1. **Haiyan Teng: Surface Climate Decadal Predictability in a Multi-Model Collection of Large Ensembles**
   Previous studies are mostly based on the ocean.
   How large is the forced predictability in daily TAS/precipitation in the near term?
   multi-model large ensemble repository from 7 models
   Use relative entropy for predictability: JSD (0: two distributions are identical, 1: there is no similarity)
   ENSO in CESM1 1800-yr piControl: Alaska vs. Equatorial Pacific both have largest changes in mean TAS, but have different changes in probability distribution with largest predictability in tropics.
   How significant is the forced predictability compared to that produced by ENSO?
   With relative entropy we can quantify and compare predictability (both forced and internal) on S2D time scales.

2. **Matt Newman: Mining Large Climate Model Datasets to Make Multi-Year Initialized Global Sea Surface Temperature Forecasts**
   "Model-analog" technique: Turn every climate model into a forecast model: Find ensemble of closest matches (analog) to observed SST/SSH anomaly, then Evolution of analog ensemble to forecast ensemble
   On decadal skill, Some ENSO events are predictable at least 2 years ahead, and this skill can be identified a priori
   Applying to new "E3SM large ensemble": Construct a model from model

3. **Flavio Lehner: Partitioning climate projection uncertainty with multiple Large Ensembles and CMIP5/6**
   Model uncertainty continues to be large in CMIP6 models and is increased from CMIP5 to CMIP6. After constraining by observation, CMIP5 and CMIP6 uncertainties are comparable.
   Large-ensembles reveal that internal variability and its change is uncertain.
   Future plan: Evaluate modes of internal variability and their change; Assess downstream effects of biases and forced changes in models of variability.

4. **Balu Nadiga: Machine Learning as a Tool for Climate Predictability Studies & Using Machine Learning to Explore Teleconnections from Lower Latitudes to the Arctic**
   Models good at realizing external-forcing related predictability, but bad at predictions of natural variability.
   Difficulty: model bias.
   Reduced order dynamical systems and predictability: Model order reduction
   Three methods comparison: LIM

5. **Ben Kravitz: Machine Learning to improve climate predictability**
   Learning internal variability improve predictability? Machine learning can do it as it is data driven. Emulate climate models to explore extreme events.

6. **Jiwoo Lee: Are newer climate models better in simulating extratropical modes of variability than older ones?: A comparison across multiple generations of climate models**
   PDO; NPGO; PNA; NPO; NAO; NAM; SAM
   Methos: Common Basis Function; Traditional EOF method
   ~800 of CMIP3, 5, 6 simulations
   Relative error on spatial pattern: Improvement in CMIP6
   Temporal amplitude:
   Outliers in AMIP often are also outliers in Historical
   Easier to diagnose root-cause of errors in AMIP mode

7. **Aixue Hu: Role of AMOC in transient climate response to greenhouse gas forcing in two coupled models**
   CESM2 and E3SM1 ECS: 5.3K, but AMOC is much weaker in E3SM1, due to the fresher subpolar North Atlantic, also the global mean surface temperature. In response to CO2 forcing, AMOC weakens more in CESM2 than E3SM1.

8. **Yingying Zhao: Removing tropical-extratropical coupled dynamics from North Pacific Climate variability**
   To what extent have ENSO-related variations contributed to the North Pacific variability?
   How to decouple tropical-extratropical?
   Methods: LIM
   Decouple loses >50% of variability in the North Pacific in ORAS4 also for time scale, but not captured by models.

9. **Youngji Joh: Enhanced interactions of Kuroshio Extension with tropical Pacific in a changing climate**
   Kuroshio Extension (KE) vs. PMM; KE vs. CP ENSO: decadal trigger for each other, after 1985 has better correlation. Why? Wind stress curl forcing shift poleward
   10yr: KE preferred decadal time scale
   What causes non-stationary KE variability? How and how much the background mean state and external forcing influence PDO?

10. **Simon Wang: Colorado River water supply is predictable on multi-year timescales owing to long-term ocean memory**
    Colorado river water supply follows the soil water storage very well. Improving soil water variability can improve predictive skill of Colorado River water supply.
    Ocean memory in the North Pacific, tropical Pacific and tropical Atlantic can improve predictive skill on multi-year timescales.
    Having a 2-year lead-time on preparing for drought could have impacts on farmers as they plan crop rotations and make business decisions.
    A long-term forecast of drought in areas impacted by the Colorado River could give managers a jump-start in preparing for wildland fire seasons.

11. **Di Chen: Connection between seasonal and future precipitation sensitivity**
    Motivation: Use precipitation seasonal cycle to narrow uncertainty in climate change precipitation sensitivity
    Large spread in precip projection, emergent constraint; seasonal cycle of precip and temp change;
    NH mid-lat land area: Seasonal change vs. climate change: frequency, intensity, amount, extreme (>99%)
    Tropical land & subtropical NH land
    Seasonal precip sensitivity appears to have connection with climate change precip sensitivity.
    Future: understand physical basis of such connection

12. **Lu Dong: Correcting the double-ITCZ bias dials down future precipitation over Mediterranean climate regions in North Hemisphere**
    Double-ITCZ can be an emergent constraint of the future winter precipitation changes in the US Southwest and Mediterranean Basin. Larger double-ITCZ bias can project a wetter winter in both regions.
    The US Southwest is connected by wet-get-wetter with double-ITCZ, and Mediterranean basin is connected by AMOC.
    Constraining the bias with observation lowers the projected precipitation increase to no change over the US Southwest and intensifies the projected decrease by 32% over Mediterranean Basin under warming.
    Future plan: Find other factors influencing the inter-model spread in precipitation projections over Mediterranean regions, besides double-ITCZ.

13. **Celine Bonfils: Can we disentangle the impact of changes in greenhouse gases and aerosols on recent decadal changes in hydroclimate?**
    Why are arid conditions spreading worldwide? Why is the western US getting increasingly arid since the 1980s while the African Sahel has recovered from its prolonged drought?
    The observed signal cannot be explained by noise, aerosol, GHG forcing alone. It is best captured by all forcing together.
    Better separation of direct and indirect aerosols effects
    Since 1950, GHG and anthropogenic aerosols have influenced together global changes in temperature, precipitation and regional aridity in two distinct ways.

14. **Jesse Norris: Assessing hydrologic sensitivity in CMIP6: internal variability versus anthropogenic forcing**
    Correlation in hydrologic sensitivity in CMIP6 between internal variability and anthropogenic forcing cases: well correlated
    Internal variability can be estimated by observation, then be used to constraint the anthropogenic forcing effect
    PC1 of Ts explains more than half of tropical mean of internal variability

Hydrologic sensitivity is reasonably correlated across CMIP6 models between internal variability and anthropogenic forcing
Suggests hydrologic sensitivity may be constrained, but diagnosing from observations is complicated.

15. **Emily Bercos-Hickey: Anthropogenic Influences on African Easterly Waves**
    WRF model 30S-60N, seudo global warming
    Number and location of waves
    AEW tracking May-Oct 2001-2010
    Under warming: 21% more AEWs in the late-century than historical
    PDF: peak is larger in late-century than historical

16. **Giuliana Pallotta Goldhahn: Multi-frequency analysis of simulated versus observed variability in tropospheric temperature**
    Do climate models underestimate observed low-frequency variability of TMT?
    To explore whether the last two generations of climate models underestimate observed low-frequency variability of mid- to upper tropospheric temperature (TMT)
    Compare the spectral feature of TMT variability in climate models and satellite data
    CMIP6 has higher power and low frequency.
    CMIP Hist have larger band power than observations.
    For 5-20 years, observed TMT variability is overestimated by CMIP5 and CMIP6.
    Future: operate on raw data, signal removal methods, use LEs

17. **Stephen Po-Chedley: Natural variability can explain model-satellite differences in tropical tropospheric warming**
    CMIP5 and CMIP6 models warm more than all observations.
    CESM LENS: Nino3.4 trend has large spread, so the effect of internal variability can be large. Choose one member which is mostly like observation.
    Tropical Pacific variability is large (multi-decadal)
    Tropical tropospheric trends can thus very widely
    High and low ECS models produce trends in accord with observations
    But high ECS models are less likely to agree with observations
    Future: better isolate forced and unforced signals

18. **Rachel Mccrary: Multi-year Predictions of Snow Water Equivalent over North America in Global and Regional Climate Models**
    NA-CORDEX
    RCMs are very wet and have large positive SWE biases
    US Intermountain West: Higher elevation mountains, reduced loses for the domain as many points remain below freezing.
    CMIP5 models oversample low and mid elevations.
    SWE losses are reduced with elevation.

19. **Naomi Goldenson: Visualizing Drivers Associated with West Coast Atmospheric Rivers using a Deep Learning Framework**
    Goal: To find sources of predictability
    Group AR days based on SOM based on large-scale fields, nodes 1-6
    The patterns vary with latitude and also angle and IVT at landfall.
    The neural net to predict based on upstream winds with various lead times
    Data is divided in half for training and testing.
    Jet exit region often has the highest relevance, with specifics depending on the pattern.

20. **Tarun Verma: Deep Learning Forecasting of High-Latitude Climate Variability**
    Large thermal inertia over Subpolar North Atlantic (SPNA), affected by the overturning circulation, predictability hotspot
    CNN: skillful forecast up to 18 months
    Q: how well does this DL
    An idealized setting: CESM piControl
    Using SST and upper ocean heat content from larger Atlantic sector
    It translates well for seasonal predictions, but not so much for multi-year predictions; tendency to overfit the training data for longer leads
    Future: Comparison with other standard benchmarks, Testing of more complex architectures, Use of transfer learning for real-time forecasts, Interpret results/gain physical insights