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Hybridizing Knowledge-Based and Machine Learning Models for Climate and Tipping-Point Prediction: Progress with Developing Hybrid Climate Model

Presented by
Troy Arcomano and Istvan Szunyogh (Texas A&M)

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

Focus of Current Efforts

- Climate change is necessarily a nonstationary process.
- We have developed machine learning techniques for prediction of nonstationary systems. (See Patel et al., Chaos 31, 033149, and arXiv:2207.0051 [cs.LG]) our goal is to incorporate these techniques into a realistic hybrid ML/knowledge-based climate model (Troy will show first preliminary results)
- We have been gradually adding new capabilities to the ML/knowledgebased climate model. Most importantly: dynamical coupling between the sea surface temperature (SST) and the atmosphere

Two Approaches to Incorporating Ocean Dynamics into our Hybrid Atmospheric Model

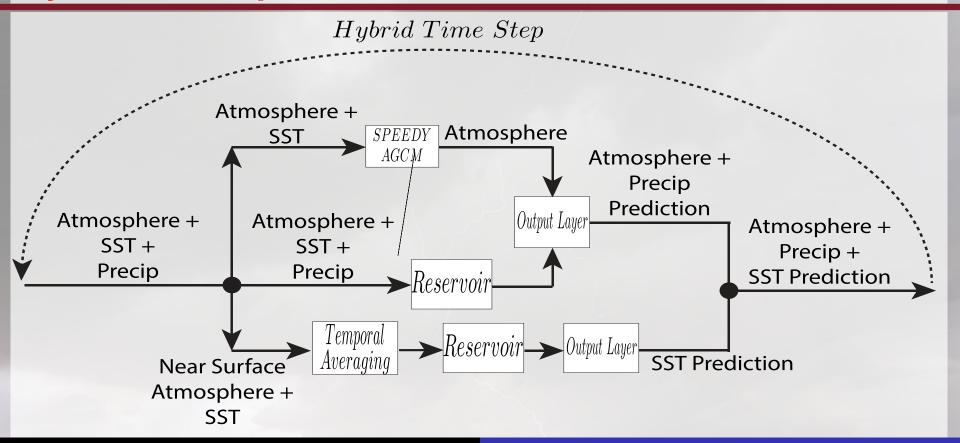
 Approach I: ML model of the SST coupled to our hybrid ML/knowledgebased atmospheric model

 Approach II: Hybrid model of the SST using a thermodynamic model as the knowledge-based component

Both approaches are being validated by simulating present climate

 Non-stationarity of the climate can be introduced in both approaches by varying a model parameter

Combining A Machine Learning Ocean Model with a Hybrid Atmospheric Model



Climate Simulation

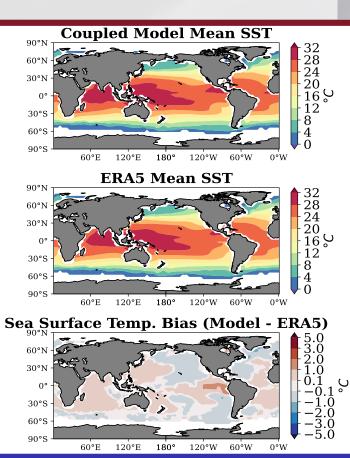
- Both the atmosphere and ocean models are trained "offline" using 26 years of ERA5 data (1981-2007)
 - The hybrid atmospheric model is trained to make 6-hour forecasts
 - Ocean model is trained to make 7-day SST forecasts

- The coupled model is run for 70 years
 - No sign of instability

Ocean Climatology

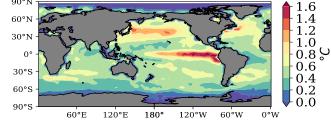
 The ML-only model can reproduce the annual climatology

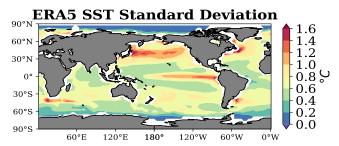
- Biases when compared to ERA5 are small
 - Better than state-of-the-art climate models with full ocean models

