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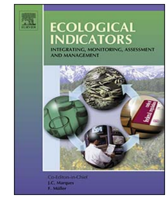

Original Article

Implications of being discrete and spatial for detecting early warning signals of regime shifts

Sumithra Sankaran[a,1,*], Sabiha Majumder[b,1], Sonia Kéfi[c], Vishwesha Guttal[a]

[a] Centre for Ecological Sciences, Indian Institute of Science, Bengaluru 560012, India
[b] Department of Physics, Indian Institute of Science, Bengaluru 560012, India
[c] Institut des Sciences de l'Évolution, CNRS, Université de Montpellier, IRD, EPHE, 34095 Montpellier Cedex 05, France

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ABSTRACT

Theory suggests that ecological systems exhibit a pronounced slow down in their dynamics, known as 'critical slowing down' (CSD), before they undergo regime shifts or critical transitions. As a result of CSD, ecosystems exhibit characteristic temporal and spatial changes which can be used as early warning signals of imminent regime shifts. For temporal data, statistical methods to detect these generic indicators of ecosystem resilience are well developed. However, for spatial data, despite a well developed theoretical framework, statistical methods such as data pre-processing and null models to detect EWS are relatively poorly developed. In this manuscript, we investigate the case of a common type of ecological spatial dataset which consists of binary values at each location (e.g. occupied/unoccupied, tree/grass or coralline/bleached). We employ a cellular-automaton based spatially-explicit model which generates data that mimics remotely sensed or field collected high-resolution spatial data with a binary classification of the state variables at each location. We demonstrate that trends in two spatial metrics, spatial variance and spatial skewness, of such binary spatial data lead to false, failed or misleading signals of transitions. We find that, two other indicators, spatial autocorrelation at lag-1 and spectral density ratio, accurately reflect CSD even with binary spatial data. To overcome the problems associated with detection of EWS using spatial variance and skewness, we investigate a data pre-processing method called 'coarse-graining' which is inspired from the physics literature on phase transitions. Coarse-graining reduces the spatial resolution of data by averaging state variables over small scales. Yet, it enables detection of CSD-based spatial indicators of impending critical transitions. In summary, our study provides a theoretical basis, and rigorous evaluation, of coarse-graining as a pre-processing step to analyse spatial datasets with discrete state classifications.

1. Introduction

Ecosystems can undergo large and abrupt shifts in their states, sometimes even for gradual changes in their drivers (May, 1977; Scheffer et al., 2001). These shifts, also called regime shifts or critical transitions, can be irreversible. Based on non-linear dynamics models, researchers have devised tools to anticipate these transitions. These tools are based on a generic principle that systems take longer to recover from perturbations as they approach the transition, a phenomenon known as critical slowing down (CSD) (Wissel, 1984; Van Nes and Scheffer, 2007; Scheffer et al., 2009). CSD leads to an increase in variance, skewness, autocorrelation and reddening of power spectra in the temporal and spatial dynamics of the ecosystem state (Kleinen et al., 2003; Carpenter and Brock, 2006; Guttal and Jayaprakash, 2008; Scheffer et al., 2009; Dakos et al., 2012; Xu et al., 2015). These characteristic trends are called generic indicators of loss of ecological resilience or generic early warning signals (EWS) of critical transitions.

Statistical methods to detect EWS from temporal data are well developed (see Dakos et al., 2012 for a review). These methods have been empirically tested, with some success, in microbial systems, aquatic systems, paleo-climatic records and financial markets (Drake and Griffen, 2010; Carpenter et al., 2011; Dai et al., 2012; Veraart et al., 2012; Dakos et al., 2008; Burthe et al., 2015; Guttal et al., 2016). Statistical detection of these signals poses various challenges, including the requirement of long and finely resolved time series data (Dakos et al., 2012; Boettiger and Hastings, 2012; Burthe et al., 2015), but such

Abbreviations: CSD, Critical slowing down; EWS, Early warning signals; PDE, Partial differential equation; EVI, Enhanced vegetation index; NDVI, Normalised difference vegetation index; acf, Autocorrelation function; sdr, Spectral density ratio

* Corresponding author.
E-mail address: sumithra@ces.iisc.ernet.in (S. Sankaran).

[1] These authors contributed equally to the study.

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data may not be available for many ecosystems. In some cases, this problem can be partly resolved by analysing spatial data over relatively small time scales (Guttal and Jayaprakash, 2009; Dakos et al., 2010; Carpenter and Brock, 2010; Kéfi et al., 2014). Spatial indicators have recently been empirically tested in laboratory experiments using aquatic microcosms and microbial systems, as well as field data from aquatic and savanna ecosystems (Drake and Griffen, 2010; Dai et al., 2013; Cline et al., 2014; Ratajczak et al., 2014; Eby et al., 2017). Increasing availability of high resolution imagery from satellite and other aerial images makes the computation of spatial indicators feasible. Therefore, rigorous development of statistical methods to detect EWS from spatial data can have huge implications in assessing the stability of ecosystems (Kéfi et al., 2014).

