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Impact Predictability: Exploring Extremes in Biosphere Dynamics with Recurrent Neural Networks

Francesco Martinuzzi[1,2,3], Miguel D. Mahecha[1,2,3], Gustau Camps-Valls[5], David Montero[2,3,4], Tristan Williams[5], and Karin Mora[2,3]

[1]Center for Scalable Data Analytics and Artificial Intelligence (ScaDS.AI), Leipzig University, Leipzig, Germany
[2]Institute for Earth System Science & Remote Sensing, Leipzig University, Physics and Geophysics, Leipzig, Germany
[3]Remote Sensing Centre for Earth System Research (RSC4Earth), Leipzig University, Leipzig, Germany
[4]German Centre for Integrative Biodiversity Research (iDiv), Leipzig, Germany
[5]Image Processing Laboratory (IPL), Universitat de València, València, Spain

Understanding Earth's terrestrial biosphere dynamics is vital for comprehending our planet's environmental health and sustainability. Recently, the frequency and intensity of extreme climate events have risen, significantly impacting the biosphere. Given the advancements of recurrent neural networks in modeling complex, nonlinear dynamics, we explore the capability of recurrent neural network models to model and predict the impacts of extreme events on biosphere dynamics. In this work, we compare four different recurrent network architectures, each with distinct features: 1) Recurrent Neural Networks (RNNs); 2) Long Short-Term Memory-based networks (LSTMs), known for their efficacy in handling long-term dependencies; 3) Gated Recurrent Unit-based networks (GRUs), which offer a simplified yet effective alternative to LSTMs; and 4) Echo State Networks (ESNs), which are distinguished by fixed internal weights and training based on simple linear regression. Our study found that while recurrent network architectures show similar performance under standard conditions, Echo State Networks (ESNs) show slightly superior performance, particularly under extreme events. However, we also identify limitations in current models under extreme conditions, underscoring the need for specialized approaches to enhance predictive accuracy in these circumstances.