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Hybridizing Knowledge-Based and Machine Learning Models for Climate and Tipping-Point Prediction: Two Examples of Recent Accomplishments

Presented by
Edward Ott (U. Maryland, PI)

Team: University of Maryland, Texas A&M University, Potomac Research LLC

Example #1: Predicting Nonstationary Dynamics and Tipping Point Behavior

- Climate change is necessarily a nonstationary process. Due to non-stationarity, the predicted future dynamical behavior will differ from past observed data available for training.

- This requires rethinking ML procedures commonly used for predicting stationary system behavior.

- We have developed machine learning techniques for prediction of non-stationary systems. (See Patel et al., Chaos 31, 033149, and arXiv:2207.0051 [cs.LG]). We plan to incorporate these techniques into our full hybrid ML/knowledge-based Earth climate model.

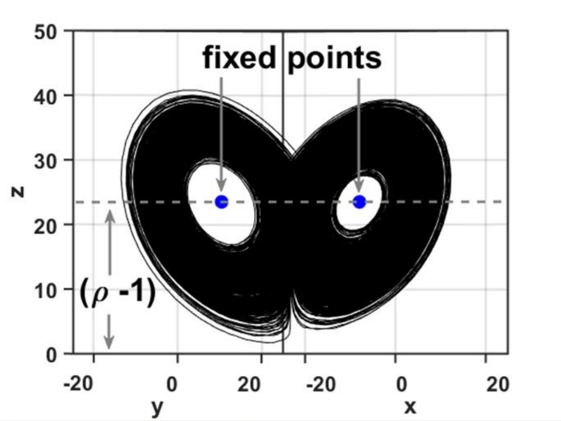
A tipping point example using the Lorenz '63 model

- Lorenz '63 equations: Models thermal convection in a fluid layer

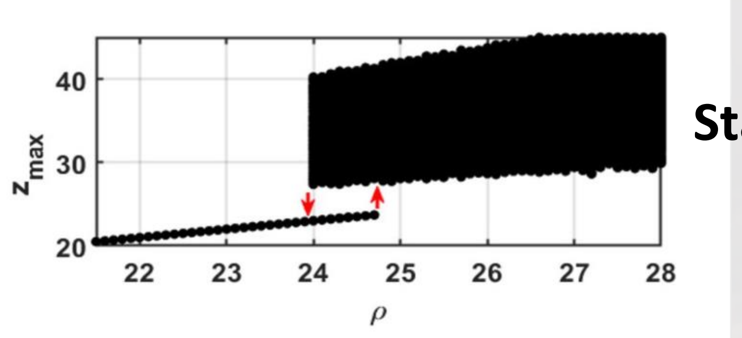
$$\frac{dx}{dt} = \sigma(y - x) + \xi_x(t)$$

$$\frac{dy}{dt} = x(\rho - z) - y + \xi_y(t)$$

$$\frac{dz}{dt} = xy - \beta z + \xi_z(t)$$



Stationary



Stationary

- $\xi_i(t)$: white dynamical noise

- We consider the tipping point that occurs as rho increases with *t* in the above range.

Tests for this example

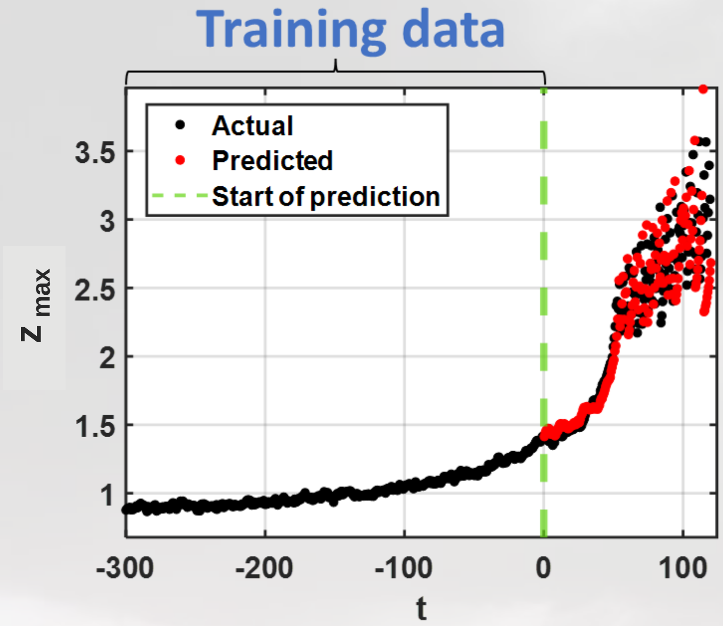
- **ML prediction only:**
  The tipping point is predicted, but, after tipping, the orbit diverges to unphysically large values.
- **ML hybridized with an inaccurate available knowledge-based-model:**

  What happens?

