# NOAA-DOE PRECIPITATION PROCESSES AND PREDICTABILITY

## WORKSHOP REPORT

Published July 2021

U.S. DEPARTMENT OF ENERGY | Office of Science

National Oceanic and Atmospheric Administration
U.S. Department of Commerce

DOE/SC-0206 | NOAA Technical Report OAR CPO-9

**Recommended Citation:**

Balmaseda M, A Barros, S Hagos, B Kirtman, H-Y Ma, Y Ming, A Pendergrass, V Tallapragada, E Thompson. 2020. "NOAA-DOE Precipitation Processes and Predictability Workshop." U.S. Department of Energy and U.S. Department of Commerce NOAA; DOE/SC-0203; NOAA Technical Report OAR CPO-9.

# NOAA-DOE Precipitation Processes and Predictability Workshop

November 30 – December 2, 2020 (Virtual)
Published July 2021

**Convened by**

U.S. Department of Commerce
National Oceanic and Atmospheric Administration
Office of Oceanic and Atmospheric Research
Climate Program Office
The Earth Systems Science and Modeling Division
U.S. Department of Energy
Office of Science
Office of Biological and Environmental Research
Earth and Environmental Systems Sciences Division

**In partnership with**

U.S. Global Change Research Program
U.S. Climate Variability and Predictability

Science Committee and Report Authors: Magdalena Balmaseda (ECMWF), Ana Barros (Duke University), Samson Hagos (DOE/PNNL), Ben Kirtman (U. Miami), His-Yen Ma (DOE/LLNL), Yi Ming (NOAA/GFDL), Angie Pendergrass (Cornell University; NCAR), Vijay Tallapragada (NOAA/NWS), Elizabeth Thompson (NOAA/PSL)

Program Organizing Committee: Jin Huang (NOAA/CPO), Renu Joseph (DOE/EESSD), Sandy Lucas (NOAA/CPO), Sally McFarlane (DOE/EESSD), Mike Patterson (US CLIVAR), Yan Xue (NOAA/NWS)

Editor and Facilitator: Victoria Breeze (NOAA/CPO)

Rapporteurs: John Coggins (NOAA/CPO); Zhe Feng (DOE/PNNL); Bryce Harrop (DOE/PNNL); Huaping Huang (DOE/LBL); Ali Stevens (NOAA/CPO); Die Wang (DOE/BNL)

Facilitator: LuAnn Dahlman (NOAA/CPO)

# Executive Summary

Our ability to predict when, where, and how much precipitation will fall is critical for decision making and responding to the impacts of extreme rainfall across a wide range of sectors and timescales. The current generation of Earth system models (ESMs), however, have large and persistent systematic errors that severely limit the ability to faithfully reproduce the many spatial and temporal scales of precipitation variability.

The NOAA-DOE Precipitation Predictability and Processes Workshop was held virtually during November 30–December 2, 2020. In partnership with the U.S. Global Change Research Program (USGCRP) and U.S. Climate Variability and Predictability (US CLIVAR), the workshop was attended by participants from the observational and modeling research communities as well as operational centers to address the challenge of precipitation predictability. More specifically, the workshop focused on precipitation predictability and physical processes for the contiguous U.S. with an emphasis on sub seasonal to multi-decadal timescales. Essentially, the workshop asked how we can improve our ability to predict precipitation variability and extremes.

The workshop was organized into four sessions that focused on 1) sources and limits of predictability; 2) key processes critical to precipitation biases; 3) interdisciplinary processes; and 4) regional precipitation. Each session included keynote presentations and panel remarks and discussions that provided succinct reviews of current knowledge and gaps and highlighted research and operational needs concerning precipitation predictability and physical processes. The workshop addressed the following thematic questions:

1. What are the sources of predictability that have the biggest influences on precipitation at weather, sub-seasonal-to-seasonal (S2S), and multi-decadal timescales, including extremes?
2. What are the key physical processes that have the strongest imprint on the model biases and precipitation predictions and projections?
3. How can we most effectively take advantage of existing observations and data (satellite and in situ) to advance process-level understanding of the key processes and predictability?
4. What are the gaps and needs for targeted observations and process studies to improve understanding and model representations of those key processes?
5. How do we benefit from national and international collaboration to make significant progress?

This workshop report is organized by discussion themes, followed by a section that highlights the key findings of the thematic questions. This executive summary provides a high-level synthesis of the discussion and findings of the “Sources of Predictability Influence Precipitation,” “Physical Processes Representation and Biases,” and forward-looking “Modeling and Observational Strategies.”

## Sources of Predictability Influence Precipitation

To accurately capture the multi-scale nature of precipitation in ESMs, emphasis should be on understanding and accurately representing large-scale atmospheric variability that modulates or forces regional precipitation, and, importantly, the feedbacks (e.g., local land-atmosphere interactions, remote ocean-atmosphere interactions) and processes that ultimately determine the interplay between regional rainfall and large-scale atmospheric variability.

**Large-scale variability:** Large-scale variability ranging from the Madden-Julian Oscillation (MJO) and North Atlantic Oscillation (NAO) at sub-seasonal scales through El Niño-Southern Oscillation (ENSO) at interannual scales and Atlantic Multidecadal Variability (AMV) and Pacific Decadal Oscillation (PDO) at decadal time scales can modulate regional precipitation through influence on large-scale atmospheric variability. This low-frequency variability (i.e., MJO, NAO, ENSO, AMV, PDO) and its predictability at different timescales provides an opportunity to predict regional precipitation. Nevertheless, significant challenges remain in exploiting this predictability in terms of understanding how, where, and when this low-frequency variability affects regional precipitation.

**Slowly Varying Processes:** Other processes that impact precipitation predictability include slowly varying surface-atmosphere interactions associated with memory of sea surface temperature, soil moisture, vegetation, and sea-ice that may influence precipitation locally, or remotely through teleconnections.

**Phenomena:** Extreme precipitation is associated with phenomena such as tropical cyclones, atmospheric rivers, extratropical cyclones, mesoscale convective systems, and lake-effect snowfall. Models should strive for a better representation of all of these weather phenomena and the large-scale environments that drive them.

## Physical Processes Representation and Biases

To improve the simulation and prediction of precipitation in ESMs, an improved understanding of processes and process interactions critical to precipitation will be needed. Significantly, model biases and drifts in models also limit the ability to predict precipitation accurately and need to be reduced.

**Process representation:** Precipitation is influenced by local processes such as surface-air interactions, stratosphere-troposphere interactions, terrestrial ecosystem processes, aerosol-cloud interactions, and remote processes such as tropically forced teleconnections. Improving representation of multi-scale processes from cloud microphysics through regional-to-global circulation is required.

**Biases:** Inadequate representation of atmospheric processes and their interactions with land, ocean, and the cryosphere in coupled models can lead to systematic biases in the mean and variable precipitation. There is a need for a systematic characterization of sources and causes of model biases that have the greatest impact on precipitation prediction, which may be facilitated by the use of a hierarchy of models and modeling experiments designed to elucidate critical processes and feedbacks.

## Modeling and Observational Strategies

Several modeling and observational strategies were highlighted as ways to make progress in reducing precipitation biases and improving precipitation simulations and predictions.

**High-resolution modeling:** Resolving multi-scale processes is critical to realizing the potential predictability of precipitation. With increasing computational power and exascale computing on the horizon, high-resolution modeling can bypass the need of certain parameterizations that are often the source of errors and biases. For example, global storm-resolving models (GSRMs) with horizontal resolution of 2-5 km and vertical resolution of ~200m can explicitly resolve deep convection above the boundary layer, bypassing the need for cumulus parameterizations. For the underlying boundary layer, resolutions higher than 200m may be necessary. The use of higher-resolution models has the potential to reduce the gap between weather and climate scales towards a unified modeling framework. Variable resolution modeling for both the horizontal and vertical scales was also highlighted as a computationally efficient method for achieving higher resolution in specific regions of interest.

**Hierarchical modeling:** A modeling framework featuring models of different levels of complexity can provide a more direct link between ESMs and observational data. For example, process-level models, such as large-eddy simulation (LES), can provide guidance on parameterization development. This helps to identify and improve physical process representations that are key to reducing precipitation biases.

**Phenomena-based model evaluation:** Nudged simulations, initialized hindcasts, and/or more sophisticated coupled data assimilation methodologies have the potential to provide useful experimental frameworks for evaluating simulations of precipitation and attributing precipitation biases to biases within local-scale features that extend to larger-scale atmospheric variability.

**Community modeling infrastructure:** Development of community modeling frameworks and infrastructures, such as the Unified Forecast System (UFS) and Community Earth System Model (CESM), can facilitate and sustain integration of community efforts in ESM development, accelerate the transition from research to operations, and yield results in which the whole is greater than the sum of the parts. While of critical importance, accelerating the transition of research to operations, however, requires significant resource investment as well as commitment and flexibility in both research and operations communities.

**Targeted and enhanced in situ and satellite observations:** Sustained and enhanced observations are needed to document the complexity of precipitation (e.g., type, duration, composition) that can be used to determine model biases and deficiencies, constrain model representation, adequately describe coupled interactions with land, ocean, ice, and aerosols, and inform new parameterizations.

**Observational-model integration:** Integrated field observations such as those from DOE's Atmospheric Radiation Measurement (ARM) user facility and other observational field campaigns are extremely useful for process-level studies, such as understanding key physical processes critical to precipitation, guiding physical parameterization developments, or testing modeling assumptions with process models for specific cases or through statistical studies. Process studies that integrate or assimilate data from observational field campaigns into models will enable better depiction of precipitation and associated extreme weather phenomena and processes.

**Collaborations between modeling and observational teams:** Developing databases of events and their global properties/precursors are needed to design and further develop modeling capabilities, form hypotheses, and test theories. Easy-to-access, documented, and centralized data archives from field campaigns are essential to facilitate collaborations between observational and modeling teams and accelerate progress. Standardizing formatting and data quality control across experiments would aid model-observation team efforts. How to effectively coordinate model development, process-level studies, and prediction and predictability research requires attention.

**Machine learning:** Machine learning and artificial intelligence (ML/AI) offer the possibility to improve analysis and reduce model biases. For example, ML/AI may be used to design and develop new data assimilation methodologies and new stochastic parameterizations for improving the simulation of natural variability. The value of machine learning in empirical bias correction, post-processing, improving parameterizations, accelerating computations, and development of surrogate stochastic models for prediction and predictability studies is recognized.