High resolution spatial data obtained from aerial images or field observations is often classified as discrete variables at fine spatial scales, representing only presence/absence of the quantity of interest. For example, a pixel of a high resolution image of semi-arid ecosystems can be classified as occupied or unoccupied by vegetation (Scanlon et al., 2007; Kéfi et al., 2007), or as woody or grassland areas (Reed et al., 2009; Eby et al., 2017); in a coral system, a pixel can be classified as coralline or bleached (Berkelmans et al., 2004). Such data are typically represented by binary (i.e. 0 or 1) values. Binary data may arise even in systems where the underlying variable is continuous, if the local states are classified based on a threshold criterion (e.g., grass dominated versus shrub dominated pixel). Consequently, binary spatial data are abundant in ecology. Development of statistical tools of data preprocessing and null models for spatial EWS of critical transitions, in particular those of discrete-valued spatial data, poses interesting challenges (Kéfi et al., 2014). In Section 2.1 of this manuscript, we argue that trends in spatial metrics like variance and skewness for binary-classified data are independent of the spatial structure of the landscape. Rather, it is determined only by the density of occupied sites in the landscape. This is true irrespective of the density at which the system may undergo a critical transition. Consequently, these metrics can lead to false, failed or misleading EWS of critical transitions.

This poses the question about whether the trends of generic spatial metrics, such as variance and skewness, can act as EWS for spatial data with discrete classification variables at fine scales. Previous studies have suggested a local averaging method called 'coarse-graining' to overcome this problem (Kéfi et al., 2014; Eby et al., 2017). A few studies have also employed coarse-graining prior to estimating spatial EWS (Dakos et al., 2011; Seekell and Dakos, 2015) but in an implicit or ad hoc manner. However, the theoretical underpinning of this data preprocessing method and its effectiveness in detecting EWS remain unclear.

The aim of this manuscript is to present an intuitive and theoretical basis for, and an evaluation of the effectiveness of, the data pre-processing step of coarse-graining in detecting EWS in binary-valued spatial data. We begin by showing the analytically expected trends of generic spatial metrics in binary-classified spatial data. We argue that trends of spatial variance and skewness of such data can be misleading in terms of detecting an imminent transition. We provide a theoretical argument for the necessity of a pre-processing step called coarse-graining to detect EWS in spatial data. We also propose a method to identify an 'optimal' scale of coarse-graining that enables detection of EWS. We illustrate the method of coarse-graining and we analyse its effectiveness using a simple spatially explicit population model. We show that after coarse-graining the data, these metrics typically show the theoretically expected trends towards an approaching transition. We also show that spatial autocorrelation and power spectrum, two other metrics for spatial data, may not need coarse-graining for the detection of EWS.

Box 1: Nomenclature

1. Ecological landscape: Matrix of cells containing densities or other ecological variable
2. Site: Each cell of the data matrix
3. Local state: Ecological measurement value (occupied by a tree or empty) in the cell
4. Ecosystem state (or regime): Average global density of the landscape
5. Coarse-grained variable: Local state variable after local averaging
6. Discrete (or binary) state spatial data: A landscape with local discrete/binary state variables

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2. Early warning metrics in binary-state spatial data and theoretical basis for coarse-graining

Consider an ecological landscape where 'raw data' at fine spatial scales is classified into binary state values, such as occupied or unoccupied, tree or grass, coral or bleached. We call such datasets binary-state spatial data (more generally, discrete-state spatial data). Below, we mathematically show that two of these metrics, spatial variance and spatial skewness, capture only density-dependent trends when applied to such raw spatial datasets. We then present a theoretical basis for the necessity for pre-processing such raw spatial data with a local averaging method, called coarse-graining, before computing spatial metrics of regime shifts.

2.1. Expected trends of spatial indicators for binary-state spatial data

Binary-state spatial data can be represented by a matrix whose entries are either 1's (representing occupied sites in the landscape) or 0's (representing unoccupied sites). We define the density of such a landscape as the proportion of occupied cells in the matrix, denoted by $\bar{\rho}$. For a landscape with a density of $\bar{\rho}$, the expression for spatial variance (σ^2_{raw}) and skewness (γ_{raw}) are given by the following identities (see Appendix A.1 for derivation of these expressions; also see Appendix S3 in Eby et al., 2017):

$$\sigma^2_{\mathrm{raw}} = \bar{\rho}(1-\bar{\rho}) \tag{1}$$

$$\gamma_{\mathrm{raw}} = \frac{1-2\bar{\rho}}{\sqrt{\bar{\rho}(1-\bar{\rho})}} \tag{2}$$

From Eq. (1), we see that spatial variance varies non-monotonically as a function of density ($\bar{\rho}$) and peaks at $\bar{\rho} = 0.5$ (i.e. at 50% cover; Fig. 1A). Spatial skewness (Eq. (2)) decreases monotonically, from large positive values to large negative values, as a function of density (Fig. 1B). At half density, i.e. a landscape with equal number of empty and filled sites, the distribution of states would be symmetric around its mean; therefore, the skewness will be zero. These above density-dependent trends of spatial variance and skewness arise due to the discrete nature of the fine scale state variables. We emphasize that the derivation of these trends depends only on the density of occupied sites in the landscape ($\bar{\rho}$) but not on its spatial configuration. Therefore, these trends are unrelated to the phenomenon of CSD that occurs in the vicinity of critical transitions.

We discuss the expected trends for two other spatial metrics: spatial autocorrelation (Dakos et al., 2010) and spectral properties (Carpenter and Brock, 2010) (see Section 3). Spatial autocorrelation measures whether state variables are correlated (or similar) over space; thus it measures the structure in spatial data. Spectral function represents spatial patterns as superposition of periodic patterns hidden in the data; this enables detection of periodicity as well as characterisation of fractals in data (Bertiller et al., 2002; Couteron, 2002; Kéfi et al., 2014). Furthermore, it is worth noting that spectral function and correlation function are related, as Fourier transforms of each other, and hence are mathematically equivalent (Reif, 2009). Hence, both spatial autocorrelation and spectral function depend on the underlying spatial structure. Unlike spatial variance and skewness of binary-state landscape data, these properties are not merely dependent on density.