of algorithmic models that introduce a machine learning approach contrary to traditional statistical modeling (Breiman, 2001). Such an approach, for instance, would look for patterns in the data themselves in order to identify changes in the underlying processes of an ecosystem. Nonetheless, despite the daunting task of building predictive mechanistic models, new model building and model selection techniques have been developed to reduce model uncertainty and optimize parameter selection (like, for example, by using regression trees in model analyses (Eynaud et al., 2013)). Clearly, a combination of approaches is probably the best strategy depending on the specifics of the ecological system in question.

One such approach studies how statistical changes in ecological dynamics can be used to infer changes in the stability of ecosystems under stress (Scheffer et al., 2015). These changes reflect loss of stability when environmental conditions push ecosystems across local bifurcation points. Bifurcation points are thresholds where the dynamics of a system change dramatically (Kuznetsov, 1995). Typical local bifurcations in ecological models are the transition to population extinction through a transcritical bifurcation (Lotka, 1925), the onset of oscillations in predator–prey models through a Hopf–bifurcation (Rosenzweig and MacArthur, 1963), or the abrupt shift to resource overexploitation through a fold bifurcation (Noy-Meir, 1975). This latter case of sudden discontinuous shifts towards new states is also termed a tipping point (Lenton et al., 2007). Strikingly, prior to all these local bifurcations, ecosystem dynamics become slow in responding to disturbances (Wissel, 1984; Strogatz, 1994). This slowing down effect leads to a decrease in recovery rate (van Nes and Scheffer, 2007), an increase in variance (Carpenter and Brock, 2006), and a rise in autocorrelation (Held and Kleinen, 2004). These statistical changes can be found across different systems (Scheffer et al., 2012), and they can be detected both in time-series (Dakos et al., 2012a) and in spatial data (Kéfi et al., 2014). Nonetheless, their operationalization for anticipating the risk of tipping points is still challenging (Dakos et al., 2015; Scheffer et al., 2015), as there are limitations in their performance. The predictability of tipping points is statistically challenging (Zhang et al., 2015), as these indicators are highly sensitive to, among others, the presence of noise, the size of the available data, the type of model used, or the type of ecological dynamics (e.g. Perretti and Munch, 2012; Dakos et al., 2012b; Boettiger and Hastings, 2012; Hastings and Wysham, 2010; Zhang et al., 2015).

Thus, other approaches have also been proposed for identifying changes in ecosystem dynamics in the vicinity to tipping points. Some are inspired from network theory. Constructing interaction networks based on cross-correlations between spatially monitored time-series (Viebahn and Dijkstra, 2014) – like vegetation dynamics at different locations in the landscape – can be used

to explore how network metrics (e.g. assortativity, clustering, or degree distributions) change when ecosystems approach a transition to desertification (Tirabassi et al., 2014). Similar network properties have been recently used to detect the loss of cooperation in evolving model communities (Cavaliere et al., 2016). One can also quantify changes in the statistical properties of recurrence networks (Marwan et al., 2009) that are derived by reconstructing the geometry of the attractor of a dynamical system using recurrence plots (Eckmann et al., 2007). Alternatively, visibility graphs can transform a time-series into a network (Lacasa et al., 2008) whose properties can again be used to distinguish different dynamical systems (Elsner et al., 2009). Other approaches are based on information theory. Mayer et al. (2006) showed how the level of disorder in a system measured by Fisher Information can be associated with different dynamical states in an ecosystem.

Here, we use the basic computational idea introduced by Alan Turing to test whether changing patterns in ecosystem dynamics are related to changes in ecosystem stability and ecological transitions. To do this, we use the concept of Kolmogorov complexity that is a measure of randomness (Kolmogorov, 1965). We estimate an approximation to Kolmogorov complexity in time-series and spatial datasets along gradually changing environmental conditions that lead to ecological transitions across different dynamical attractors.

The approximation to Kolmogorov complexity that we use in this paper is suitable for small size data and it has been applied to several fields (Soler-Toscano et al., 2014), but not yet to ecology. For example, this approximation to Kolmogorov complexity was used to investigate biases related to the human conception of randomness; for example the cognitive ability to generate pseudo-random sequences of events. Gauvrit et al. (2013) found a slight progression of Kolmogorov complexity with age in children who were asked to imagine a random sequence of 8 coin tosses, showing that algorithmic complexity approximates our subjective notion of randomness. Moreover, Kolmogorov complexity has been used to characterize the state of consciousness in brain-damaged individuals (Casali et al., 2013), brain activity patterns in response to different stimuli (Boly et al., 2015), or even the structure of natural and social networks (Zenil et al., 2014).

The paper is structured as follows. In Section 2, we introduce the notion of Turing machines, define Kolmogorov complexity, and explain how we approximate Kolmogorov complexity using the Block Decomposition Method (BDM). Section 3 describes the simulated time-series and spatial ecological data we used as case studies, whereas Section 4 summarizes how we analyzed the data to compute Kolmogorov complexity. We present our results in Section 5, and discuss them in Section 6.

## 2. Quantifying complexity: Turing machines, Kolmogorov complexity, and the Block Decomposition Method (BDM)

### 2.1. Turing machines

Turing machines are abstract computational devices, capable of executing simple rules that form a program. They were introduced by Turing (1937) as a mechanism to investigate formal properties of computational problems. Universal Turing machines are central in Algorithmic Information Theory (Solomonoff, 1964a,b; Kolmogorov, 1965; Chaitin, 1975). A universal Turing machine  $M$  is a programmable device (like electronic computers) that can solve every computable problem provided that an appropriate program is given as input together with the data the program is applied to.

Turing machines have a *head* (processor) and a *tape* (memory) divided in discrete *cells*. The head can read and write symbols. There is a finite number of states in which the head can be. These states are different for each machine. At each computational step,

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