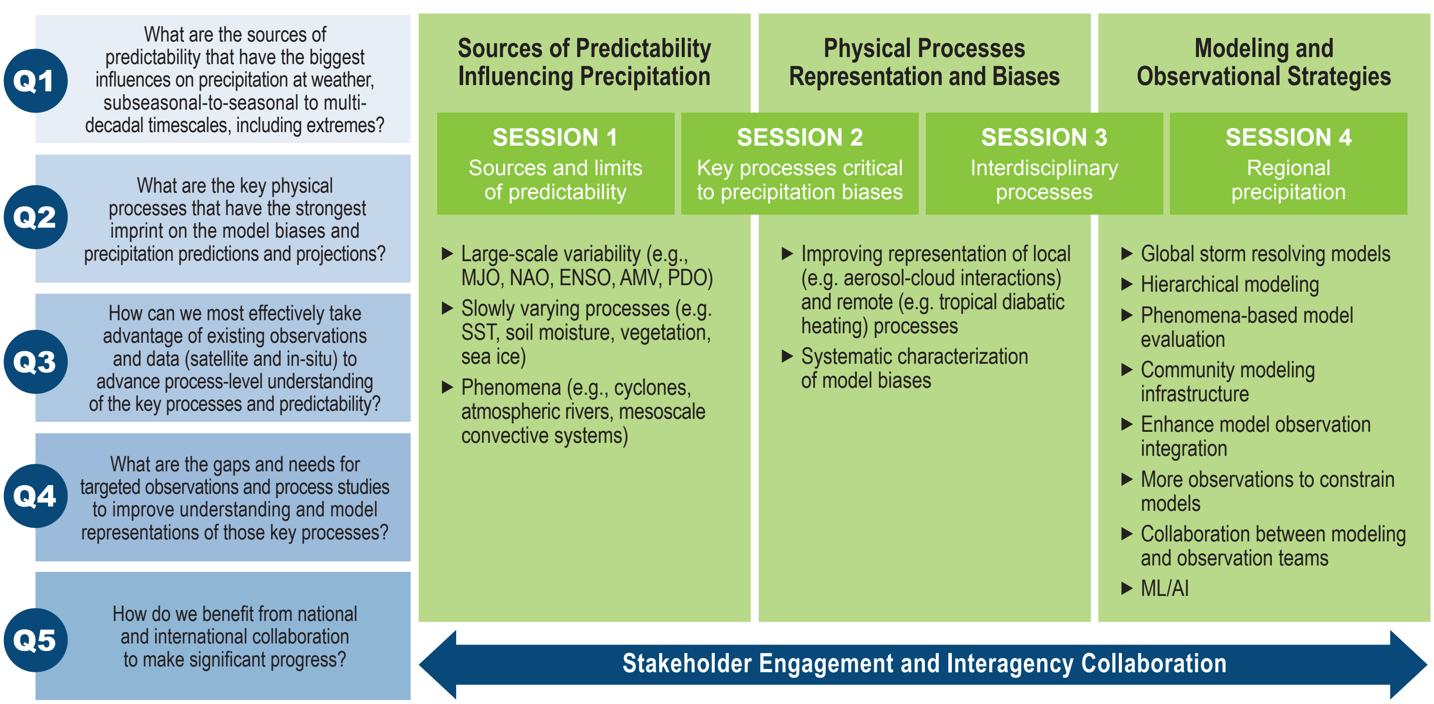
## Interagency Coordination of Science and Connecting to Services

Collaboration across individual agency program investments in observing, understanding, and modeling precipitation process representations for improved predictability can continue to be fostered through the interagency groups of the USGCRP and the US CLIVAR. The newly formed Interagency Council for Advancing Meteorological Services (ICAMS) also offers the possibility for coordination to accelerate the transition of innovative research into operational predictions.

## Stakeholder Engagement

Finally, the workshop emphasized the importance of communication among predictability researchers, operational personnel, and end users. Workshop participants considered it critical to identify which variables, at what temporal and spatial scales, lead times, and confidence levels, are of most practical value for specific applications.

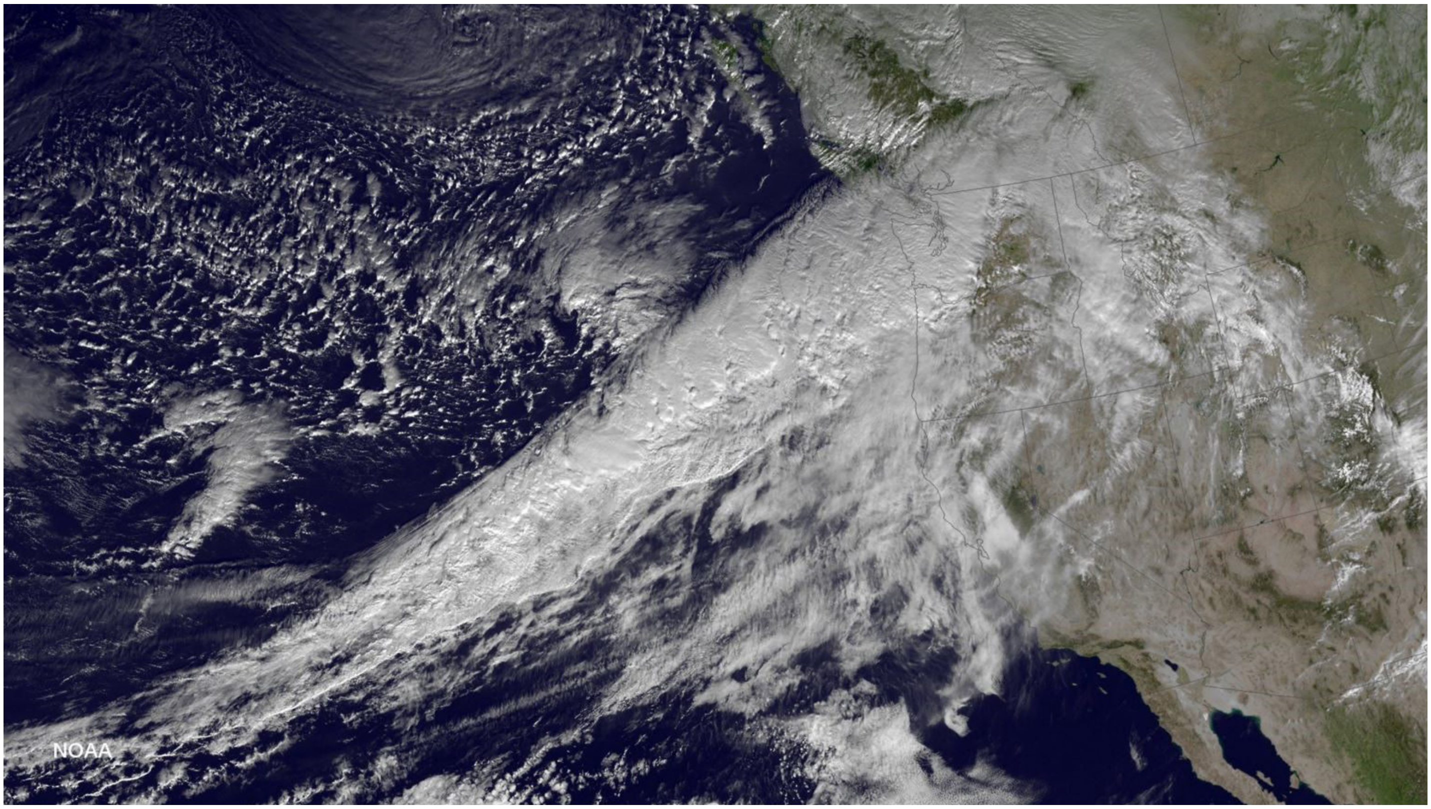
**NOAA-DOE Precipitation Processes and Predictability Workshop Thematic Questions and Key Findings**




Summarizing thematic questions and key findings from the NOAA-DOE Precipitation Process Predictability Workshop.

# Contents





# Workshop Introduction and Motivations

Weather and climate precipitation extremes (e.g., flood and droughts) have large societal impacts. A key to reducing these impacts is to be able to anticipate when, where, and how much precipitation will fall. Although models have a good track record of predicting global and regional temperature, precipitation related fields are not captured as well. The challenges in forecasting precipitation have been acknowledged by the U.S. Congress and the Executive Office of the President with several established mandates, including the 2017 Weather Act, the 2021 Earth System priority at the Office of Science and Technology Policy (OSTP) involving the water cycle, and the newly formed Interagency Council for Advancing Meteorological Services (ICAMS).

The National Oceanic and Atmospheric Administration (NOAA) has recently launched the Precipitation Prediction Grand Challenge (PPGC) Initiative to help further align research efforts across NOAA in the coming years. The U.S. Department of Energy (DOE) Earth and Environmental Systems Sciences Division (EESD) has both a broad interest in water cycle predictability—the 2018 EESD strategic plan identifies Integrated Water Cycle as one of its 5 grand challenges—as well a focused interest in precipitation processes in the context of Earth system predictability and extreme events.


**Figure 1.** NOAA Precipitation Prediction Grand Challenge (PPGC) Strategic Objectives.

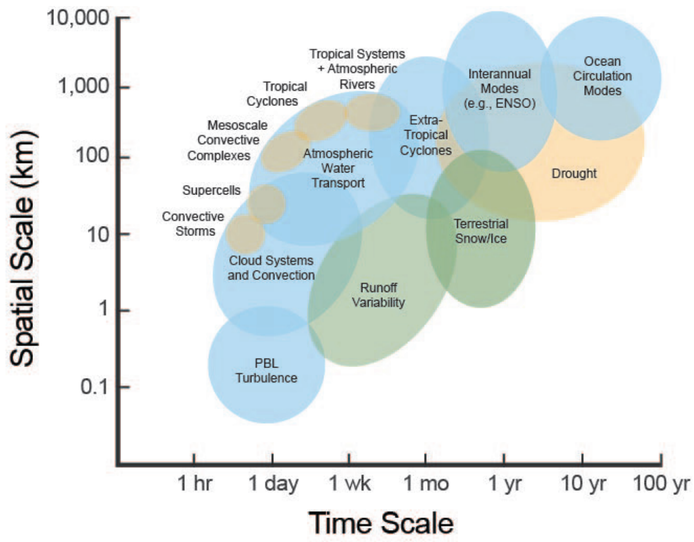



**Figure 2.** Spatial and temporal characteristics of atmospheric processes and features relevant to precipitation. (Source: 2019 Benchmarking Simulated Precipitation in Earth System Models Workshop Report)

To accelerate progress in addressing precipitation biases and improving precipitation simulations and predictions across a broader set of timescales, it is important to understand the current limits of predictability and highlight opportunities for extending the predictability limits.

To this end, NOAA and DOE, in partnership with the U.S. Global Change Research Program (USGCRP) and U.S. Climate Variability and Predictability Program (US CLIVAR), jointly organized a community workshop focused on advancing understanding of precipitation predictability and processes and exploring ways to reduce precipitation biases. The workshop scope considered precipitation processes and predictability over the contiguous U.S. in the context of global models, with a focus on sub-seasonal to multi-decadal timescales.

The workshop brought together the observational and modeling research communities as well as operational centers to address the following thematic questions:

1. What are the sources of predictability that have the biggest influences on precipitation at weather, sub-seasonal-to-seasonal (S2S), and multi-decadal timescales, including extremes?
2. What are the key physical processes that have the strongest imprint on the model biases and precipitation predictions and projections?

3. How can we most effectively take advantage of existing observations and data (satellite and in situ) to advance process-level understanding of the key processes and predictability?
4. What are the gaps and needs for targeted observations and process studies to improve understanding and model representations of those key processes?
5. How do we benefit from national and international collaboration to make significant progress?

