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Short communication

Anchored in 'average thinking' in studies of arid rangeland dynamics – The need for a step forward from traditional measures of variability

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There is a wide consensus that arid and semi-arid environments are highly variable in space and time. The most frequent approaches to describe and analyze arid and semi-arid rangelands are based on the usage of averages and Normal distributions as main references to describe spatial and temporal differences. We argue that rangeland ecology science should move forward in methods to better capture the patterns of rangeland dynamics, rather than just focusing on simple measures of variability. We provide different simulated time series data in order to illustrate the limitations of some currently used methodologies. We call for the application of time series methods in order to better understand complex dynamics in arid and semi-arid rangelands.

1. Introduction

There is a wide consensus that arid and semi-arid environments are highly variable in space and time (Ellis and Swift, 1988; McAllister et al., 2009). Variability is a concept of high interest in rangeland ecology and should be tackled as an inherent quality of rangeland dynamics rather than a disturbance, in order to provide help to understand and manage variable systems (Easdale and Domptail, 2014). The most frequent approaches to describe and analyze arid and semi-arid rangelands (hereafter called arid) are based on the usage of average as a main reference to describe spatial and temporal differences. The problem arises when comparisons of simple statistical descriptors of rangeland dynamics from different regions, which should be treated as preliminary descriptions due to simplicity, are then implicitly used to depict their temporal behavior.

One of the used approaches in comparing rangeland dynamics is the direct use of average rainfall and mean Normalized Difference Vegetation Index (NDVI) as proxies, and estimations of average net primary production (NPP) or average forage production (e.g. Paruelo et al., 1997; Anyamba and Tucker, 2005; Hunt and Miyake, 2006; Golluscio et al., 2010; Eisfelder et al., 2014). The most frequent temporal windows to perform and compare averages are the annual and seasonal periods, or fixed periods based on definitions of the length of vegetation growth, or as a binary model (i.e. annual dry and wet periods). There is an implicit assumption that any other intra-annual or inter-annual patterns or cycles are considered as not relevant or directly ignored as noise.

Variability is often described using statistics that are based upon these averages. For example, variability is said to be tackled by the way of exploring anomalies. The case of an anomaly is generally defined when a monthly, seasonal or annual (e.g. NPP or rainfall) deviation is beyond a pre-defined threshold based on an average of a time series. For instance, an anomaly could be defined with a deviation of at least twice the mean standard deviation for a month above or below the *n*-year mean (Eisfelder et al., 2014), or as a percentage (e.g. 40% or 60%) above or below the average (Anyamba and Tucker, 2005). The mean plus or minus two standard deviations corresponds to a 95% confidence interval, and this normal distribution is the main argument that support a definition of significant anomalies (Shackleton, 1986; Vellinga and Wood, 2002). For a random and normally distributed time series, one datum every twenty data would be considered anomaly.

Variability is also said to be tackled by the coefficient of variation (CV, [standard deviation mean^{-1}]) (Ellis and Swift, 1988), and in

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particular to compare different ecological regions or gradients (e.g. Jobbagy et al., 1995; von Wehrden et al., 2010; Easdale and Aguiar, 2012; Irisarri et al., 2012). Furthermore, a threshold based on CV was proposed as a way to provide an operative definition that distinguishes between equilibrium and not-equilibrium dynamics in arid and semi-arid rangelands (e.g. Ellis and Chuluun, 1993; Behnke et al., 1993; Okayasu et al., 2011; von Wehrden et al., 2012). The rule of 33% of CV in precipitation gained consensus among many scholars (von Wehrden et al., 2012) and have strong theoretical and management implications. Below this threshold, systems are said to be at equilibrium, which implies that ecosystem dynamics is controlled by internal factors (i.e. density-dependent). In this case, stocking rate is one of the most important managerial decisions in livestock systems (e.g. Holecheck, 1988). On the other hand, above that threshold rangeland dynamic is said to be mostly driven by external factors such as climate. Hence, opportunistic stocking strategies and mobility are emphasized to cope with variability. Some authors discussed the theoretical implications of this dichotomy, emphasizing some contradictions and proposing ways to overcome the problems (e.g. Illius and O'Connor, 1999; Fernandez-Giménez and Allen-Diaz, 1999; Briske et al., 2003; Vetter, 2005). However, less effort is posed to shed-light on the problems embedded in methods that are used to study such dynamics.

