AI MODELING OF COMPLEX REAL-WORLD ECOSYSTEM DYNAMICS

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We propose a novel symbiosis of *echo state neural network AI* (ESNN), *empirical nonlinear dynamics* (END), and *global sensitivity analysis* (GSA) with *high-performance computing* (HPC) to simulate/forecast complex real-world soil-moisture dynamics reconstructed from high-dimensional field and remote-sensing data. Soil-moisture dynamics are integral to plant growth and ecosystem functions, climate change and weather prediction, and pollution mitigation. Complexity emerges endogenously from strong nonlinear interactions among soil-moisture co-variates, which potentially co-evolve along *attractors* bounded within a low-dimensional subset of state space. ESNN can learn long-term nonlinear dynamics on attractors with relatively few degrees of freedom regardless of the complexity/dimensionality of the system itself. This makes ESNN a valuable *dimension-reducing* technique for analyzing complex nonlinear soil-moisture signals. Recent proof-of-concept demonstrates that ESNN can learn complex nonlinear dynamics from clean data generated by closed 'toy' models. However, in modeling open real-world systems we do not know all covariates involved or whether/how they interact. We do not directly observe state-space dynamics and must infer them from noisy data. We seek to make ESNN a skillful simulator/forecaster of complex real-world physical systems by using: (1) END pre-processing to test data inputted into ESNN for nonlinear dynamics, reconstruct real-world state-space dynamics that ESNN is targeted to learn, and make these dynamics easier to learn by ensuring that inputted data are denoised and stationary and co-variates in the data set are causally interactive; and (2) GSA post-processing with HPC to optimize quickly best performing ESNN hyperparameter architectures. Preliminary results indicate that ESNN can skillfully learn complex nonlinear dynamics from soil-moisture sensor data and reliably forecast out-of-sample. We will leverage nonlinear forecasting power to develop an AI-based early-warning system of catastrophic soil-moisture events (extreme droughts, wildfires, landslides, foundation stability of buildings and other structures under sea level and climate change extremes, etc.) patterned after those in the cyber-breach literature.

PRESENTER BIO: Huffaker's research reconstructs nonlinear spatial and temporal dynamics of endogenously unstable real-world and experimental systems from observational data, maps out and measures causal interactions in real-world networks, and constructs data-driven biophysical models of real-world system dynamics with recurrent neural network AI modeling.