Detecting slowness in ecosystems

Report for the ESDL early adopters

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Abstract

Ecosystems around the world are at riks of critical transitions due to increasing anthropogenic preasures and climate change. However, it is not clear where this risks are higher or where ecosystems are more vulnerable. Here we measure slowness on primary production proxies for marine and terrestrial ecosystems globally. Slowness is an indicator of potential instabilities and the risk of regime shifts. While slowness is not a universal indicator for critical transitions, it can be used for detection of annomalies.

Introduction

Ecosystems world wide are increasingly at risk of critical transitions or regime shifts[1–4]. Regime shifts are large, abrupt and persistent changes in the function and structure of ecosystems[5,6]. Under current trends of climate forcing, green house gas emissions, pollution, and human appropriation of net primary productivity, ecosystems are increasingly expected to undergo more frequent and severe regime shifts. The problem is identifying where ecosystems are most at risk and whether early detection allow enought time for prevention or active recovery.

When a dynamic system is close to a threshold it leaves a statistical signature on its time series known as critical slowing down[7–9]. It takes longer to recover after a small disturbance, which translates into increases in variance, autocorrelation, and skewness or flickering[9,10]. Critical slowing down is therefore an indicator of the resiliene. Resilience is the ability of a system to withstand disturbances without loosing its function, structure, and hence its identity[11,12]. To date, the simplest, multi-system, and transparent resilience metric is recovery time[13,14]. How to combine different early warnings based on critical slowing down? Or is it possible to use critical slowing down indicators to create maps that identify the most vulnerable ecosystems? These are both open questions and key frontiers of research[10].

The aim of this report is to showcast how the Earth System Data Lab (ESDL) can be used to address these questions. The ESDL offers a unique opportunity to investigate how ecosystems are responding to anthropogenic forcing and where are they most at risk of critical transitions. Here I use use proxies of primary productivity for ecosystems world wide and calculate slowness, one of indicators for critical slowing down. The results should be interpreted as a training exercise of a young researcher participating on the ESDL early adopters program. The discussion outlines future steps to improve the analysis.

Methods

The primary productivity of an ecosystem is a fingerpring of its metabolic activity and can be observed from space for both marine and terrestrial systems. Data streams on gross primary productivity for terrestrial systems, and chlorophile A for aquatic systems, were used to measure slowness. For both data streams low resolution data cubes were used with a 8 days temporal resolution and a 0.25 degree spatial resolution. For terrestrial productivity time series from 2001 to 2011 were used, while for marine systems the time series cover the period 1997 to 2018, in both cases to avoid missing values. All time series were first normalized to zero mean and unit variance. Missing values were filled with the mean annual cycle before applying a time series decomposition using a Fourier filter that as a result produced the long-term variability, annual cycle, fast oscillations, and trend of each time series.

The trend and long-term variablity were used to calculate variance (as standar deviation), an indicator of critical slowing down[10]. A rolling window of 100 time steps (weeks) was used to compute the standar deviation, with an overlap of 50 steps between rolling windows. While a rolling window for each time step is preferred, Lenton shows that partially overlapping or non-overlapping windows also works. A partially overlaping window was used to reduce the computational burden. A simple linear model was fitted regressing the standard deviation against the time index of the rolling windows. This procedure allowed the use of the slope to filter out in space which pixes present increase in variance. Places with particularly high variance increase were further investigated by applying other indicators of critical slowing down such as autocorrelations, and return rates.

Results

Computing slowness on primary productivity proxies of global ecosystems allow us to identify where ecosystems might be at risk of critical transitions, or already undergoing abrupt changes (Fig 1). For example, increases in standard deviation for gross primary productivity in terrestrial ecosystems reveal areas of South America that have been recently shifted to large soja plantations in Northern Argentina, Uruguay and Paraguay, as well as deforestation fronts in Gran Chaco forests. Another example is regions close to the Benguela system in the Western coast of Africa, or the areas in front of the Chilean coasts.

The preliminary results show that the trend itself does not render strong patterns of increase in variance. Perhaps the Fourier filter is too strong transformation to the time series (overfitting) to leave variation enought for useful early warnings. Long term trends, however, were useful for detecting examples of ecosystems changing. For instance, terrestrial systems of the Victoria region in Australia show early warning signals before heat wave events of March 2010, where an annomaly of +0.68C was detected marking the hottest month recorded since 1992. The time series of gross primary productivity capture such climatic shocks as well as the recovery afterwards, and the early warnings can be used for detection of disturbances that destiblize ecosystems.

Combining multiple streams of data for detecting early warnings is at the frontier of research. The ESDL offers an opportunity to explore such possiblities. Places where slowness has increased in the past can be used as training datasets for future develoment of early warnings with machine learning. Critical slowing down techniques are known to fail where the dynamics are driven by stochastic process, or when time series are too short with respect to the time scale underlying the dynamics. It is theoretically possible to use detection with slowness to lable places with syndromes of losses of resilience, and use feature extraction to detect other places where data streams are similar but slowness is not present. Last, the data cube also offers the opportunity to assess cascading effects of regime shifts. While in this preliminary exercise the detection of causality was not successful, further work can use randomizing procedures to take advantage of the space dimension for detecting signals when time series are short. I hope to have the opportunity to continue exploring this research ideas with the ESDL. All the code to reproduce this study is available at: https://github.com/juanrocha/ESDL

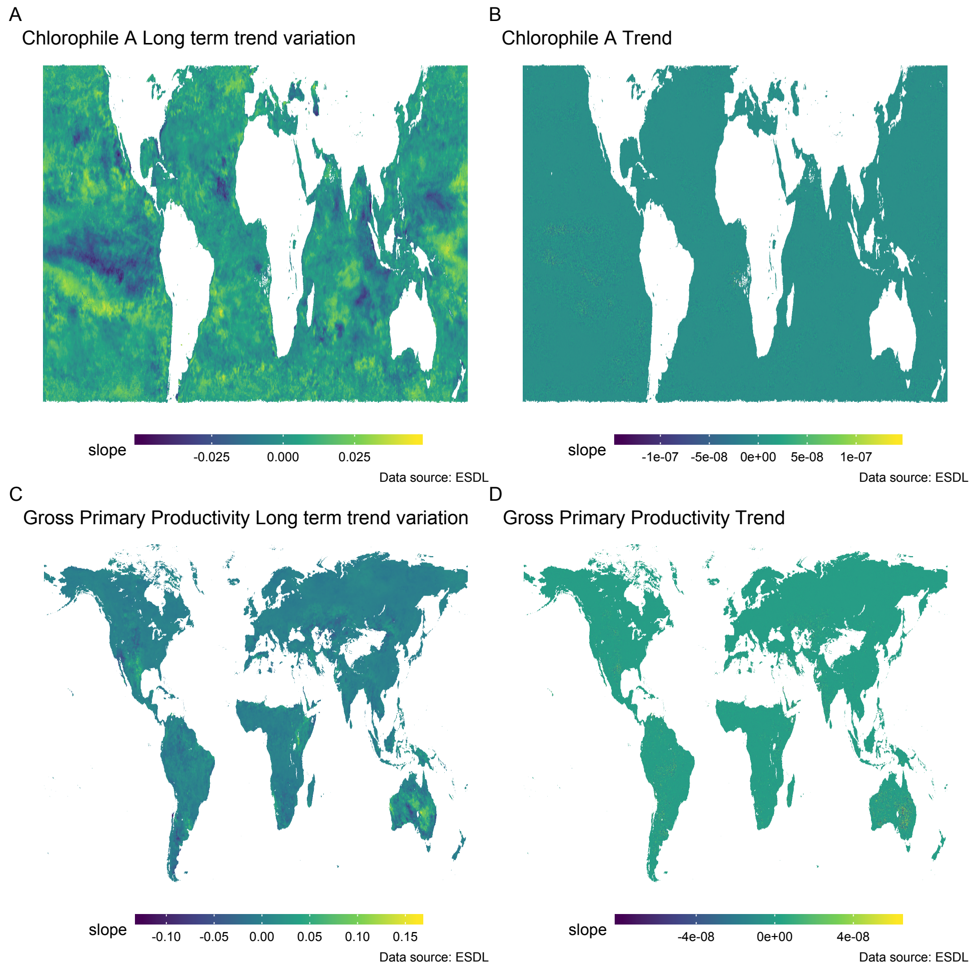

Figure 1: **Measuring slowness in global ecosystems.** Time series of chlorphile A and gross primary productivy are used to observe critical slowing down by calculating the standar deviation of the standardized time series. The trend and long term variability resultig from a Fourier filter are used to fit linear models on slowness as response to a rolling window. The slopes of these models show where variation and autocorrelation are increasing in terrestrial and marine systems.

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