The main problem with these proposed methods, when used to distinguish among different arid rangeland dynamics, is that they are wrong or ineffective. In particular, methods are mostly based on strong assumptions such as normal distributions, linearity and independence between successive values of the time series data, which rarely could be met. Hence, they are inadequate to provide useful information about the ecosystem dynamics. In order to capture the patterns of rangeland dynamics, we argue that there is a need to move forward from simple measures of variability, especially when long time series are available such as in the case of remotely sensed data. We provide different simulated time series data in order to illustrate the limitations of these methods, while comparing the outcome from a simple Fourier analysis (i.e. power spectrum). We call for the application of time series methods in order to effectively tackle ecosystem dynamics in arid rangelands.

2. Some examples of time series with equal statistical properties

In order to illustrate some of the mentioned problems, we generated six different time series that represent different hypothetical arid rangeland dynamics (e.g. as measured by series of monthly NDVI). We developed the series with completely different dynamical patterns but using the same statistical properties: mean zero and standard deviation [$2^{-1/2} = 0.707$] (Fig. 1).

Sinusoidal functions represent perfectly periodic systems (Fig. 1A, B, C), and have the same statistical properties (i.e. the standard deviation of a sinusoidal wave is defined by the amplitude divided by the square root of two; see Cartwright, 2007). The main difference among the sinusoidal functions is their frequency. In time series, frequency refers to a phenomenon that repeatedly occurs per unit of time in a given period. Hence, the first series represent a typical dynamic with an annual frequency-domain component that defines a cycle with two phases (e.g. winter and summer, Fig. 1A). Then, double frequency means that two cycles are included within the same unit of time (Fig. 1B) and represent intra-annual cycles. Finally, half a frequency refers to a biannual frequency-domain component (Fig. 1C), as an example of an inter-annual cycle.

The other time series are different kinds of noise called white, red and blue (e.g. Box and Jenkins, 1970; Ljung and Box, 1978; Rudnick and Davies, 2003). We used time series that represent these kinds of noise because they are well described and studied in environmental science (e.g. Kaytala et al., 1997; Balmforth et al., 1999). They were created by using the normally distributed random number generator from python (Van der Walt et al., 2011), and the parameters were mean zero and standard deviation 0.707, as the sinusoidal functions. First, the Gaussian white noise is a time series that have a constant spectral density and is not self-correlated (i.e. the successive values are independent from each other (Fig. 1D)). Second, the red noise is dominated by low level frequencies, and is positively self-correlated (Fig. 1E). Finally, the blue noise is a time series dominated by high level frequencies, with negative self-correlation (Fig. 1F).

Notwithstanding the technical aspects that define the different time series, we would like to emphasize that the six time series would be categorized as having similar dynamics if we only use mean and standard deviation, or coefficient of variation, as unique descriptors, masking the dissimilarities among the different patterns of behavior. In order to provide an example of the application of a simple method that can discriminate differences in time series dynamics, we analyzed the power spectrum of the same six time series with Fourier analysis (Fig. 2). The power spectrum, or also called periodogram, describes how the variance of the series is distributed over the frequency components, and helps in the identification of the frequencies with the higher signals or power. The nature of the spectrum gives also valuable information whether the dynamic is periodic or not. For example, the sinusoidal functions are periodic systems with only one clear signal, differing among them in the frequency-domain component as we explained above (Fig. 2A, B, C). For these cases, the power spectrum clearly discriminates among annual, intra-annual and inter-annual dynamics for the three sinusoidal functions, respectively. The other three series that relate to different kinds of noise are not periodic, with a constant spectral density in the case of the white noise (Fig. 2 D), low level frequencies in the red noise (Fig. 2E), and high level frequencies in the blue noise (Fig. 2F).