The report is organized as follows. First, the workshop sessions are summarized in the context of the thematic questions. Four sessions were held: 1) sources and limits of predictability; 2) key processes critical to precipitation biases; 3) interdisciplinary processes; and 4) regional precipitation. Interagency and agency program perspectives are provided in the next section, followed by a final section that synthesizes the key findings to the thematic questions of the workshop.

# Workshop Themes

## SESSION 1: Limits And Sources Of Predictability

The Limits and Sources of Predictability Session was motivated by enhancing understanding of predictability limits and identifying strategies for realizing these limits to increase prediction skill in variables that meet user needs. *Figure 3* shows a schematic of the theme of the session. The session was split into two parts, with the first half featuring a keynote from Kristian Strommen (Oxford University), and panel remarks from Andrew Robertson (Columbia University/IRI), Frederic Vitart (ECMWF), Meghan Cronin (NOAA/PMEL), and Stephanie Henderson (University of Wisconsin). The second half of the session featured keynote speaker Kathy Pegion (George Mason University) and panelists Aneesh Subramanian (University of Colorado), Ruby Leung (DOE/PNNL), Tom Delworth (NOAA/GFDL), and Russ Schumacher (Colorado State University).

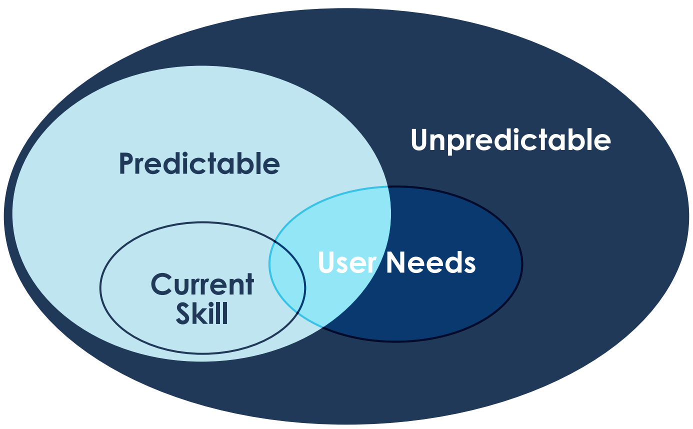



**Figure 3.** Schematic representing the general concept of predictability, including understanding predictability limits and strategies for realizing them as prediction skills that meet user needs. Sizes of bubbles can vary based on timescales and spatial scales of the issues of interest. (Courtesy of Kathy Pegion)

### Potential sources and limits of predictability

To discuss potential sources and limits of predictability, one must consider the scales of interest. For timescales of several weeks, it has been well known that the Madden-Julian Oscillation (MJO) is an important source of predictability while the El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), and Quasi-Biennial Oscillation (QBO) provide predictability at seasonal and interannual scales. At multi-decadal scales air-sea interactions over the extratropical oceans are the main potential sources of predictability.

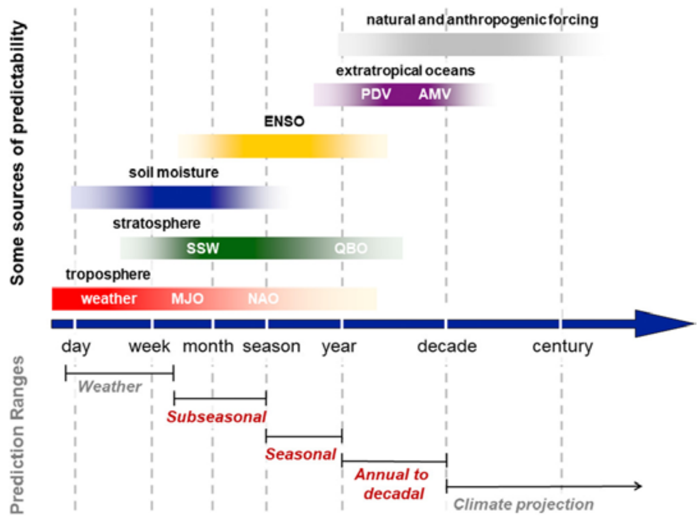



**Figure 4.** Schematic depiction of (bottom) temporal ranges and (top) sources of predictability for weather and climate prediction. From Merryfield, William J., et al. "Current and emerging developments in sub-seasonal to decadal prediction." *Bulletin of the American Meteorological Society* 101.6 (2020): E869-E896. © American Meteorological Society. Used with permission.

While significant progress has been made in understanding the various sources of predictability noted above, substantial challenges remain in terms of understanding their associated limits of predictability, their connection to regional precipitation, and how well their underlying mechanisms are represented in current Earth system models (ESMs). Indeed, there is much research to be done on how to capitalize on and exploit these various sources of variability—this exploitation is commonly viewed as forecasts of opportunity. To understand forecasts of opportunity, suppose we have an accurate forecast for where and when the MJO is in the active phase (i.e., enhanced rainfall in a particular region): We then have the opportunity to make a more skillful forecast of precipitation. The challenge is then to predict the phases of the MJO and then how they affect precipitation. More generally, representing the various sources of S2S predictability and their interactions (e.g., ENSO, MJO, QBO, Sudden Stratospheric Warmings [SSWs]) in models has been known to be critical (Merryfield et al. 2020), but ESMs still struggle to accurately capture the associated rainfall variability and even the various sources of predictability. For example, capturing the tropical diabatic heating processes associated with, say, the MJO or ENSO modifies mid latitude circulation and regional precipitation, and yet ESMs still struggle to capture these processes with sufficient accuracy.

Another significant source of precipitation predictability is that many surface components of the Earth system have variability on much longer time scales than the atmosphere. Surface-atmosphere interactions such as heat and moisture exchanges that are influenced by this "memory" or "persistence" in sea surface temperature (SST), soil moisture, vegetation, and sea-ice may contribute to precipitation locally or remotely through teleconnections.

In addition to the sources of rainfall predictability discussed above, recent research points to the importance of regime dynamics as a potential source of precipitation predictability. In this context regime dynamics is due to non-linear interactions between atmospheric transient eddies (e.g., weather) and the mean flow. These interactions can lead to regimes or quasi-persistent atmospheric states that then become potential sources of regional precipitation predictability. For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) model skill at predicting the winter NAO is primarily attributed to its ability to capture interannual variations in the latitude of the eddy-driven jet stream. However, accurately capturing eddy-mean flow interactions remains a challenge such that many models often fail to forecast these regimes beyond two weeks' lead.

Local processes also impact precipitation predictability. These include local land-surface feedbacks (e.g., soil moisture; vegetation feedbacks) and associated circulation changes (Teng et al. 2019), and aerosol cloud interactions.

## The role of tecÙology (ML/AI, high-performance computing, and observations)

Numerous new and emerging technical capabilities offer the potential to make game-changing advances to the science of predictability and prediction. For example, a leap to exascale computers will not only allow the design and deployment of ultra-high-resolution models but also allows larger numbers of ensembles to quantify natural variability. Machine learning and artificial intelligence (ML/AI) are also expected to improve analysis and correction of model biases, as well as lead to new data assimilation methodologies and new stochastic parameterizations for use in scale-aware models. Advances in satellite observations and autonomous platforms for in situ measurements of the structure of the atmospheric boundary layer and ocean mixed layer over the open ocean are expected to revolutionize model initialization through coupled data-assimilation, which would likely improve initialization accuracy and reduce initialization shock, thus leading to improved precipitation forecasting capabilities. (See Session 3 for additional discussion of the ocean-atmosphere boundary.)

## Integration activities

How to effectively coordinate model development, process-level studies, and prediction and predictability research requires attention. More effective collaboration across the weather and climate communities and improved engagement of forecast users are needed. Specifically, there are concerns that too many sub-critical modeling efforts on a wide range of topics may impede progress compared to larger, collaborative efforts focused on a few critical areas. The impressive model improvements over the last 10 to 20 years such as improvements in ENSO variability and Arctic sea-ice processes are examples where sustained integrated community efforts can yield results in which the whole is greater than the sum of the parts. Prediction of some important sources of S2S predictability, such as MJO (Kim et al. 2018), has improved significantly over the past decade thanks to decades of coordinated effort and investment (*Figure 5*).

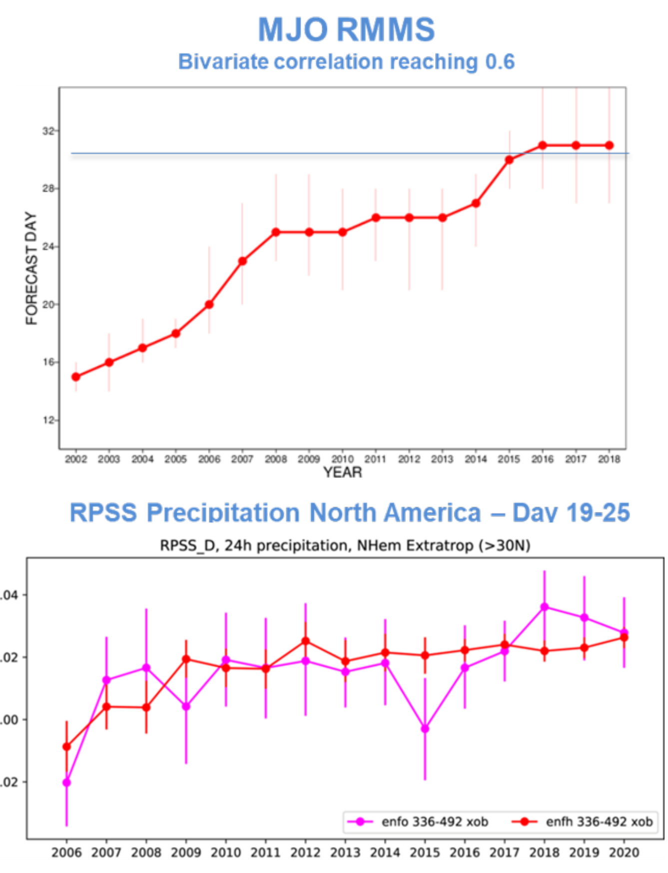



**Figure 5.** (Left) MJO and (Right) North American precipitation forecast skill trend in ECMWF forecast system.

These successes could be repeated for the prediction of precipitation through integration, a focus on key processes, and exploiting new technology and methods.

