Multi-year Earth system variability, predictability, and prediction breakout summary

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Current RGMA research (presented in 21 talks)

Prediction and Predictability

Use relative entropy to quantify prediction skill; largest source is forced predictability in the tropics (Haiyan Teng)

Hindcasts with partial data assimilation show skill 2-3 years in advance; use statistical models to convert to Colorado River water supply, deficits of which are directly linked to reduced crop yield and increased wildfire severity in terms of burned areas (Simon Wang).

Longer term projections

Progress in quantifying the partitioning of sources of uncertainty between scenario, model, and internal variability (Flavio Lehner)

Two drivers of future aridity: GHG-driven intensified wet-dry patterns, and aerosol-driven shifts in ITCZ and regional patterns (Celine Bonfils)

Same ECS in E3SM and CESM, but larger TCR in E3SM related to much weaker AMOC (Aixue Hu)

Longer term projections (continued)

Need to understand how precipitation responds in key regions, and then relate to different scenarios (Jesse Norris)

Use NA-CORDEX regional models, and CMIP5 models; future projections show less snow in general, but models with better topography show grid points that retain snow at higher altitudes (Rachel McCrary)

Emergent constraints

Seasonal cycle of precipitation to constrain future precipitation projections (Di Chen)

Emergent constraint of double ITCZ for winter precipitation changes (Lu Dong)

Use of methods other than Earth system models (e.g. ML, LIM)

Use of ML-based analog method to predict ENSO (Matt Newman)

Machine learning to explore teleconnections from lower latitudes to the Arctic; predict SST in the North Atlantic using ML methods; reservoir computing outperforms LIM (Balu Nadiga)

Use LIM to separate ENSO influences on extratopics; de-coupling reduces extratropical variability and time scales in observations but not in models (Yingying Zhao)

Use LIM to define temporal changes in connections between KE and CP ENSO; (Youngji Joh)

Use of methods other than Earth system models (e.g. ML) (continued)

Deep learning method developed to forecast high latitude climate (Tarun Verma)

Apply machine learning to learn the model's internal state (modes of variability) for better predictability (e.g. IPO, ENSO); Use machine learning to rapidly generate new realizations (more ensembles) (Ben Kravitz)

Use deep learning applied to West Coast atmospheric rivers (Naomi Goldenson)

Internal variability vs. external forcing

Simulated vs observed variability in tropospheric temperature; use multi-model and linear and higher order detrending to remove forced signal; natural variability can explain model-satellite differences in tropical tropospheric warming (Giuliana Pallotta Goldhahn)

In CESM LE there is large internal tropical Pacific decadal variability in tropospheric temperatures, but lower ECS models correspond better with observations (Steve Po-Chedley)

Common bias function and EOF methods applied to assess simulation quality of extratropical modes of variability, CMIP3, CMIP5, CMIP6 models; PDO, AMO, PNA, etc. (Jiwoo Lee)

African easterly waves (AEWs) in tropical channel model: late century has stronger AEWs, 21% more (Emily Bercos-Hickey)

Multi-year changes of climate internal variability and effects on regional climate and wildfires (Yen-Heng Lin).

Gaps and opportunities

Use a deep learning method to predict features themselves instead of manually-generated and could be used for other applications

Need to better understand forced changes in variability

Need to articulate what we can get from different techniques (ML, LIM, ESMs)

Use AI/ML to combine observations and models for evaluation of forced versus internally generated predictability

Use ML applied to the initialization problem

Utilize the generic nature of AI/ML techniques for advancing the field of multi-year predictions and predictability, e.g. combining model simulations and observations to produce a better (unbiased) state/model, finding nonlinear relations among high dimension problems, fitting to a hierarchy of models to study their dynamical nature, searching for emergent constraints, initial conditions, etc.

To advance predictability/prediction, need to address: Biases in processes; error compensation through coupled processes from cloud-convection processes; weaker wind and weaker damping; good El Nino for wrong reasons; and models that are physically biased (e.g. El Nino bias related to MJO bias)

Better understanding of the aerosol response (direct, indirect) and decadal climate response to evolving aerosol emissions related to potential forced changes in modes of variability