3. Discussion

'Average thinking' is a metaphor that represents the prevalence of some qualitative assumptions in some of the frequently used approaches and methods aimed at tackling spatio-temporal dynamics of arid rangelands. In particular, we point out two main qualitative assumptions that should be revised in future research.

One of the main qualitative assumptions regards to the reference value. The assumption is the consideration of predefined windows of time, which are then relevant to analyze temporal behaviors. The annual and seasonal periods are defined by the length of the photoperiodic cycle, determined by physical principles (i.e. a year is defined by twelve fixed months and a season by three fixed months). While photoperiod influence vegetation dynamic (e.g. phenology), other factors such as climate can increase or reduce the annual or seasonal length due to the vegetation responses to changing environmental conditions (e.g. Menzel, 2000; Cramer et al., 2001). Fixed periods of time defined by strictly focusing on the length of vegetative growth period have also restrictions (e.g. Wessels et al., 2007; Fabricante et al., 2009; Easdale and Aguiar, 2012). In these cases, the problem is that winter phase is eliminated as not relevant and the annual cycle is only represented by a subset of data. This procedure assumes that every annual cycle begins in spring and is not influenced by the previous winter. We emphasize that a periodic cycle of ecosystems or vegetation communities can be much more variable than a calendar year or a fixed period of time and should be tackled adequately (e.g. as shown in the examples by different frequencies