## Promising areas of opportunity for progress in precipitation predictability research

1. **Processes:**
   a. Local feedbacks as potential sources of predictability: Land- and ocean-surface feedbacks are known sources of predictability, yet the process representations for these will require further improvements. Specifically, memory of soil moisture as a potential source of predictability needs to be examined further, and feedbacks related to sea-ice coverage are another source of predictability at shorter timescales.
   b. Diabatic heating as source of predictability: The value of tropical variability (e.g., MJO and ENSO) in predictability is well recognized. The potential generalizability to other forms of heating signals, such as those associated with extra-tropical and Arctic SST anomalies and in frontal areas, as potential sources of predictability need to be examined. The diabatic heating over large tropical rainforest areas, and their interplay with major tropical deep convection centers, needs attention.
2. **Modeling:**
   a. Resolving multi-scale processes: Resolving multi-scale processes is critical to realizing potential predictability of precipitation. Continued effort in improving physical processes in high-resolution models and improving their computational efficiency to expand their application from weather prediction to S2S and beyond is needed.
   b. Unified or seamless modeling: Unified modeling of weather and climate, based on a combination of high-resolution regional and global modeling, has great potential for fully realizing potential predictability, particularly at S2S scales due to its ability to better resolve multi-scale processes.
   c. Machine learning for a range of applications: The potential value of machine learning in empirical bias correction, post-processing, improving parameterization, accelerating computations, and development of surrogate stochastic models for prediction and predictability studies was recognized as an area that requires additional focused research.
3. **Diagnostics and Predictability:**
   a. Large-scale weather regime-based approach: Predictability depends on the weather/climate regime in complex ways that deserve systematic examination. In the meantime, progress can be made through identifying and exploiting windows of opportunity for prediction that arise from this regime dependence.
   b. Systematic investigations of impacts of model biases: Examination of the relationship between predictability estimate and biases in models is needed. Indeed, biases that have the greatest impact on prediction and predictability estimates need to be identified so that efforts to reduce these biases can be prioritized.
   c. Research in air-sea and air-land coupling and precipitation processes and their impacts on prediction and predictability: Continued basic research on air-sea and air-land interactions and the three-dimensional (3D) structure of moisture and precipitation, with increased focus on reducing model biases and uncertainties that arise from initialization and observation errors as well as from representation of boundary-layer and cloud processes, is required. Exploiting advances in remote-sensing and autonomous in situ measurements of the atmospheric boundary layer and ocean mixed layer can lead to improved initialization and coupled data-assimilation.
4. **End-to-End Systems:**
   a. Stakeholders/users engagement: Communication among predictability researchers, operational personnel, and end users is critical to identify which variables, at which temporal and spatial scales, lead time, and confidence level, are of most practical value for specific applications.
   b. Integration: While each of the items listed above has value, even more significant progress can be made through their integration. Specifically, integration of the observational and modeling process-level studies, predictability and prediction experiments, machine learning and computational development activities, and stakeholder engagements can be implemented as community activities. The successes of S2S (Mariotti et al. 2019) and other efforts are encouraging examples of potential progress that can be made through large multi-agency national and international integrated efforts.

# SESSION 2: Key Processes Critical to Precipitation Biases

This session discussed key processes relevant to precipitation in observations and ESMs and identified the deficiencies and missing physics in current models, to gain insights for further improving the prediction and simulations. The keynote was from Chris Bretherton (University of Washington), featuring panel remarks from Shaocheng Xie (DOE/LLNL), Ming Zhao (NOAA/ GFDL), Steve Nesbitt (University of Illinois Urbana-Champaign), and Courtney Schumacher (Texas A&M University).

## Leading source of model precipitation biases over the U.S.

The spatial resolutions of contemporary weather forecast models are generally around 10 km, and climate models are generally run with resolutions of 25-100 km. For all models, sub-grid scale processes, such as convection, turbulence or microphysics, cannot be resolved directly and must be parameterized. However, many precipitation biases are associated with inadequate representation of these processes in the models. Over the U.S., mesoscale convective systems (MCS) are one of the leading phenomena that many global climate and weather forecast models struggle with. MCSs contribute more than 50% of warm season precipitation over the Great Plains and more than 40% of cold season precipitation over the southeast U.S. (Jiang et al. 2006, Feng et al. 2019). Models generally underestimate the mean precipitation over the Great Plains, mostly associated with MCSs during the warm season. The diurnal cycle of precipitation in the models tends to peak early compared to observations and miss the secondary nocturnal peak associated with the MCSs.

Other major sources of precipitation biases include the representation of atmospheric rivers and tropical cyclones as well as the extreme events associated with them. At 50 km, ESMs can capture some gross features of these phenomena, but they still struggle with simulating their life cycle, intensity, and rainfall types (convective and stratiform).

## Modeling strategies

A hierarchical model approach (i.e., a modeling framework with different levels of complexities) can provide a direct link between ESMs and observational data (*Figure 6*). For example, process-level models, like large-eddy simulation (LES),

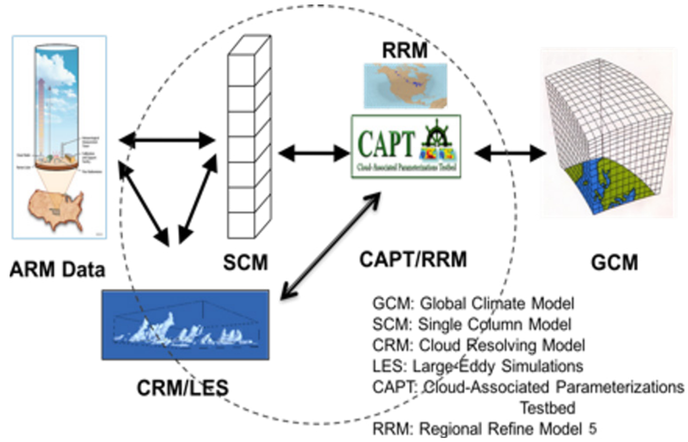



**Figure 6.** A hierarchy modeling framework jointly supported by DOE programs.

can provide guidance on parameterization development. This helps to identify and improve physical processes that are key to precipitation biases at the process level.

Another strategy to connect observations and models is phenomena-based model evaluation in which models are explicitly evaluated on their ability to reproduce observed phenomena such as atmospheric rivers or specific cloud regimes (Zhao 2020, Ma et al. 2021). Nudged model simulations (Zhang et al. 2014), realistically initialized hindcasts (Phillips et al. 2004, Williams et al. 2013), or coupled data assimilations can be useful tools to elucidate process behavior relevant to these phenomena.

With increasing computational power, high-resolution modeling can bypass use of certain parameterizations usually required in process-level studies. For example, a global storm-resolving model (GSRM) intercomparison project, named DYAMOND: DYnamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (Satoh et al. 2019, Stevens et al. 2019), was recently organized by major modeling centers around the world for the first time. These GRSMs are run with horizontal resolutions of 2 to 5 km and vertical resolutions of 200 to 500 m and can directly simulate organized convection. Results from these simulations have shown promising improvements of diurnal cycle of precipitation, tropical cyclones, and organized convection. While the initial phase focused on simulation of the boreal summer, the next phase is focused on simulation of winter season processes.

## Observations

Detailed field observations such as DOE's Atmospheric Radiation Measurement (ARM) facility are extremely useful for process-level studies, such as understanding key physical processes critical to precipitation, guiding physical parameterization developments, and testing assumptions with process models for specific cases or through statistical studies. For MCSs, ground- and space-based radars and field measurements offer detailed depictions of their characteristics. For example, radar observations can provide detailed vertical structure of convection and rainfall types (convective and stratiform). However, there is still no unifying theory for explaining many characteristics of MCSs, such as life cycle. Targeted field campaign observations of MCS life cycle and associated processes alongside model/assimilation experiments will be needed to better understand and simulate MCSs.

## Outlook for the future

With the approaching Exascale computing era, the line between weather and climate modeling becomes less distinct as ESM resolutions become finer. The same set of fast physical processes operate at both weather and climate scales.

There is a need to realize the synergy between weather and climate, and to bridge the gap between them to address precipitation biases and their impact on precipitation predictability. There are multiple pathways forward. ML/AI have shown great promise in driving the improvement of climate modeling. To illustrate, Brenowitz and Bretherton (2019) developed a convection parameterization constructed with neural networks for coarser-grid ESMs to predict the column mean residual heating and moistening due to diabatic processes. In particular, these neural networks were trained with GSRM simulations, with the goal of making the coarse- grid ESMs evolve like "reference" fine-grid GSRMs. Further modeling strategies including hierarchical modeling approach as well as phenomena-based model evaluation, and high-resolution modeling can be used to investigate precipitation biases.

It remains critically important to make connections between observations and models. Over the past several decades, modelers have made great progress with process understanding developed from observations. Priority should focus on process understanding using new observations that can be analyzed in innovative ways (e.g., ML/AI) to apply observations to guide model development and vice versa.

# SESSION 3: Interdisciplinary Processes

This session discussed key processes and interactions relevant to precipitation that are important in the transition zones on either side of an interface such as ocean-atmosphere, land-atmosphere, and troposphere-stratosphere connections and interactions between aerosol-cloud-precipitation microphysical processes. The session had five speakers. The keynote was from Elizabeth J. Thompson (NOAA/PSL), and panel remarks from Andrew Gettelman (NCAR), Ana Barros (Duke University), Abigail Swann (University of Washington), and Yaga Richter (NCAR).

## Important processes and the associated interactive representation of precipitation

**Aerosol-cloud-precipitation interactions:** Aerosols are critical for the coupled hydrologic cycle and need to be better understood and represented in models to accurately simulate precipitation for the correct reasons (Benedetti et al. 2018). Important processes include interactions between aerosols and aerosol impacts on cloud microphysics including drop size distribution, mixed and frozen phase cloud processes, and aerosol-radiation interactions (Morrison et al. 2021). Microphysical processes affect convective clouds of all scales. Cloud and precipitation formation are linked to aerosol physics as the sites where cloud drops and ice crystals form. Aerosols also alter radiation, both directly (smoke, dust plumes, pollution like black carbon soot and sulfate), and indirectly (modifying clouds). These radiation effects can also affect precipitation by impacting thermodynamic profiles, including instability in the lower atmosphere and/or absorption and heating in aerosol layers. For aerosols and precipitation in particular, a multi-pronged and multi-phase approach is needed. The models must consistently treat these processes and work between cloud turbulent scales to mesoscale or synoptic scale cloud dynamics.

**Multi-scale interactions:** Energy and moisture cascade between scales from larger (500 to 2000 km) to smaller (turbulence). It is critical to understand the energy sources and sinks at different scales, and for models to capture the mesoscale, diurnal, and topographic feedbacks and physical processes responsible for connecting these scales (e.g., Eghdami et al. 2018). These energy dissipation pathways and processes need to be better understood and captured in models to accurately predict persistence, intermittency, and instability dynamics of precipitation (Tao and Barros 2010). It is necessary to seamlessly represent and account for these processes across scales.


**Figure 7.** Graphical representation of transition zones that impact precipitation predictability and bias at a variety of time and spatial scales.

Processes at each scale have different levels of predictability, which need to be accounted for in forecasting S2S-to-multidecadal precipitation patterns and their hydrologic risk such as flooding and drought (Kim and Barros 2001).

**Stratosphere-troposphere interactions:** Forecasting stratosphere-troposphere interactions relevant for precipitation, which include SSWs (Butler et al. 2017, King et al. 2019) and QBO-MJO relationships (Kim et al. 2020), requires several model improvements. These include better vertical resolution in the stratosphere (for representing the QBO), more accurate simulation of deep convection (particularly its depth), improved gravity wave parameterizations, and more realistic simulation of the polar vortex and its coupling to the surface. The processes responsible for the observed QBO-MJO relationships are not yet fully understood. Model development is needed to harness the predictability shown in observations between stratosphere-troposphere interactions such as determining the dynamical basis for explaining SSWs and QBO-MJO teleconnections.

