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Emergent and divergent resilience behavior in catastrophic shift systems

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ABSTRACT

Resilience in dynamic ecological systems has been intuitively associated with the ability to withstand disturbances in system drivers represented as shocks. Typically shocks are characterized as instantaneous, and isolated non-interacting events with the system dynamics corresponding to a fixed potential well. However, ecological systems are subject to continuous variation in environmental drivers such as rainfall, temperature, etc. and these interact with the ecosystem dynamics to alter the potential well. These variations are typically represented as a stochastic process. Furthermore, with climate change, the stochastic characteristics of the environmental drivers also change, thereby impacting the well dynamics. To characterize the resilience behavior under continuous variation in system drivers, and contrast it with that subject to instantaneous shock in system drivers, we employ the canonical catastrophic shift system as an example, and demonstrate emergent and contrasting divergent resilience behavior of the measures as the properties of the system-driver couple change. These behaviors include variability induced stabilization or enhancement of dynamic regimes, regions of sensitivity to dynamic regime transitions and existence of trap or escape regions. Furthermore, we introduce the concept of iso-resilience curves which are employed to design travel paths in resilience landscapes. These results provide valuable insights for managing resilience attributes associated with dynamic regime transitions in catastrophic shift systems under instantaneous shock and continuous variability in system drivers.

1. Introduction

Catastrophic shift systems have been used as a model to explain a range of phenomenon from lake eutrophication (Carpenter et al., 2001; Dent et al., 2002), shrub grass transition (Carpenter et al., 2001; Scheffer et al., 2001), algal overgrowth in corals (Bellwood et al., 2004; Cote and Darling, 2010), insect outbreak dynamics (Strogatz, 1994) and others (Folke et al., 2004). The ubiquitous characteristics that these phenomena share are bi-stability, abrupt switching between alternate dynamic regimes, and hysteresis (Carpenter et al., 2001; Scheffer et al., 2001; Folke et al., 2004; Holling, 1996; Scheffer and Carpenter, 2003; Walker et al., 2004). Bi-stability implies that the long-term dynamics converges to one of two stable points depending on the initial condition. The set of all initial states that converge to a specific stable point is referred to as its basin or domain of attraction (DOA). When the system is stochastic in nature, then the deterministic concept of DOA is replaced by the probabilistic concept of dynamic regime (Scheffer and Carpenter, 2003; Brand and Jax, 2007). Each DOA or dynamic regime is typically associated with its unique characteristic dynamics, processes, and feedbacks, such as turbid versus clear lake, shrub versus grass dominated landscape, etc. (Scheffer et al., 2001). These systems have the capacity to switch to the alternate DOA or dynamic regime through a sudden or rapid transition, when system parameters, typically under the influence of external stress such as climate change, cross a critical threshold. More importantly, they exhibit a hysteresis effect, where the new dynamic regimes are sustained even after the removal of the stressor that caused the transition.

Resilience is broadly understood as the ability to withstand a change such that the dynamical behavior remains relatively unaffected (Folke et al., 2004; Holling, 1996, 1973; Turner, 2010). The concept of resilience has also been associated with other related and often overlapping concepts such as vulnerability, adaptability, persistence, robustness, resistance, redundancy, stability, recovery, ability to self organize, transformability, flexibility, and ability to learn (Carpenter et al., 2001; Cote and Darling, 2010; Folke et al., 2004; Brand and Jax, 2007). Resilience also holds one of the key wedges in sustainability science (Carpenter et al., 2001; Cote and Darling, 2010; Brand and Jax, 2007; Perrings, 2006) and is increasingly being used for developing strategies to mitigate climate change (Cote and Darling, 2010; Folke et al., 2004; Janssen et al.,

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2006; Turner et al., 2006). Climate scientists have predicted changes in both the mean and the extremes in future climate forcings due to anthropogenic climate change (Field et al., 2012; Solomon et al., 2007). Increases in climate variability, and occurrence of extreme events such as temperature extremes in the form of heat and cold waves (Schar et al., 2004; Stott et al., 2004), increased occurrences of droughts and floods (Pall et al., 2011; Timmermann et al., 2011), increased frequency of hails (Mahoney et al., 2012), etc. can have significant impact on ecosystem processes such as vegetation growth and mortality (Hirota et al., 2012), occurrence of fires (Hirota et al., 2012), patterns of herbivory (Hamilton et al., 2005), etc. Hence, climate change can alter ecosystem behavior by: (i) directly changing the system parameters; and (ii) altering other aspects of system driver such as frequency, intensity, variability and asymmetric bias (Kumar, 2013).