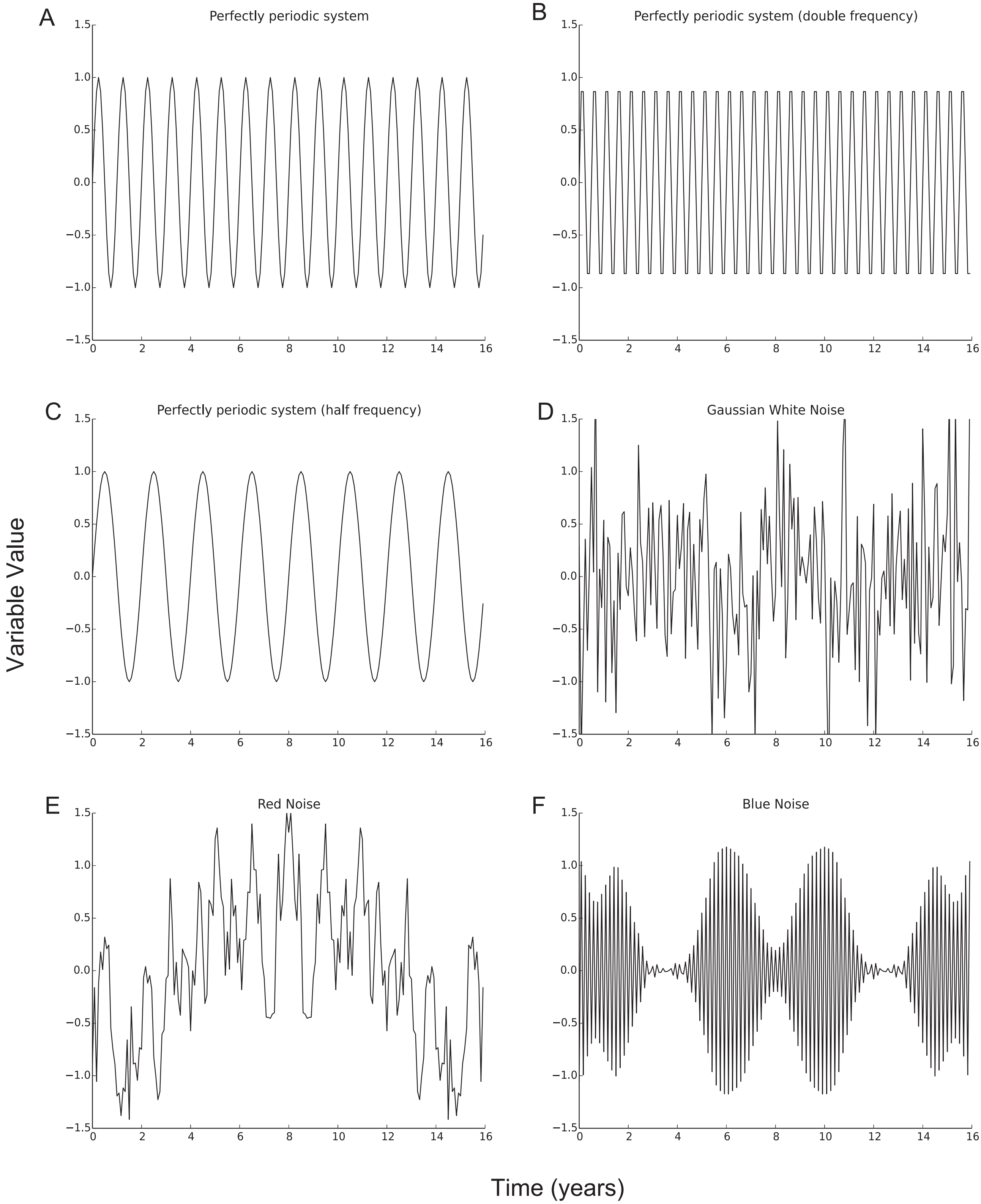

Fig. 1. Six different time series generated with the same statistical properties: mean zero and standard deviation 0.707. Series A, B and C are sinusoids with the same amplitude (=1), and frequencies 1, 2, and 0.5, respectively. D is a white noise series with Gaussian distribution, E is a low-frequency red noise, and F is high-frequency blue noise.

–Fig. 1A–C–, and different power spectrums, Fig. 2A–C).

The other qualitative assumption is related to variation. There is a common confusion between measures of statistical variability (i.e. standard deviation, variance) and temporal variability (i.e. trend, seasonality, short and long–term cycles). Several series might have the same statistical variability properties but very different temporal variation. As a consequence of this confusion, there is an assumption that temporal series in rangelands has a Normal

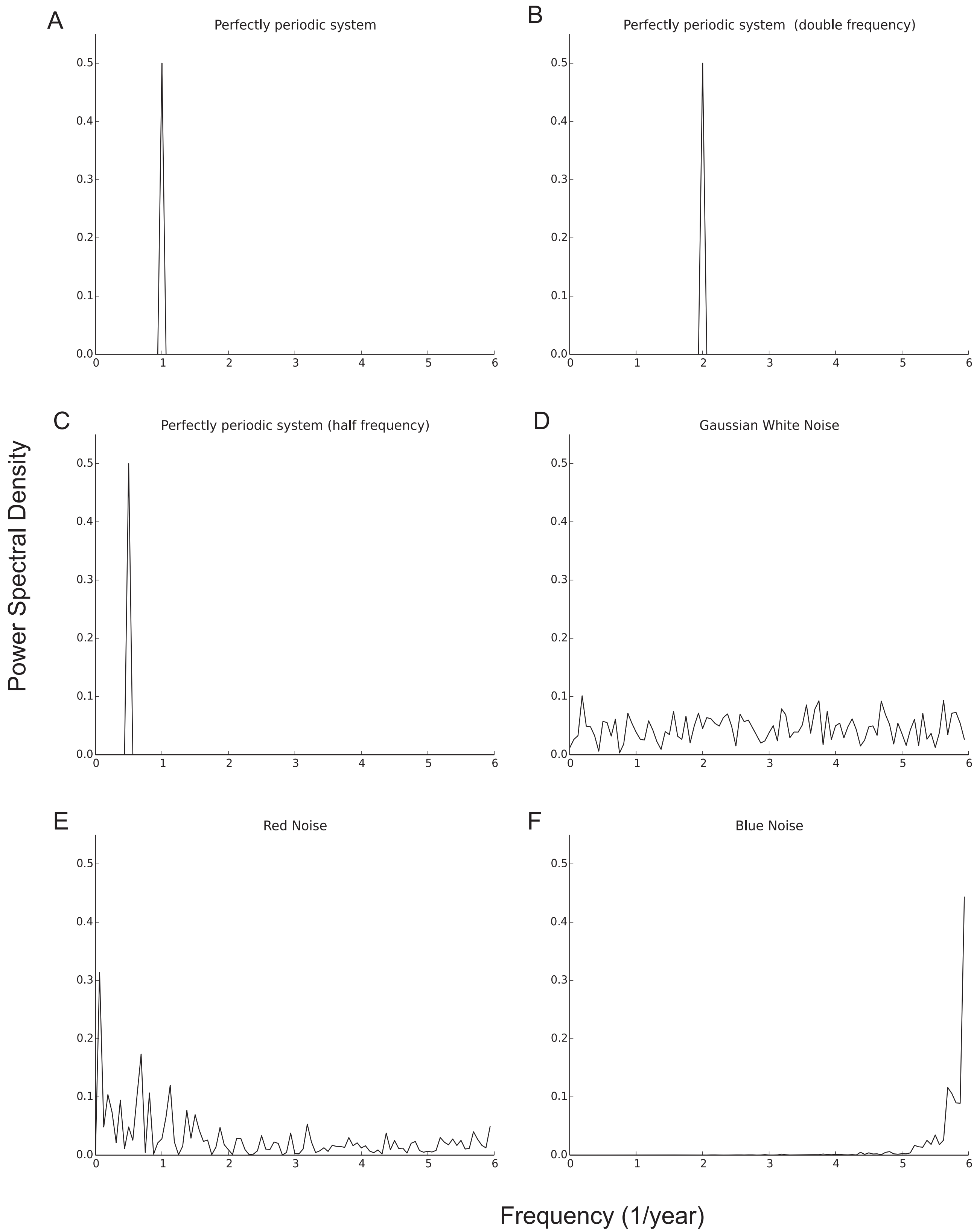

Fig. 2. Power spectrums of the simulated time series, calculated with Fourier transform. The references are the same as Fig. 1.

distribution and independence, for which the average is a robust reference value and CV a useful statistic to depict and compare variability (i.e. measured as the distance between the extreme values and the reference value). However, several time series with equal mean and CV can be very different in terms of the patterns of their dynamics (Fig. 1).

In order to capture the diversity of patterns of rangeland dynamics, different methods should be used, in particular when long time series are available, such as in the case of remotely sensed information. We emphasize that time series data sets should be treated as interdependent data. Procedures that reduce variance and ignore time dependency among successional values should be avoided, as in the case of pre-determined reference periods (i.e. annual or seasonal averages from monthly original data), and statistics based on Normal distribution assumption. As a step forward from traditional measures of variability, some classical time series analysis such as Fourier transform provides enormous resolution power to transform signals between time (or even spatial) domain and frequency domain components (Smith, 2003). These kind of methods are sophisticated enough to discriminate inter- and intra-annual dynamics and should be used in future research. In the provided example, mean and standard deviation as descriptors would consider all time series as similar, while a simple power spectrum analysis can discriminate six different categories of temporal patterns (Fig. 2). Another modern time frequency analysis such as wavelets can help to capture rapid changes in ecosystem dynamics (e.g. Martínez and Gilabert, 2009; Campos and Di Bella, 2012; Carl et al., 2013), which are far beyond the possibilities of simple descriptive statistics. Arid rangeland ecology science should move a step forward from variability as a static concept based on 'average thinking' approaches, towards studies of the patterns of rangeland dynamics and temporal behaviors at different time scales.

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