**Terrestrial ecosystems:** The responses of plants to climate can have a significant impact on surface climate but these responses remain highly uncertain (Swann et al. 2016, Zarakas et al. 2020). Plants affect many aspects of surface climate such as relative humidity and precipitation, and the effects depend on location, meteorological conditions, and plant types. Land-surface properties can impact surface climate both directly (through the surface energy budget, primarily latent heat flux, and the impact of carbon dioxide on the atmosphere including radiative effects) and indirectly through atmospheric feedbacks (large-scale circulation responses to changes in horizontal gradients of moist static energy).

**Ocean and the transition zone (and similar for ice):** Ocean-atmosphere processes are complex, multi scale, and are a combination of local and remote forcing in a coupled environment (Yu 2019, Fairall et al. 1996a, b, 2003, Edson et al. 2013). Ocean-atmospheric exchanges influence continental U.S. (CONUS) precipitation patterns by altering moisture transport (i.e., moisture sources and sinks) and the general atmospheric circulation (examples include but are not limited to Shin et al. 2006, Branstator 2014, Henderson et al. 2017, Capotondi et al. 2020, Xiong and Ren 2021). When general circulation changes, it can promote or inhibit CONUS precipitation, tropical convection, and its teleconnections to CONUS. There are also Arctic pathways to the altering of general circulation and CONUS precipitation. Observation and modeling teams must work together to understand important factors that impact ocean-atmosphere exchanges. More data, more model development (dynamical and empirical), and more model diagnostics are needed to understand precipitation observations in CONUS and related precursor precipitation around the world (i.e., related to CONUS by changing the general circulation and moisture transport), understand predictability sources over ocean, and improve or augment CONUS precipitation forecasts.

## Seasonal-to-multi-decadal modes of variability and associated precipitation patterns

Models struggle with predicting variability beyond mean precipitation (i.e., frequency, intensity, etc. are not well forecasted). Models often do not accurately predict the mean state of precipitation or its persistence correctly, and this causes issues in trying to understand and predict the variability and regimes at smaller scales. Models struggle due to incomplete, insufficient, or missing physics at the interfaces. Important interfaces include land-vegetation-air interactions, air-sea fluxes, coupled boundary layers, and aerosol-cloud-microphysics-radiation interactions.

CMIP6 (Coupled Model Intercomparison Project Phase 6) models do not reproduce the observed QBO MJO relationships, and these models are only beginning to represent the QBO alone. SSWs and their coupling to the surface are well represented, but only in some models. The tropical mean state (ENSO) and its flavors from year to year or even within seasons are not well simulated. This affects CONUS precipitation predictions across all climate-to-weather scales. Organized strong tropical precipitation on intraseasonal (MJO) to synoptic and meso (hurricanes) scales can influence CONUS precipitation through teleconnections and global circulation—these scales of precipitation are still not well predicted.

Simulations of precipitation in global climate change scenarios require improvement, including improved understanding of the contributions of uncertainty and forcing from major transition zones and interdisciplinary processes such as stratosphere-troposphere, land-ocean-air-sea-ice, and cloud-aerosol interactions. Each of these processes alone has a large impact on surface weather and climate, as well as combined. Biases in land-surface properties (either prescribed or varying) impact surface climate forecasts and produce uncertainty in forecasts.

Successful CONUS precipitation prediction hinges on successful predictions of SST, which are challenged by limitations in modeling the ocean mixed layer and air-sea fluxes. Ocean models and ocean reanalysis lack realistic mixing and turbulence, and thus the representations of resulting seawater properties such as temperature, salinity, and fluxes are also flawed.

## Observational and modeling strategies

More unified model systems could be developed that can add appropriate complexity and consistency across scales. They should include more recent knowledge on wave-air-sea-interfaces, the ocean mixed layer and ocean turbulence, aerosol-cloud interactions, land-surface heterogeneity, and stratosphere processes such as gravity wave interactions with deep convection. The advances made in these areas in research models and climate models could be introduced into weather models, and vice versa. This would improve predictions and also allow for more holistic testing and identification of model biases.

Model strategy and scope could be improved. For example, CONUS precipitation prediction requires accurate multi-scale, multi-location air-sea, cloud-aerosol physics, land surface, and troposphere stratosphere interaction to be captured in fully coupled global models. CONUS precipitation relies on both remote and local forcing, at many time scales such as the mean state on interannual-to-seasonal scales plus additional small-scale variability superimposed on the mean state. Recent advances in model complexity and resolution could also take advantage of past high-resolution field campaign data through model-observation integration.

Increased spatial, vertical, and temporal resolution in models has been shown to improve certain aspects of forecast skill and the ability to harness known sources of predictability in forecasting CONUS precipitation (e.g., increased model resolution of known terrain features, improved spatial resolution of ocean and air-sea interaction). Increased resolution improves many aspects of coupled forecasts, while vertical and horizontal (i.e., 3D) improvements in model resolution are also needed for other applications. The effective resolution must also be considered (numerical model effects render the effective resolution of the model coarser than the stated grid box sizes), and relative to the resolution of precipitation triggers such as terrain, SST gradients, aerosol sinks and sources, and land sources of heat and moisture from plants.

## Promising areas of opportunity for progress

Gaps in fundamental understanding and known sources of model error (described above) are important to tackle in the near-term. For brevity, they are not repeated here. Additional examples are provided in the following paragraphs.

Unified modeling systems that span weather to climate need to include surface-troposphere stratosphere connections, and seamlessly and physically describe exchanges between ocean-ice-land-biology-aerosol-atmosphere components. As an example, NOAA is developing the next generation Medium-Range Weather/S2S forecast system, built on the community-based Unified Forecast System (UFS) with six fully coupled components (ocean-atmosphere-sea ice-wave-land-aerosol). A unified multi-scale model approach has the potential to be more skillful and useful than separate scale-dependent parameterizations or tuning coefficients at interfaces. This unified approach would help improve scientific understanding and allow consistency in research and modeling across scales, such as the ability to test the same problem or parameterization across scales

More data is needed to constrain many coupled models. This applies to land-surface models, air-sea interaction, and aerosol-cloud-microphysics-radiation interactions. Observations of the ocean mixed layer, fluxes, SST, aerosol sources and sinks, cloud microphysics and growth rates, radiative processes, plant properties, shallow or non-precipitating clouds, and the resulting 3D evolution of heat, moisture, and momentum in the atmosphere are all imperfectly observed and not available at most locations. These observations are needed to more effectively and comprehensively compare to models, to determine their biases and deficiencies, and to form new or improved parameterizations. Observations are needed at the air-sea interface in key climate regions known to impact CONUS precipitation predictions and predictability, such as the Maritime Continent, far western Pacific Ocean, coastal zones of the U.S., and the emerging Arctic. To improve convective parameterizations, observations that provide better understanding of how convection is modified by its environment and how convection modifies the environment are needed. Long-term, high-resolution satellite precipitation tracking methods, such as tracking of MCSs, large precipitation envelopes, MJOs, and atmospheric rivers are also needed for better understanding large-scale convective systems and validating model prediction.

The sinks and sources of energy and moisture (i.e., dissipation across scales) need to be accounted for and identified in observations and models. This includes the small-scale processes that influence the growth of larger systems and larger patterns, or the way in which the small-scale processes result from larger-scale patterns. The predictability of each energy source or sink needs to be identified, as well as how these affect the resulting predictability of surface climate and water extremes on longer time scales.

Better characterization of the role of land-surface properties and processes is needed so that representation of these processes can be prioritized and tackled efficiently. This includes providing very specific treatment of land-surface properties and processes in models such as soil moisture, plant type, evaporative resistance, albedo, aerodynamic resistance, etc.

Collaborations between modeling and observational teams are key. This includes building databases of events and their global properties/precursors to build empirical models, form hypotheses, and test theories. More easy-to-access, documented, and centralized data archives could be formed from field campaign data so that collaborations between observation and modeling teams could develop quicker and more efficiently. Uniform formatting and somewhat-consistent data quality control across experiments would aid model-observation team efforts.

## SESSION 4: Regional Precipitation

The Regional Precipitation session highlighted aspects of precipitation predictability and processes that are of particular importance at regional scales and to specific U.S. regions. Dave Novak, the director of NOAA's Weather Prediction Center, gave a keynote presentation in the session. The panelists in this session, Lynn McMurdie (University of Washington), Marty Ralph (Center for Western Weather and Water Extremes), Anita Rapp (Texas A&M University), and Johnna Infanti (NOAA/CPC) provided their perspectives on various topics including observational field campaigns, atmospheric rivers impacting the precipitation forecasts for the west coast of U.S., and seasonal precipitation biases in the southeastern U.S.

### Phenomena and processes of particular importance for U.S. regional precipitation predictability and prediction biases

The U.S. encompasses a wide variety of climates and thus weather; precipitation phenomena that dominate some regions occur rarely or never in others, some of which have the potential for sources of predictability. A partial list of precipitating phenomena with varying relevance to different regions includes:

- Midlatitude cyclones: Primary drivers of precipitation over large swaths of the CONUS, especially outside of the subtropics, are midlatitude cyclones and the associated frontal systems.

- **Mesoscale convective systems (MCS):** A key phenomenon for U.S. precipitation, MCSs contribute substantially to precipitation in the Great Plains in spring and summer and to winter precipitation in the southeast U.S.
- **Tropical cyclones:** Rainfall associated with hurricanes and other tropical cyclonic events is a large but highly intermittent contributor to precipitation, especially extreme events.
- **Atmospheric rivers:** 75% of variance in storms along the west coast are related to atmospheric rivers.
- **Lake-effect snow:** A substantial factor for wintertime precipitation in certain U.S. regions.
- **Orographic precipitation effects:** Regions that include or are influenced by substantial topography include areas of enhanced average precipitation, marked by events that can occur whenever airflow is forced upward by topography, and other regions where precipitation on average and in individual events is suppressed by interactions between topography and airflow.

Corresponding to the variety of phenomena that lead to precipitation in different U.S. regions, the implications of precipitation for water resources and hazards differ fundamentally from one region to another. Thus, meeting the differing needs for precipitation prediction across the nation necessitates a variety of activities in the realms of both research and applications. At the same time, all precipitating phenomena occur within the context and influence of the atmospheric circulation and its variability, so improving understanding of and ability to predict the atmospheric state across spatial scales is essential for continued improvement of both prediction and predictability of U.S. precipitation at the regional scale. Large-scale modes of variability, including ENSO, MJO, Atlantic Multidecadal Variability (AMV), and the Pacific Decadal Oscillation (PDO), influence U.S. regional precipitation via teleconnections, or waves in the atmospheric circulation that propagate around the globe, which can provide sources of predictability on sub-seasonal-to-interannual timescales. Predicting regional precipitation, particularly beyond the two-week timescale, requires accurately predicting the circulation and phenomena driving these events. The large-scale atmospheric circulation and its teleconnections to precipitation are intertwined with the biases in modeling precipitation across all timescales, from weather and S2S prediction to simulations of long-term climate.