An understanding of the concept of resilience helps us to answer questions such as how does a complex system absorb and respond to unexpected shock or variations in drivers (Cumming et al., 2005); what aspects of the complex systems are prone to behavioral changes under such a shock or variability (Folke et al., 2004; Brand and Jax, 2007); what type and strength of shock or variability in the driver does it take to cause behavioral changes in particular aspects of a complex system (Carpenter et al., 2001); which direction should our efforts be invested to prevent dynamic regime transitions (Cote and Darling, 2010; Holmgren and Scheffer, 2001), etc. In this context, the space and time scales at which we analyze the problem play a significant role in the formulation of resilience measures (Carpenter et al., 2001). We define resilience as the ability of a system's DOA or dynamic regime to maintain its structure, process and feedbacks when subject to shock or variation in drivers at a particular spatial and time scale of interest. Resilience can thus be interpreted as a higher order description of system dynamics (Brand and Jax, 2007; Anderies et al., 2006; Folke, 2006) that can capture characteristics of emergent behavior such as catastrophic shifts, hysteresis, dynamic regime change, etc. for which simple space and time derivative based equilibrium and stability analysis are not suitable (Holling, 1973).

Two of the most commonly used resilience attributes are 'engineering resilience' and 'ecological resilience' (Holling, 1996; Gunderson, 2009). While engineering resilience is defined as the rate at which the system recovers to the stable state following an isolated shock in the system driver (Holling, 1973, 1996; Folke et al., 2004), ecological resilience is defined as the amount of shock that a system can withstand without a change in the dynamic regime (Gunderson, 2009; Tilman and Downing, 1994). More recently, there have been efforts to include other resilience attributes such as 'latitude', 'precariousness' and 'resistance' (Folke et al., 2004; Walker et al., 2004; Brand and Jax, 2007). While the definition of latitude is similar to size of DOA, precariousness represents ecological resilience, and resistance is associated with activation potential. Several other resilience measures based on thermodynamic and information theory (Fath et al., 2003, 2006) have also been proposed. In general, there can be multiple representations of resilience, each of which capture overlapping but different attributes. A particular attribute of a DOA or dynamic regime might be highly resilient to one type of shock in the driver but less resilient to other types of shocks (Cote and Darling, 2010; Folke et al., 2004). For example, tropical savanna are highly resilient to fires, but not to over grazing (Scheffer et al., 2001; Folke et al., 2004; Holmgren and Scheffer, 2001); managed marine coral communities might be able to bounce back from small scale thermal or nutrient shocks faster by increasing engineering resilience, however, this would be at the risk of being wiped off by large scale shocks thereby decreasing ecological resilience (Cote and Darling, 2010).

Although these past studies provide some insight into resilience, particularly in response to isolated instantaneous shock in system drivers, a theoretical framework for understanding resilience in systems driven by continuously varying drivers represented as a stochastic process has not been developed. In this paper we develop a mathematical framework that provides important insights on different resilience measures and how they change with the properties of the system and the driver variability. We hope that this development will also provide an interpretive framework for data driven investigations that use a probabilistic approach for the interpretation of the empirically observed dynamics (Scheffer et al., 2012; Marani et al., 2013). We use the canonical catastrophic shift system to develop this framework to quantify resilience at aggregate spatial scales (spatially averaged) and stationary time scales (transient behavior is not considered) by arguing that different resilience attributes give rise to different measures (Brand and Jax, 2007; Holling, 1973). We provide insights by comparing the resilience of the system when subject to instantaneous shock and continuous variation in system drivers.

Developing on the work of past resilience quantifications (Carpenter et al., 2001; Folke et al., 2004; Walker et al., 2004), we propose a system-driver-attribute triplet framework to quantify resilience. This triplet framework is best captured by asking the question: 'resilience of which behavioral characteristics, to what shock or variability in driver, and in what attribute'. Resilience 'of' can be system DOA or dynamic regime or other behavioral characteristics (Kumar, 2001) which include function, process, feedbacks, etc.; resilience 'to' can be the specific changes in the driver such as instantaneous shock or continuous variation in driver, etc.; resilience 'in' can be distance to unstable threshold (ecological resilience), size of the DOA (width of the stability domain), mean dynamic regime residence time (fraction of time spent in the dynamic regime), mean passage times (switching frequency between adjoining connected dynamic regimes), etc. We also note that scale at which our resilience measures proposed are important and in this study we deal with aggregate spatial scales and stationary time scales.

The primary goal of this paper is to define resilience measures for a dynamical system subject to continuous variation of drivers modeled as stochastic noise, and provide a comparison with those corresponding to instantaneous shock in drivers. We use catastrophic shift system as the canonical form of the model for illustration in this paper. Two ecological models are used as illustrations to provide context for comparing and contrasting these resilience measures. Out goal here is not to study these ecological systems in conventional detail, but to provide insights into the use of resilience measures as applied to these systems. In Section 2, we develop the mathematical framework for the resilience measures in a catastrophic shift system subject to instantaneous shock, and continuous variation in system drivers characterized as (a) Gaussian white noise, and (b) Markovian dichotomous noise. Gaussian white noise captures random uncorrelated driver variability while Markovian dichotomous noise allows us to capture more structure in the driver variability. Using this mathematical framework, we develop resilience measures under instantaneous shock and continuous variability in system drivers (Sections 3 and 4 respectively). We then analyze the characteristics of these resilience measures under varying system and driver parameters and highlight the emergent behavior. Subsequently, in Section 5 we develop the concept of iso-resilience and in Section 6 we provide discussions on the applications of our modeling approach. In Section 7 we provide concluding remarks along with some broader implications of the results.

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