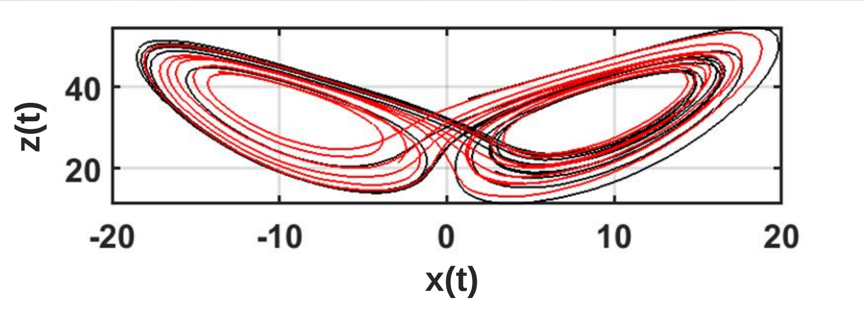
The ML acting alone diverges after tipping. The knowledge-based model acting alone does not tip. But when the two are combined in a hybrid, the tipping point and the post-tipping behavior are accurately obtained:

System parameter time-dependence:

$$\rho(t) = \rho_0 + \rho_1 \exp\left(\frac{t}{\tau}\right)$$



$90 \leq t \leq 100$



z_{max} are the (rescaled) z-values at which $xy - \beta z = 0$

Example #2: COMPARISON OF OUR HYBRID ML/PHYSICS-BASED MODEL WITH A CONVENTIONAL STATE OF THE ART CLIMATE MODEL

OUR TERRESTIAL CLIMATE HYBRID MODEL

The ML component uses ~ 1000 reservoir computers each assigned to prediction of its own local region, trained individually in parallel.

The physics-based code (called SPEEDY [Molteni, 2003]) has reduced resolution relative to operational weather codes (36,800 grid points), but realistically incorporates relevant physics [3 dimensionality (latitude, longitude, and height), and terrestrial geography (continents, oceans, ice covered regions, mountains)].

The atmospheric time series used for training and for assessing the accuracy of predictions is the ERA5 data from the European Center for Medium Range Weather Forecasting. (Training ~ 20 years)

Atmospheric Variables Comparison with Conventional SoA Model (E3SM)

(bias) = (10 year free run climate prediction) – (ERA5 data)

- **Energy Exascale Earth System Model (E3SM)**
  - **Fully coupled Earth system model**
  - **Run on ~6000 CPU cores**
- **Our Hybrid Model**
  - **ML-Driven SSTs**
    - **Other boundary conditions are climatological**
  - **Once trained can be run on a desktop computer**
    - **10-year simulation ~2 hours**

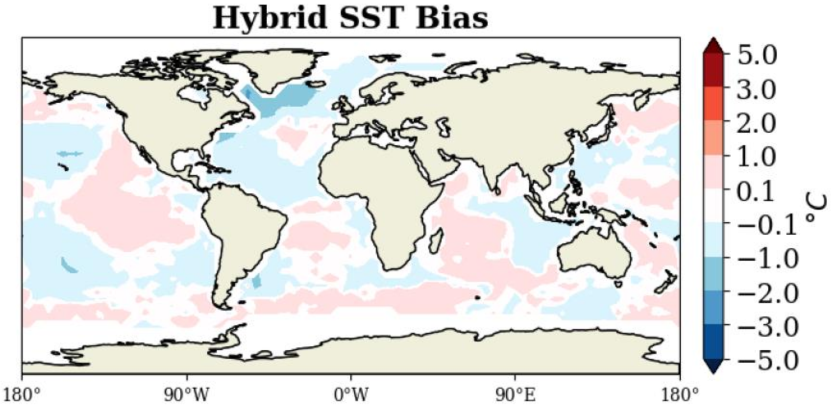
	Temperature			
Model	Min Bias	Max Bias	Mean Bias	RMSE
E3SM	-3.24	6.87	-0.77	1.62
Hybrid	-0.92	2.38	0.19	0.49
SPEEDY	-6.56	7.11	0.83	3.22

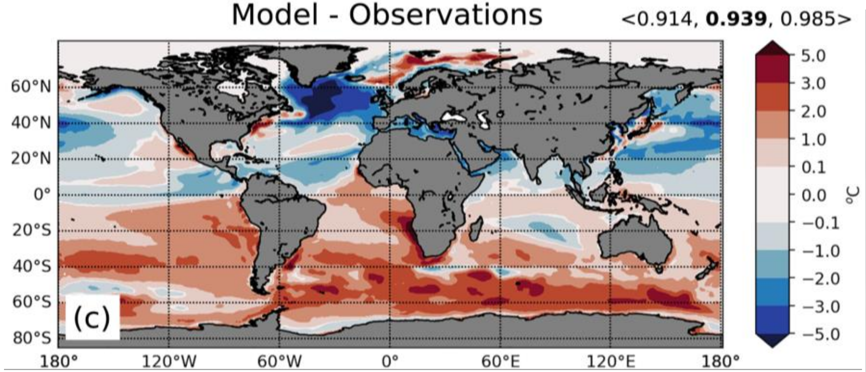
	Zonal Wind			
Model	Min Bias	Max Bias	Mean Bias	RMSE
E3SM	-7.38	3.79	-0.26	1.53
Hybrid	-1.73	1.83	0.12	0.60
SPEEDY	-6.93	20.7	0.63	2.30

The hybrid has the lowest bias magnitude in all cases.

Sea Surface Temperature (SST) Comparison

- **We also devised a machine learning ocean model which we coupled to our hybrid atmospheric model obtaining the following results:**
  - **Stable during a 10-year free run**
  - **Biases are lower for the hybrid than for the state-of-the-art model**





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TAKE AWAYS FROM THE TWO EXAMPLES PRESENTED (AND OTHERS)

- **Our hybrid ML/knowledge-based climate prediction approach shows the potential for significant benefits with respect to accuracy, cost, and computational speed.**

- **The prediction system appears to be stable over the climatological time scales tested.**