2.3 Multi-year Earth system variability, predictability

Leads: Ben Kirtman, Jerry prediction Meehl, Chris Patricola

Haiyan Teng: Surface Climate Decadal Predictability in a Multi-Model Collection of Large Ensembles

Decadal prediction do not focus on land surface

Study forced predictability due to ENSO using MM LE using Relative entropy

Use of Relative entropy helps
(CESM-PI control) largest mean change doesn't match largest distribution changes
(MM LE) largest information gain is over the tropics whereas the largest changes are over higher latitudes

Matt Newman: Mining Large Climate Model Datasets to Make Multi-Year Initialized Global Sea Surface Temperature Forecasts

Find model analogs in large model repository for real time forecasts: CMIP5 and NMME analogs

How well does this work? Qualitative matches month 6 skill with NMME hindcasts for SST, Precipitation

DPLE vs CMIP5 analog: Also works for multi year forecasts & even better for Tropical Pacific, even up to year

Simple, cheap way to predict, before trying out more sophisticated methods

Next E3SM LE

Flavio Lehner: Partitioning climate projection uncertainty with multiple Large Ensembles and CMIP5/6

Revisiting Hawkins and Sutton for CMIP5/6

Large ensemble of projections helps quantify uncertainty in climate sensitivity

Challenges: for GMT the uncertainty is higher in CMIP6 wrt CMIP5, models that warm more for historic period also warm more in projections (way to constrain the estimate), Runoff sensitivity was all over the place, working towards constraining it using observations

Gaps: role of internal variability in climate sensitivity

Balu Nadiga: Machine Learning as a Tool for Climate Predictability Studies & Using Machine Learning to Explore Teleconnections from Lower Latitudes to the Arctic

Models are better at forced predictability, on other hand they are bad at internal predictability (e.g., large drifts)

Reduced order models for predicting such climate modes: LIM vs DL approaches

Reservoir computing: very good results for lorenz model, also works for PI control over NA sector, works better for sparse data situations than LIM

Ben Kravitz: Deep Learning for Creating Surrogate Models of Precipitation in Earth System Models & System identification techniques for detection of teleconnections within climate models

Jiwoo Lee: Are newer climate models better in simulating extratropical modes of variability than older ones?: A comparison across multiple generations of climate models

Evaluate 5 atm modes, 2 ocn modes against observation using two methods: Common Basis Function, EOF

across CMIP3, CMIP5,CMIP6:

with generation of CMIPs we see improvements in spatial patterns (more blue colors for later generation)

Aixue Hu: Role of AMOC in transient climate response to greenhouse gas forcing in two coupled models

Couldn’t take notes due to network issues

Yingying Zhao: The impacts of tropical-extratropical coupling on Pacific climate variability: observations vs. climate models

ENSO extratropics teleconnections, study by uncoupling the dynamics using LIM framework

Coastal NA region is most affected by ENSO-NPO coupled dynamics (adds variability), also provides longer inertia

Youngji Joh: Enhanced interactions of Kuroshio Extension with tropical Pacific in a changing climate

It was described in an earlier study that coupled KE-ENSO decadal variability is enhanced in future

Additional Questions: If the relationship is non stationary and if it statistically significant; study it using LIM

They find: it is non stationary via changes in Atmospheric response to KE

Next: why is it non stationary

Simon Wang: Colorado River water supply is predictable on multi-year timescales owing to long-term ocean memory

Regional application of multi-year prediction

Colorado river supply shows quasi decadal variations, also correlated to soil moisture

Partial data assimilation experiments to separate out the impacts of ocean vs soil moisture

Transition of low frequency modes (ENSO, PDO) provide predictability rather than the peak state

Implications for fire, crops,

Di Chen: Connection between seasonal and future precipitation sensitivity

Finding emergent constraints for seasonal precipitation changes using temperature changes

Tropics versus mid latitude: models do not agree in mechanism

Lack of observations

Lu Dong: Correcting the double-ITCZ bias dials down future precipitation over Mediterranean climate regions in North Hemisphere

Sharper seasonal cycle of precipitation in future, related to aleutian low, westerly jet and ITCZ

How Double ITCZ bias affect this relation using CMIP5 models

Celine Bonfils: Identifiable decadal signatures of greenhouse gases and particulate atmospheric pollution on the changing hydroclimate

GHG and aerosols both influence historical hydroclimate,

Two mechanisms:

1st: mainly due to GHG, partially compensated by aerosols along with the volcanic forcing

2nd: more subtle, interhemispheric contrast, shift of ITCZ (tied to larger anthropogenic aerosols in NH)

More observations are needed to see it

Jesse Norris: Evaluating hydrologic sensitivity in CMIP6: internal variability versus anthropogenic forcing

Emily Bercos-Hickey: Anthropogenic Influences on African Easterly Waves

WRF TCM to study anthropogenic effect on African Easterly waves (historical vs late century)

Track AEW and compare densities; more wave tracks in late century (detected 21% more)

PDFs of curvature vorticity also broadens (mostly in the South track?)

Giuliana Pallotta Goldhahn: Multi-frequency analysis of simulated versus observed variability in tropospheric temperature

Compare climate models (CMIP5/6 historical) and satellite data wrt TMT variability

Depends on noise removal strategy

Variability is overestimated in climate models

Stephen Po-Chedley: Natural variability can explain model-satellite differences in tropical tropospheric warming

Rachel Mccrary: Mulit-year Predictions of Snow Water Equivalent over North America in Global and Regional Climate Models.

Naomi Goldenson: Visualizing Drivers Associated with West Coast Atmospheric Rivers using a Deep Learning Framework

Tarun Verma: Deep Learning Forecasting of High Latitude Climate Variability

Yen-hing Lin: Causes of recent changes in extreme wildfire in California's Yen-Heng Lin South Coast

Strong and dry offshore winds in OND (from great basin towards the California coast) makes conditions favorable wildfires over the south coast long term changes in MJJAS/OND circulation (Z250, SLP, VPD) are seen in observations that enhance probability of heat extremes/wildfires

Challenge: CMIP models can not capture such circulation changes