Precipitation forecast skill over the CONUS, although slightly improved in the past decade, lags behind other forecast-improvement metrics like hurricane track and intensity and global 500 hPa geopotential heights. There are significant issues with forecasting the location and magnitude of precipitation at regional and local scales. Factors influencing the poor precipitation forecast skill for weather prediction include underestimation of heavy rain, overestimation of light rain, inaccurate representation of the diurnal cycle of precipitation (especially with precipitation maxima too early in the day); weather ensemble systems also suffer from overconfident ensembles. Parameterized convection and cloud microphysics are sometimes responsible for biases in precipitation. Increased resolution is one factor that can provide a pathway to improvement for some processes, but it is not a panacea; for extreme precipitation globally, models with 25-km resolution are no better at capturing extreme precipitation than conventional, coarser-resolution ESMs (Bador et al. 2020), and improvements in present-day precipitation at higher resolution may not be related to multi-decadal changes in precipitation (Nishant and Sherwood 2021). Comparing different ESM runs without their convective parameterizations nonetheless reveals important differences in simulated precipitation, which could be due to other fundamental aspects of the models such as their dynamical core (Maher et al. 2018). Even the convective-scale, high-resolution regional models and their ensembles suffer from diminishing skill despite assimilation of radar data and explicit representation of convection. The displacement of MCSs and associated cold pools and placement of heavy rainfall degrade the deterministic and probabilistic forecasts for extreme weather events. Both global and regional weather models also suffer from lack of critical observations or inability to use cloud-impacted observations in the data assimilation systems for improved initial conditions and for model evaluation and process understanding that underlie improvements in prediction capabilities. Model biases in precipitation due to land and atmosphere initial state are shown to be a barrier to adequate precipitation prediction on S2S timescales and longer timescale prediction/projections in several regions of North America (Infanti and Kirtman 2016).

## Modeling strategies

Improving the predictions of precipitation requires using higher-resolution global and regional models, as well as improved physics and data assimilation, well calibrated ensembles, and sophisticated post processing techniques (including use of ML/AI). NOAA is currently moving towards development of the UFS as a community-based, coupled, comprehensive ESM supporting NOAA's operational weather forecasting suite and the Weather

Enterprise. The forecast skill priorities for UFS Medium Range Weather (MRW) application (Global Forecast System) include reduction of precipitation bias and reduction of the over-forecast of light precipitation and under-forecast of moderate-to-heavy precipitation, and improvement of diurnal cycle of precipitation, especially afternoon onset and nighttime maxima of warm-season precipitation in the global models. On the sub-seasonal scales (Global Ensemble Forecast System), improvements are sought in precipitation anomaly correlation coefficient in weeks two to four, as is reduction in systematic biases. The UFS Short Range Weather (SRW) application aims at developing high-resolution Rapid Refresh Forecast System (RRFS, *Figure 8*) as an ensemble system consolidating and replacing various high-resolution regional models currently available in operations (*Figure 9*). Priorities for RRFS include improvements in treatment of sub-grid clouds, surface/planetary boundary-layer physics, diurnal cycle, radiative fluxes, cold air damming, and convective initiation. In addition, improvement in initialization and forecasts of cloud/precipitation features are expected through improved data assimilation algorithms and better use of a variety of in situ and remote-sensing observations. The sub-3km on-demand Warn of Forecast (WoF) System currently under development for future use in operational forecasts will provide additional guidance for extreme weather events.

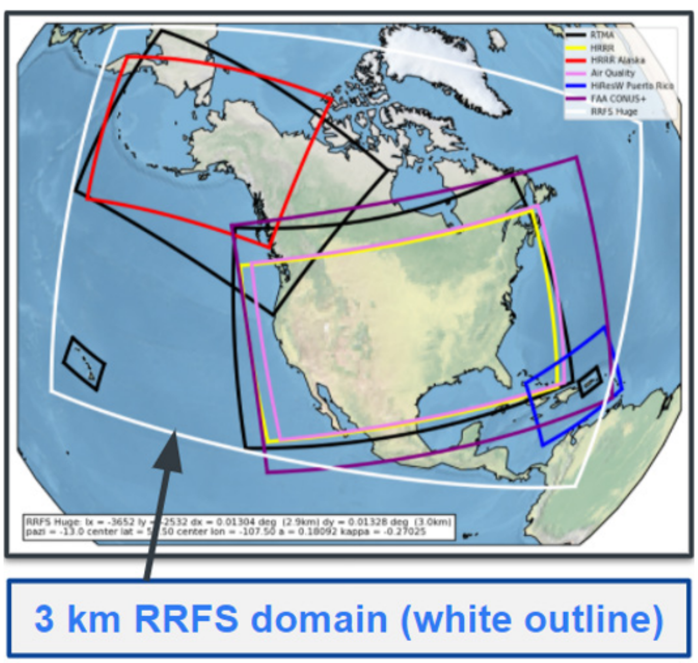



**Figure 8.** UFS-based Regional Rapid Refresh Forecast System (RRFS) to replace several mesoscale modeling systems currently in use at National Centers for Environmental Prediction (NCEP) operations.

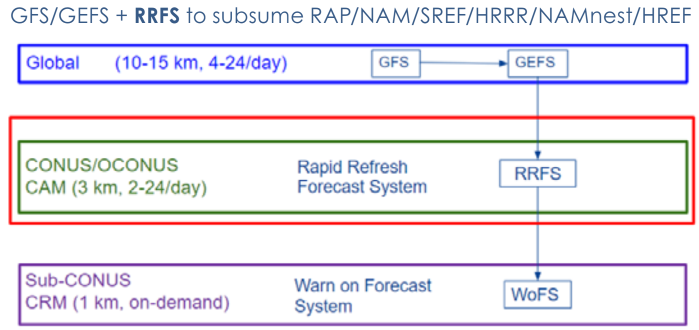



**Figure 9.** Consolidation of global and regional modeling systems towards simplified production suite in NCEP operations.

In addition to the current operational capabilities, there is also an increasing need for specialized high resolution regional models for forecasting precipitation along the U.S. west coast impacted by landfalling atmospheric rivers. This is envisioned through development of an Atmospheric River Analysis and Forecast System (AR-AFS) that can be built upon the research capabilities demonstrated by the West-WRF (West Weather Research and Forecasting) developed at the Center for Western Weather and Water Extremes. This follows similar efforts currently undertaken to develop a Hurricane Analysis and Forecast System (HAFS) through transitioning the high-resolution Hurricane Weather Research and Forecasting (HWRF) system currently used for the hurricane predictions in operations.

From the opposite end, as ESMs converge toward regional-scale simulations, one promising advance is variable-resolution grids (e.g., Zarzycki et al. 2015), which allow high resolution regionally along with the full physics and global water and energy budget representation that are key to prediction on interannual-to-multidecadal timescales.

## Observations

Observations are critical to improve understanding that enables us to advance the representation of physical processes (e.g., convection, cloud microphysics, planetary boundary layer, and turbulence) in both weather and climate models, hence the need for continuous investments in observing systems and field campaigns. Several efforts in the past five and next three years have examined and will examine precipitation in midlatitude cyclones: OLYMPEX (Olympic Mountains Experiment) and IMPACTS (Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms). The OLYMPEX field campaign (November 2015–January 2016; Houze et al. 2017) observed interactions between mountains and synoptic circulation that are a common prediction challenge, especially in the Pacific Northwest but also in other regions. The ongoing IMPACTS campaign (NASA 2020) hopes to sample snowstorms with coordinated observations from the surface using two National Aeronautics and Space Administration (NASA) aircraft (ER2 and P3). Snow and ice present substantial challenges to modeling as well as satellite-based observations, which are often crucial over more northern parts of the nation and less frequent but can be crippling for the southern regions, as seen in Texas in February of 2021. The ongoing Atmospheric River Reconnaissance (AR Recon) field program aims at collecting observations in the vast data gap regions of the North Pacific and use them for real-time assimilation into operational models along with high-resolution regional models for improved atmospheric river and west coast precipitation forecasts. The upcoming TRACER (TRacking Aerosol Convection interactions ExpeRiment) field campaign that the DOE's ARM facility will undertake starting in fall 2021 will observe convection at high spatial and temporal resolution over a range of environmental and aerosol regimes across the full life cycle of convective events. Convection is a key phenomenon driving precipitation and extreme precipitation. As it is complex, with many important factors taking place at small spatial scales (from the scale of aerosol particles to individual clouds), accurate prediction of convection is held back by gaps in understanding that are best addressed by continued observations of convection in the atmosphere.

In addition to field campaigns, ongoing satellite (including Global Precipitation Measurement [GPM]; Skofronick-Jackson et al. 2017) and comprehensive surface-based observing networks, both station- and radar-based, continue to be essential to improving precipitation prediction, including at regional scales. Some components of the observing network, like SNOTEL (Snow Telemetry; Serreze et al. 1999), are especially valuable in particular regions of the nation. Maintaining existing observations is necessary to developing the long-term records that can provide the foundation for examining variations in precipitation that occur, especially at timescales of decades and longer. These records are irreplaceable for capturing the one realization of weather and climate that every locale, region, the nation, and the planet experience. Further efforts to process these observations into data products are important in using observations to inform precipitation prediction. Observational uncertainties and inconsistencies among data sets can hamper calibrating both dynamical and statistical models for prediction.

## Communications and social science

It is necessary to bridge the gap between the information that the weather and climate modeling communities can offer and the information that decision makers need in order to take informed action. Engaging social scientists can help in communicating probabilistic forecasts, including the possibility of low-probability but high-impact events, to the public and to decision makers. The needs are tremendous for local communities. Communicating what is possible, including the 10th percentile, 90th percentile, and most likely mode is more helpful to the user community than the 50th percentile. Addressing all facets of forecasts for multiple users to enable adequate and timely response is critical. For prediction on timescales up to decades, decision makers need to know the bounds of what they should plan for—particularly what the risks of locally new and high-impact events will be.

## Outlook for the future and next steps

Forecast improvements are driven by what is measured. To improve models of precipitation specific to particular regions, it is critical to measure and target the precipitation characteristics or phenomena that are most important at the scales relevant to citizens and to decision makers. Extreme precipitation cannot be predicted without predicting the circulation/phenomena that drive these events. To get precipitation (regionally) right, circulation must also be right — the specific aspects depend on the region.

It is important when looking at regions to avoid a zero-sum mindset and take a thoughtful approach when allocating effort and attention to improving models for particular regions, so that the community does not feel that regions are competing against each other for resources for model improvement. It is critical for modeling and observational communities to work hand in hand to address critical gaps in understanding of the physical processes and provide better data sets for initialization and evaluation.

# Agency and Interagency Program Perspectives

Recognizing that interests and investments in precipitation processes and predictability science span several agencies, NOAA and DOE organizers, in addition to summarizing their precipitation science priorities and research directions, invited presentations by other agencies involved in USGCRP and interagency programs to share their interests and identify activities that contribute to advancing the observations, process understanding, and modeling of precipitation across space and timescales, while emphasizing the climate and Earth system focus of the workshop.

NOAA is committed to provide more accurate, reliable, and timely forecasts at almost every timescale spanning from the next hour to daily to decadal. NOAA is called upon to "collect and utilize information in order to make usable, reliable, and timely foundational forecasts of sub-seasonal and seasonal temperature and precipitation" by the Weather Research and Forecasting Act of 2017. However, today's state-of-the-art models exhibit systematic errors that are as large as the real precipitation signal NOAA is trying to model, and the magnitude of these errors (especially in global models) has remained essentially the same since the late 1990s. To reduce model errors and improve precipitation forecast skill, NOAA established the PPGC Working Group (PPGC WG) in early 2020. The PPGC WG was charged to develop a NOAA strategy to accelerate improvements in global models that will lead to advances in precipitation prediction skill. The goal of PPGC is to provide more accurate, reliable, and timely precipitation forecasts across timescales, from mesoscale weather, through week three to four, S2S, to seasonal to decadal (S2D), through the development and application of NOAA's fully coupled ESMs. The major six pushes of NOAA through the PPGC Initiative are to (1) improve end-user products through continuous user engagement and social science to more effectively communicate the forecast, (2) assimilate and integrate data, then regularly produce supporting data sets, including reanalyses and reforecasts, (3) address global model systematic errors, (4) establish traceability of error sources, (5) change the paradigm and target regions around the globe that host sources of prediction predictability, and (6) improve global water vapor and boundary-layer observations. NOAA strives to build strong partnerships across the community to make progress on this grand challenge.

DOE's strategic plan released in 2018 has a goal to advance prediction of the Earth system and identify what predictability limits might be. DOE has a strong emphasis on predictability, through the continuous advancement in Earth system modeling and process-level research combined with observational systems to understand how predictability limits might play out in the Earth system. The modeling efforts at DOE contribute to the enhancement of predictive understanding by examining the co-evolution of the natural and human systems. The Energy Exascale Earth System Model (E3SM) is the flagship model that is being developed with the goal of overcoming the disruptive transition to the next era of computing. Extensive model analysis of regional and global ESMs and multisector models jointly facilitate the predictive understanding of the water cycle. Additionally, recognizing the importance to improve modeled precipitation, DOE conducted a workshop in 2019 that focused on "Benchmarking Simulated Precipitation in Earth System Model" to develop quantities targets for demonstrating model improvements. Two main thrusts drove the workshop dialogue: identify a holistic set of observed rainfall characteristics that could be used to define metrics to gauge the consistency between ESMs and observations; assess state-of-the-science methods used to evaluate simulated rainfall and identify areas of research for exploratory metrics for improved understanding of model biases and meeting stakeholder needs. DOE also focuses on one of the biggest limits to Earth system predictability — cloud aerosol interactions. The role of clouds, aerosol-cloud-precipitation interactions, and their impacts on the Earth's radiative balance are focused research areas supported at DOE through the Atmospheric System Research (ASR) program and ARM user facility. In fall 2021, DOE will conduct workshops on artificial intelligence for Earth system predictability (AI4ESP), with a goal to leverage new ML/AI capabilities to enhance understanding and extension of predictability that will optimally improve predictions.

The National Science Foundation (NSF) supports a range of research projects to enhance understanding of phenomena and processes related to precipitation. They span a host of spatial and temporal scales, from hurricanes, snowstorms, floods, and hailstorms to prolonged drought. NSF also sponsors measurements through targeted field programs that address issues such as model biases. The COVID-19 pandemic has currently impacted several field campaigns. In addition, rapid advances in new technologies in observing, modeling, and simulation provide unprecedented insights into processes and phenomena and their associated predictability. Through efforts such as the Community Earth System Modeling (CESM) Large Ensemble effort, an attempt is being made to help interpret the observational record and assess internal climate variability of the coupled Earth system.

NASA supports several space-based and sub-orbital missions providing measurements and supporting research to understand precipitation processes and phenomena (*Figure 10*). These include the GPM and CubeSat missions, measuring precipitation at the surface, layer-by-layer intensity, and drop-size distributions, illuminating differences between convective and stratiform systems, the diurnal cycle of precipitation globally, and annual snowfall contributions from shallow-versus-deep falling snow events. The future Aerosol – Clouds, Convection, and Precipitation Mission, preparing for launch in 2030, moves from focusing on targeted observables to integrating cloud, aerosol, and precipitation processes. The Precipitation Measurement Missions Science Team supports investigations using satellite, aircraft, and ground measurements to better understand and improve modeling of precipitation, the water cycle, climate, and weather.

The Department of Defense (DOD) interest in precipitation centers on impacts to aviation, ground, and sea assets and operations, including weapons, safety, and operational systems. Prediction on S2S and longer timescales focuses on drought, flooding, and water availability/quality, which can impact global stability. Numerical modeling is conducted by both the Air Force and Navy, with each using different platforms.

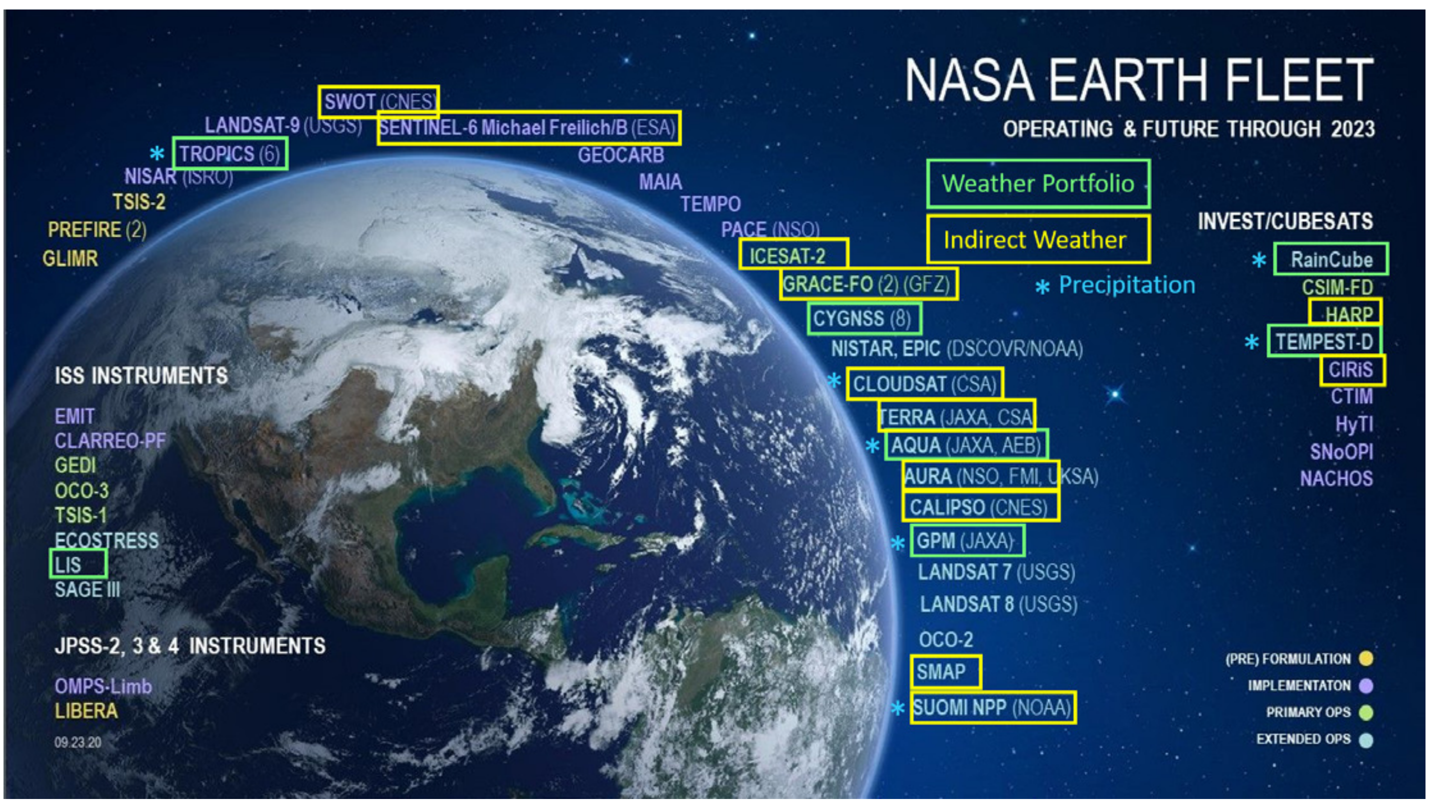



**Figure 10.** Constellation of NASA planned and operating space-based systems, highlighting weather-related missions (green boxes), indirectly related missions (yellow boxes), and missions directly addressing aspects of precipitation (asterisks). (Figure courtesy of Gail Skofronick-Jackson)

Neither the Air Force nor Navy run climate models, instead relying on data from the Intergovernmental Panel on Climate Change (IPCC) and National Climate Assessments to inform installation planning in the U.S. and overseas. Defense meteorological satellites include a new system under development (EWS-G1) to provide microwave cloud and weather imagery and pilot CubeSats (Global Environmental Monitoring System [GEMS]) providing microwave temperature and moisture profiles with intent to share with partnering agencies when operational.

OSTP announced high-level interest in Earth system predictability (ESP) in the 2021 federal research and development budget priorities, identifying ESP and Earth system prediction as vitally important for preparing for and responding to extreme natural events such as droughts, floods, heat waves, wildfires, and coastal inundation. The 2022 priorities memo called for agencies to collaborate in the development of a national strategy for predictability and its practical use. A Fast Track Action Committee (FTAC) was established in FY2020 under the National Science and Technology Council to identify barriers and opportunities to improve Earth system prediction. The FTAC engaged senor agency officials and program managers from multiple agencies (DOE, DOD, NASA, NOAA, NSF, USDA, and USGS) to compile agency activities, gaps, and needs as well as solicited input from the science community through a National Academy of Sciences, Engineering, and Medicine round table and workshop and a request for public input. The resulting FTAC report on ESP Research and Development presents a strategic framework to connect theory, observations, process research, modeling and data assimilation. It also provides a roadmap for implementing activities to explore and harness the predictability of Earth's water cycle, precipitation extremes, and associated biosphere and human interactions (NSTC 2020).

ICAMS was formed in July 2020 in response to the 2017 Weather Act to improve interagency coordination of meteorological services and is co-led by OSTP and NOAA. ICAMS represents the first major re-structuring of the nation's meteorological services administrative framework in more than 50 years. ICAMS aims to improve U.S. meteorological services via an Earth system approach, providing societal benefits with information spanning local weather to global climate. The signed charter is for 10 years.

The US CLIVAR Program, sponsored by NASA, NOAA, NSF, and DOE, promotes grassroots community engagement to scope and implement research activities to accelerate progress in understanding the role of the oceans in climate variability and change, including the phenomena and processes that drive precipitation variability and predictability. Through interagency funded workshops, working groups, and research projects, the program is studying air-sea interactions from the tropics to mid- and high latitudes; studying the use of water isotopes to understand changes in the water cycle; applying new data science tools and large initial-condition model ensembles to interpret the observed climate record, differentiate internal variability from forced climate change, and quantify uncertainties in past and future climate change; promoting best practices for linking process studies and model improvement; characterizing processes spanning oceans, atmosphere, land surface, and the cryosphere that drive predictability from S2S to multi-year to decadal timescales; and implementing new Climate Process Teams to develop, evaluate, and implement new convection parameterizations and techniques within ESMs informed by newly acquired observational and field campaign data.

Collaboration across individual agency program investments in observing, understanding, and modeling precipitation process and predictability can continue to be fostered to meet the goals of the ESP roadmap through the interagency groups of ICAMS, the USGCRP, and the US CLIVAR Program.

# Key Findings: Response to Thematic Questions

This section synthesizes the key findings from the keynote presentations, panel remarks, and discussions during the workshop in the context of the workshop's five thematic questions.

## Question 1: What are the sources of predictability that have the biggest influences on precipitation at weather, S2S, and multi-decadal timescales, including extremes?

The presentations and discussions during the workshop highlighted intra-seasonal-to-decadal variability (e.g., NAO, MJO, ENSO, PDO, AMV), slowly varying processes (e.g., SST, soil moisture, vegetation, and sea-ice), and phenomena such as tropical cyclones, atmospheric rivers, extratropical cyclones, and MCSs as important sources of predictability that influence precipitation on multiple time scales. Many of these sources are related to complex phenomena that are multi-scale in nature or that involve interactions among the components of the climate system. Predictability depends on weather and climate regimes in complex ways. Significant challenges remain in exploiting predictability in terms of understanding how, where, and when this low-frequency variability affects regional precipitation. Predicting regional precipitation requires accurately predicting the large-scale circulation that drives regional precipitation variability, better representation of slowly varying processes and their associated influence, and better capturing localized physical processes associated with weather phenomena.

## Question 2: What are the key physical processes that have the strongest imprint on the model biases and precipitation predictions and projections?

Key physical processes identified as important contributions to model precipitation biases include surface-atmosphere interactions over land, ocean, and sea-ice; deep convection; and aerosol-cloud-precipitation interactions. Models have difficulty capturing the persistence of soil moisture and vegetation feedbacks that influence fluxes of heat and moisture to the atmosphere that are recognized as potential sources of predictability. Ocean-atmosphere processes are complex, multi-scale, and combine local and remote forcing in a coupled environment; they influence CONUS precipitation by altering moisture transport (i.e., moisture sources and sinks) and the general circulation. Many precipitation biases are associated with inadequate representation of sub-grid-scale processes, such as convection, turbulence, or microphysics that cannot be resolved directly and must be parameterized in global models. Model precipitation biases are also associated with challenges in simulating multi-scale interactions. Energy and moisture cascade between scales from larger (2000-500 km) to smaller (turbulence). Precipitating cloud systems are influenced by processes across a range of scales including aerosol-cloud interactions at micron scales, impacts of local or mesoscale topography, and mesoscale or synoptic-scale dynamics. Models often do not capture the persistence of regimes or transitions between them correctly; thus, improving simulation of multi-scale processes that can influence regime transitions, such as interactions between eddies and mean flow, remains a challenge.

## Question 3: How can we most effectively take advantage of existing observations and data (satellite and in situ) to advance process-level understanding of the key processes and predictability?

The workshop highlighted that enhanced integration between observations and modeling will more effectively use existing observations and data to advance process-level understanding of the key physical processes and predictability. The following tools were identified to enable progress in this area:

- Using a hierarchical modeling strategy, in which process-level models that are more closely tied to observational scales provide insight to fully coupled global models, that can help integrate observations and models at different scales. Intensive long-term observations such as DOE's ARM facility data are extremely useful to guide physical parameterization developments and to test assumptions with process-level models.
- Conducting phenomena-based model evaluation with realistically initialized hindcasts is another strategy to connect observations with models.

- Improved nonlinear and multi-scale data assimilation methodologies and better use of a variety of in situ and remote-sensing observations can improve initialization and representation of important features of cloud/precipitation systems.
- Machine learning provides innovative ways of observational analysis in support of process understanding, analysis and correction of model biases, accelerating computational efficiency, and development of surrogate models for process and predictability studies.
- More easy-to-access, centralized data archives from field campaigns as well as routine observations that contain well-documented data with more uniform formatting and consistent data quality will enable quicker and more efficient collaborations between observation and modeling teams. Examples of efforts like obs4MIPs (Ferraro et al. 2015) can facilitate modeling progress by making observational data more accessible to modelers.

## Question 4: What are the gaps and needs for targeted observations and process studies to improve understanding and model representations of those key processes?

The gaps and needs for targeted observations and process studies to advance process understanding and modeling are summarized in the following areas:

### Targeted and enhanced in situ and satellite observations:

To optimize observations and data sets for prediction initialization, evaluation, and process understanding. This includes enhancement of existing observation networks, applications of new observing technologies to fill in observation gaps in key regions, targeted observations focusing on specific high-impact events, and integrated data sets for process understanding and process-level model diagnosis.

Some specific gaps identified include:

- Observations to constrain coupled model representation of the land-atmosphere interaction, air-sea interaction, boundary-layer dynamics, ocean mixing, and aerosol-cloud-microphysics-radiation interactions.
- Observations to improve convective parameterizations through better understanding of how convection is modified by its environment and how convection modifies the environment.
- Development of long-term, high-resolution satellite precipitation tracking methods to understand large-scale convective systems, such as tracking of MCSs, large precipitation envelopes, MJOs, and atmospheric rivers.

### Process studies that include observational field campaigns integrated with modeling/data assimilation

- To provide detailed depictions of the characteristics of MCS life cycle and associated processes leading to better understanding and simulations of MCSs and precipitation prediction in the continental U.S.
- To improve the representation of physical processes (e.g., convection, cloud microphysics, planetary boundary layer, and turbulence) in ESMs.
- To reduce model biases and uncertainties that arise from initialization and observation errors in air-sea interaction, land-atmosphere interaction, 3D structure of moisture and precipitation, and representation of boundary-layer and cloud processes.

### Emerging modeling strategies:

- **Unified weather and climate modeling:** Due to limitations in computer power, weather and climate models have necessarily focused on representation of the processes that are most important to predictions at the time scales of interest to each community. As computing power increases, the line between weather and climate modeling becomes less distinct as each discipline can expand the set of processes and time scales that they resolve. A more unified approach that includes testing of model parameterizations at both weather and climate scales, and coordination around challenges common to both disciplines such as numerics and modeling infrastructure, can potentially lead to reductions in systematic biases and improved sub seasonal to decadal predictions.
- **Community modeling infrastructure:** Development of community modeling infrastructure, such as the UFS and CESM, can facilitate sustained integrated community efforts in ESM, accelerate the transition from research to operations, and yield results in which the whole is greater than the sum of the parts. While of critical importance, accelerating the transition of research to operations, however, requires significant resource investment, and commitment and flexibility in both the research and operations communities.

- **High-resolution modeling:** With increasing computational power, high-resolution modeling is becoming a desirable approach to conduct process-level studies to understand key areas such as complex terrain and to forecast regional phenomena impacting precipitation, such as atmospheric rivers and hurricanes, while bypassing the usage of certain parameterizations. In addition, coupling with a high-resolution ocean model is needed in order to simulate the impacts of mesoscale ocean eddies, western boundary currents, and SST fronts on weather and climate.
- **ML/AI:** Machine learning and artificial intelligence tools and techniques can be used in many ways to enhance a predictive understanding of precipitation. ML/AI can be used to simplify parameterizations of subgrid-scale variability, thereby accelerating computations; develop new data assimilation methodologies; develop more efficient post-processing capabilities; and create new stochastic parameterization for surrogate models.
- **Understanding multi-scale processes:** Precipitation is a complex manifestation of many processes and phenomena that unfold across microphysical, local, regional, and global scales. To sustain continued progress in precipitation predictability, it is essential to continue grounding technological advances with work to advance understanding of the many interactions that lead to and influence precipitation and the ability to predict it.

## Question 5: How do we benefit from national and international collaboration to make significant progress?

Coordinated focus by the national and international community can lead to significant progress in improving predictive skill of important processes related to precipitation predictability in weather and climate models. For example, a strong focus on observational and modeling studies of the MJO through several U.S. and international working groups over the past 20 years has improved forecast skill for the MJO.

Many U.S. agencies have common interests in precipitation predictability and processes research, and each agency carries unique capabilities and specific mission goals. USGCRP Interagency working groups (e.g., IGIM, USGEWEX, Obs IWG) provide a venue for U.S. agencies to coordinate their plans and investments, and at times collaborate. US CLIVAR is also an effective national coordination and planning mechanism, with a focus on research to understand the role of the atmosphere, oceans, and land systems in climate including the phenomena and processes that drive precipitation variability. Agencies involved in USGCRP and US CLIVAR have collaborated and jointly supported many field experiments and modeling studies.

USGCRP collaboration across individual agency program investments in observing, understanding, and modeling of precipitation processes and predictability can also benefit from the recent OSTP/FTAC planning process on Earth system predictability, and the emerging ICAMS coordination of meteorological services in the U.S., spanning local weather to global climate.

To make significant progress in understanding precipitation processes and extend predictability in coupled models, it is also important to engage international agencies and programs, such as the World Weather Research Programme and the World Climate Research Programme (including CLIVAR, GEWEX).

## Summary

The workshop identified many areas where future progress can be made to improve the predictability of precipitation processes in both weather and climate models. The workshop identified key sources of predictability and key physical processes that need further study through coordinated observation and modeling efforts; emphasized the need to better integrate observations and models using strategies such as improved data assimilation and ESM evaluation, use hierarchies of models to understand relevant processes and their manifestation as precipitation, and more unified modeling across weather and climate scales; identified ways in which new techniques such as ML/AI could be applied to improve precipitation predictability; and identified needs and mechanisms for national and international collaborations to make significant process.

# References


Bador, M., Boé, J., Terray, L., Alexander, L.V., Baker, A., Bellucci, A., ... & Vanniere, B. (2020). Impact of higher spatial atmospheric resolution on precipitation extremes over land in global climate models. *Journal of Geophysical Research: Atmospheres, 125*(13), e2019JD032184. https://doi.org/10.1029/2019JD032184

Benedetti, A., Reid, J.S., Knippertz, P., Marsham, J.H., Giuseppe, F.D., Remy, S., ... & Terradellas, E. (2018). Status and future of numerical atmospheric aerosol prediction with a focus on data requirements. *Atmospheric Chemistry and Physics, 18*(14), 10615-10643. https://doi.org/10.5194/acp-18-10615-2018

Branstator, G. (2014). Long-lived response of the midlatitude circulation and storm tracks to pulses of tropical heating. *Journal of Climate, 27*(23), 8809-8826. https://doi.org/10.1175/JCLI-D-14-00312.1

Brenowitz, N.D., & Bretherton, C.S. (2019). Spatially extended tests of a neural network parametrization trained by coarse-graining. *Journal of Advances in Modeling Earth Systems, 11*(8), 2728-2744. https://doi.org/10.1029/2019MS001711

Butler, A.H., Sjoberg, J.P., Seidel, D.J., & Rosenlof, K.H. (2017). A sudden stratospheric warming compendium. *Earth System Science Data, 9*(1), 63-76. https://doi.org/10.5194/essd-9-63-2017

Capotondi, A., Wittenberg, A.T., Kug, J.S., Takahashi, K., & McPhaden, M.J. (2020). ENSO diversity. In McPhaden, M.J., Santoso, A., & Cai, W. (Eds.), *El Niño Southern Oscillation in a Changing Climate* (65-86). John Wiley & Sons.

Edson, J.B., Jampana, V., Weller, R.A., Bigorre, S.P., Plueddemann, A.J., Fairall, C.W., ... & