



The applications of empirical dynamic modeling in environmental science

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Natural systems are often complex and dynamic (i.e. nonlinear), making them difficult to understand using linear statistical approaches. Linear approaches are fundamentally based on correlation. Thus, they are ill-posed for dynamical systems, where correlation can occur without causation, and causation may also occur in the absence of correlation. “Mirage correlation” (i.e. the sign and magnitude of the correlation change with time) is a hallmark of nonlinear systems that results from state dependency. State dependency means that the relationships among interacting variables change with different states of the system. In recent decades, nonlinear methods that acknowledge state dependence have been developed. These nonlinear statistical methods are rooted in state space reconstruction, i.e. lagged coordinate embedding of time series data. These methods do not assume any set of equations governing the system but recover the dynamics from time series data, thus called empirical dynamic modeling (EDM). EDM bears a variety of utilities to investigating dynamical systems. Here, we provide a step-by-step tutorial for EDM applications with rEDM, a free software package written in the R language. Using model examples, we aim to guide users through several basic applications of EDM, including (1) determining the complexity (dimensionality) of a system, (2) distinguishing nonlinear dynamical systems from linear stochastic systems, and quantifying the nonlinearity (i.e. state dependence), (3) determining causal variables, (4) forecasting, (5) tracking the strength and sign of interaction, and (6) exploring the scenario of external perturbation. These methods and applications can be used to provide a mechanistic understanding of dynamical systems.