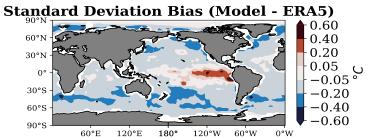


Ocean Climatology

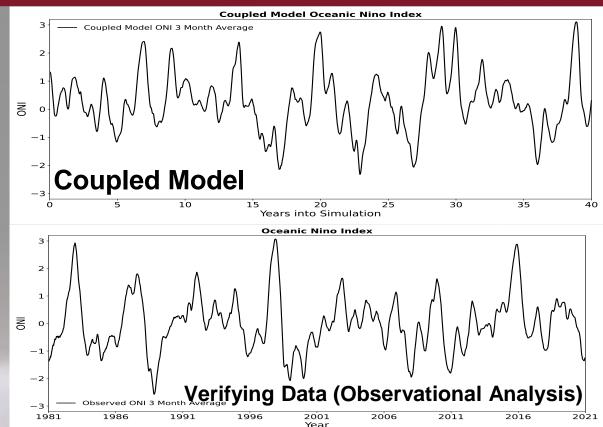
- The ML-only model can reproduce ocean variability
 - Average standard deviation of the monthly means during the 70year free run
 - Compared to ERA5 (1981-2021)
 - Captures major ocean currents and extension regions (e.g. Gulf Stream and Kuroshio Extension)







A Test of Our Coupled Model's Ability to Capture Ocean-Atmosphere Dynamical Interaction: ENSO

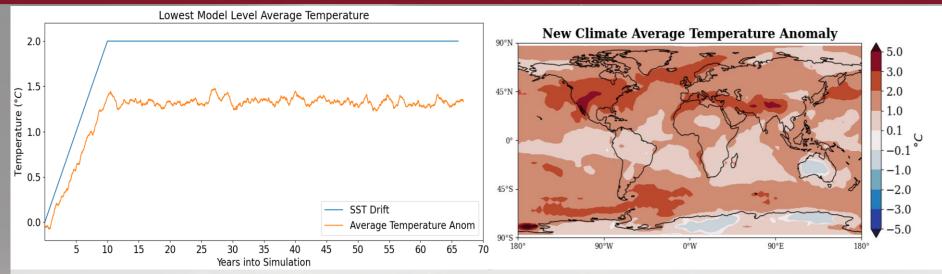


 Coupled model produces realistic ocean and atmospheric response to ENSO

Next Step: Incorporating Nonstationarity in Hybrid Model

- Can the hybrid atmosphere-only model trained on the past and present climate extrapolate to a new climate?
- Our past work (Patel et al., Chaos 31, 033149, and arXiv:2207.0051 [cs.LG])
 allows for the input of hypothetical nonstationary forcing into a hybrid
 model
 - We ultimately intend to do this for the hybrid coupled model with CO2 forcing
- As a first step, we have performed a preliminary series of experiments with our already-trained hybrid atmospheric model where the SSTs rise according to a hypothetical scenario

Hybrid Atmosphere with Nonstationary SST (VERY Preliminary)



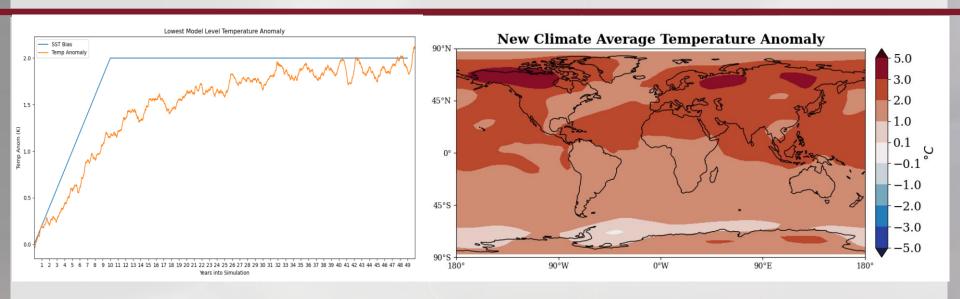
- The SST boundary conditions in the SPEEDY component of the trained hybrid are adjusted by:
 - [New SST] = [Current SST Climatology] + [assumed drift (blue curve)]
- The hybrid model is stable during this new climate
 - Shows nonstationary response

TAKE AWAYS

 Our hybrid ML/Knowledge-based climate model shows the potential for benefits with respect to accuracy and computational speed.

- Machine learning can be used to model and couple components of the Earth System
 - Able to capture interactions between the atmosphere and ocean (ENSO)
 - Our coupled model can be run at a small fraction of the computational cost compared to state-of-the-art numerical models
- Preliminary results show our coupled model can respond to a nonstationary signal and produce stable predictions

SPEEDY Reference Experiment



- Simulation of hypothetical climate change situation
 - New SST = Current SST Climatology + assumed drift (blue curve)
- Hypo linear drift term over 10 years until it plateaus at 2K