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Original Research Article

Network based early warning indicators of vegetation changes in a land–atmosphere model

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ABSTRACT

Numerous model studies demonstrate that ecosystems might not shift smoothly with a gradual change in resource concentration. At specific points, vegetation can suddenly shift from one stable state to another. To predict such undesirable shifts, statistical indicators are proposed for early warning prediction. These so-called classical indicators can address whether vegetation state is moving towards the tipping point of an abrupt transition, however when the transition will occur is hard to predict. Recent studies suggest that complex network based indicators can improve early warning signals of abrupt transitions in complex dynamic systems. In this study, both classical and network based indicators are tested in a coupled land–atmosphere ecological model in which a scale-dependent hydrology-infiltration feedback and a large scale vegetation–precipitation feedback are represented. Multiple biomass equilibria are found in the model and abrupt transitions can occur when rainfall efficiency is decreased. Interaction network based indicators of these transitions are compared with classical indicators, such as the lag-1 autocorrelation and Moran's coefficient, with particular focus on the transition associated with desertification. Two criteria are used to evaluate the quality of these early warning indicators and several high quality network based indicators are identified.

1. Introduction

Ecosystems do not necessarily shift gradually with changes in the amount of resources (Scheffer et al., 2001; Ripple and Beschta, 2006; Móréh et al., 2009; Claussen et al., 2013; Dekker, 2013). Observed patterns strongly suggest that multiple equilibria exist under similar climate regimes (Hirota et al., 2011; Staver et al., 2011b; Scheffer et al., 2012), which implies that ecosystems may shift from one stable state to another (Rietkerk et al., 2004; Hirota et al., 2011). More importantly, most of these transitions are subcritical as the shift is irreversible (Scheffer et al., 2009; Kéfi et al., 2013). Such critical transitions may lead to catastrophic changes of the landscape (Staver et al., 2011a) and result in regular vegetation patterns (Rietkerk et al., 2004), which in turn strongly affects local climate through biophysical and biochemical feedbacks (Bonan, 2008; Seneviratne et al., 2010; Dekker et al., 2007).

To anticipate to potential catastrophic transition of ecosystems, numerous studies have tried to find early warning indicators of the transition to desertification (Rietkerk et al., 2004; Kéfi et al., 2007a; Scheffer et al., 2009; Dakos et al., 2008). The phenomenon of 'critical slowing down', expressing that the recovery rate of the system to perturbations decreases near such a transition, has lead to useful early warning indicators, such as the lag-1 autocorrelation (van Nes and Scheffer, 2007; Scheffer et al., 2009). Also indicators based on the changes in spatial correlation of vegetation patterns have been developed (Dakos et al., 2010). In general, however, these classical indicators show only irregular monotonic behaviour and it is difficult to determine how close the system is to transition and when to give an alarm. Ideally, one likes to have the availability of indicators which give a sharp peak just before the transition.

Indicators based on complex interaction networks were shown to have this desired 'peaky' property when applied to a highly conceptual ecological model, the local positive feedback model (Tirabassi et al., 2014). Although the network based indicators have a higher quality factor, for this model also the classical indicators perform well regarding the desertification transition. A more

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challenging test of the capabilities of network based indicators is the scale-dependent feedback model suggested in Rietkerk et al. (2002). For this model, two classical indicators (lag-1 autocorrelation and Moran's coefficient, see Section 2.2) show unexpected trends when approaching the critical transition (Dakos et al., 2011).

As was indicated in Dijkstra (2011), the structure of the multiple equilibria in a scale-dependent feedback model is complicated because of the appearance of a multitude of saddle-node bifurcations. Near the transition to the desert state, many other unstable steady states influence the spatio-temporal behaviour of the vegetation field. It suggests that the self-organization mechanisms in such a model increases the complexity of the spatial and temporal correlations of the vegetation signal, which decreases the performance of the classical indicators. It is therefore interesting to investigate how network based indicators will perform in such a scale-dependent feedback model. Moreover, the network indicators will yield more information than looking alone at the patterns themselves as being possible indicators.

In the present study, the land–atmosphere model as presented in Konings et al. (2011) is used to test the performance of network based indicators regarding the desertification transition. This model couples land surface processes (Rietkerk et al., 2002) and the dynamics of the atmosphere boundary layer (Konings and Katul, 2010). It captures two important positive feedback mechanisms, the small-scale biomass-infiltration feedback (Rietkerk et al., 2002) and the large-scale precipitation-transpiration feedback (Entekhabi et al., 1992; Dekker et al., 2007). At small scales, increasing biomass is able to promote water infiltration rate, which provides more soil water and in turn maintains more biomass (Rietkerk et al., 2000). At large scales, increased precipitation leads to more biomass, which can increase transpiration rate and recharge water vapour in the atmosphere. Consequently more rainfall events can occur and increase the amount of precipitation (Entekhabi et al., 1992). In addition to these feedbacks, also the seasonal variability of rainfall, which is shown to be important in arid and semi-arid regions (Baudena and Provenzale, 2008; Good and Caylor, 2011; Siteur et al., 2014), is represented in the model.

Output from a large number of simulations with this model are used to reconstruct interaction networks from which early warning indicators of transitions are derived. The performance of these indicators is compared with those of classical indicators with the aim to understand the behaviour of these indicators near the desertification transition. In Section 2 the essential features of the land–atmosphere model and the complex network methodology are described. Results of the simulations of the land–atmosphere model are presented in Section 3.1 and the performance of the classical and network based early warning indicators is presented in Section 3.2. A summary and discussion of the results is given in Section 4.

2. Model and methodology

2.1. The land–atmosphere model

The land–atmosphere model (Konings et al., 2011) couples a one-column atmospheric boundary layer (ABL) model (Konings and Katul, 2010) with a scale dependent feedback vegetation model (Rietkerk et al., 2002). The ABL model is seasonally forced to capture the African monsoon variability (Konings et al., 2011). The vegetation model considers the interactions among surface water, biomass dynamics and soil moisture (Rietkerk et al., 2002). The surface energy balance contains the turbulent momentum and moisture exchange between the land and atmosphere (Konings et al., 2011). In this study, state-dependent stochastic noise is included for biomass, surface water and soil moisture to represent unresolved processes (Dakos et al., 2011; Tirabassi et al., 2014); the detailed equations of the model are presented in Appendix A. A full description of the model can be found in Konings et al. (2011).

The fundamental characteristic of the land–atmosphere coupling is the water and energy exchange between the land surface and the ABL. The vegetation model simulates the biomass dynamics and determines the sensible and latent heat fluxes. The sensible heat flux (H) changes the boundary layer height (h) while the latent heat flux (LE) affects the specific humidity (q) of the atmosphere. Convective rainfall occurs when h crosses the Level of Free Convection (LFC) and the Lifting Condensation Level (LCL). The LFC is the altitude where the lifted parcels become buoyant, while the LCL is the height where the condensation starts. When rainfall occurs, the amount of rainfall is determined by the total moisture content in the atmosphere and a rainfall efficiency (η, Eq. (A.7)). The parameter η will be the main control parameter in the model and controls (together with other processes as transpiration, etc.) the total amount of annual precipitation (Konings et al., 2011). When η =1, the simulated mean annual precipitation is approximately 365 mm yr^{-1}. Note that the mean annual precipitation (P) is dependent on the strength of the vegetation–precipitation feedback. Thus η is used as an index to represent the dryness of climate.

The model was applied on 75 $\times$ 75 grid cells. Surface runoff, soil water spread and biomass colonization were considered as main land surface processes (Eqs. (A.8), (A.9) and (A.15)). The energy balance was calculated for each grid cell. However, spatial averaged sensible and latent heat fluxes were used to estimate water and energy exchanges between the land and atmosphere. To extract biomass equilibria under specific climate, the simulation started with a relative high initial biomass. The time step for atmospheric convection was 150 s, while biomass was updated once per day. The model was run until the biomass state reached equilibrium. As a criterion for reaching the equilibrium, we required that the maximum (over the whole grid) relative difference of the annual mean values of the biomass field between two neighbouring years was less than 0.5%.

The land–atmosphere model accounts for the annual cycle of solar radiation. Moreover, the observed climate forcing data (slope γ and intercept ϕ of the free atmosphere for specific humidity q and potential temperature θ, see Appendix A) contains seasonal atmospheric variability. To remove strong seasonal correlations due to forcing in the biomass time series $\hat{B}_i^n$, where i refers to a location in space (i.e., a specific grid cell) and n to the time index, the average over M years (M = 5 in this paper) is removed for each day of the year. More specifically, for daily data with $n(j, k) = 365 \times (j-1) + k$ (leap years ignored), the detrended time series B_i^n is determined from

$$B_i^{n(j,k)} = \hat{B}_i^{n(j,k)} - \frac{1}{M}\sum_{j=1}^{M} \hat{B}_i^{n(j,k)}. \tag{1}$$

The correlation coefficient between B_i^n and $\hat{B}_i^n$ is less than 0.2 in all randomly selected values of i, implying that the annual cycle is successfully removed from each time series. Note that the detrended biomass B_i^n can have negative values as it is an anomaly with respect to the seasonal cycle. All biomass time series referred to below in this paper are seasonally detrended.

2.2. Early warning indicators

'Critical slowing down' is demonstrated as the essential character of dynamic systems approaching a critical transition (Scheffer et al., 2009). This theory focuses on the recovery rate of a system when it turns back to the equilibrium state from a small perturbation. If the system state is far from the tipping point, the