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Proceeding Paper

Partitioning of Net Ecosystem Exchange Using Dynamic Mode Decomposition and Time Delay Embedding †

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Abstract: Ecosystem respiration (Reco) represents a major component of the global carbon cycle. An accurate estimation of Reco dynamics is necessary for a better understanding of ecosystem–climate interactions and the impact of climate extremes on ecosystems. This paper proposes a new data-driven method for the estimation of the nonlinear dynamics of Reco using the method of dynamic mode decomposition with control input (DMDc). The method is validated on the half-hourly Fluxnet 2015 data. The model is first trained on the night-time net ecosystem exchange data. The day-time Reco values are then predicted using the obtained model with future values of a control input such as air temperature and soil water content. To deal with unobserved drivers of Reco other than the user control input, the method uses time-delay embedding of the history of Reco and the control input. Results indicate that, on the one hand, the prediction accuracy of Reco dynamics using DMDc is comparable to state-of-the-art deep learning-based methods, yet it has the advantages of being a simple and almost hyper-parameter-free method with a low computational load. On the other hand, the study of the impact of different control inputs on Reco dynamics showed that for most of the studied Fluxnet sites, air temperature is a better long-term predictor of Reco, while using soil water content as control input produced better short-term prediction accuracy.

Keywords: ecosystem respiration; dynamic mode decomposition with control; time delay embedding

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1. Introduction

Carbon losses from ecosystems affect climate change. Ecosystem respiration (Reco), the sum of autotrophic and heterotrophic respiration, represents a major component of the global carbon cycle. Accurate estimation of Reco dynamics is necessary for a better understanding of ecosystem–climate interactions and the impact of climate extremes on ecosystems. This paper proposes a new data-driven method for the estimation of the nonlinear dynamics of Reco using the method of dynamic mode decomposition (DMD), an emerging tool for the analysis of nonlinear dynamical systems.

Ecosystem respiration is typically described as an exponential function of temperature based on the law of thermodynamics [1]. This function is defined based on certain parameters, such as temperature sensitivity, which are assumed to remain constant. However, several studies have pointed to the dependence of these parameters on other drivers of Reco [2] . Such issue is partially compensated in regression models by the use of temporal moving windows for parameters estimation [3].

The Eddy Covariance (EC) technique is widely used to measure the net ecosystem exchange (NEE) which is the difference between Reco, the total CO2 release due to all respiration processes, and the gross carbon uptake by photosynthesis (GPP). The two CO_2 fluxes Reco and GPP are derived from NEE by applying partitioning methods. Recently deep learning-based methods have been proposed for modeling Reco dynamics [4,5] using EC measurement of night-time NEE when photosynthesis, and therefore GPP, is assumed to be 0. These approaches provide data-driven equation-free estimates of Reco with the flexibility to include other meteorological and biological drivers affecting Reco during the daytime to achieve the NEE partitioning task. In spite of their improved performance compared to state-of-the-art empirical methods, they require a sufficient amount of training data as well as extensive tuning of the used deep networks' hyper-parameters. Accordingly, the trained model cannot take into account some short-term variations in ecosystem respiration.

2. Methods

The Koopman operator [6] enables the transformation of finite-dimensional nonlinear system dynamics to an infinite-dimensional linear dynamical system. Finding the eigenfunctions of the Koopman operator, however, remains a major obstacle to its implementation. DMD is a simple numerical algorithm that approximates the Koopman operator with a best-fit linear model that advances measurements from one time step to the next ([7], [8]. It is an equation-free system identification method where the underlying dynamics of the system are learned from snap-shot in time of measurement data. DMD decomposes system dynamics into temporal modes whereby each mode represents a fixed oscillation frequency and decay/growth rate. It has been extended to deal with dynamical systems with exogenous control input (DMDc) [9].

In this paper, we propose a new data-driven yet physics-aware method for the dynamical modeling of Reco, which can serve as an NEE partitioning method. The proposed approach is based on using DMDc in a sliding temporal window approach. The system state Reco is represented as a linear dynamical model with an autonomous component in addition to an exogenous component which is a function of control input. The control input to the system can be soil or air temperature (Tair) in accordance with the thermodynamics law or any other observed drivers such as soil water contents (SWC). Such modeling of Reco dynamics allows to disentangle the exogenous effect of the control input, e.g., Tair, from the autonomous dynamics of Reco, and hence allows to intervene on the control input to study its effect on the system. To deal with unobserved drivers of Reco other than temperature or any user control input, we make use of time-delay embedding (TDE) of the history of the system's state and control input. According to the Takens theory [10], such an embedding guarantees, under certain conditions, that the system will learn the trajectories of the original system. The TDE in DMDc has been shown to facilitate the treatment of nonlinear systems with linear models [11]. Another advantage of using TDE in the proposed method is that it allows for learning Reco dynamics from short data as it compensates for using advanced measurement in time. This is relevant as it enables ecosystem forecast taking into account short-term variations in the system dynamics.

3. Results

We used the half-hourly EC Fluxnet 2015 data [12] measured at multiple Fluxnet sites with different vegetation types and average temperatures to investigate the impact of different control inputs, e.g., Tair and SWC, on Reco dynamics. The model is trained on night-time NEE which is assumed to be the ground-truth values of night-time Reco. The day-time Reco values are then predicted using the obtained model with future values of control input. The method is validated on Reco short-term and long-term forecast periods with different control inputs. The obtained results indicate that: (1) The performance of the proposed method is comparable to the recently proposed deep learning-based NEE partitioning methods, yet it has the advantages of being a simple and almost hyper-parameter-free method with a very low computational load. (2) The use of TDE facilitates learning Reco dynamics from very short data, i.e., up to one night samples of NEE. (3) For most of the studied Fluxnet sites, Tair is a better long-term predictor of Reco, while using SWC as control input produced better short-term forecast accuracy.

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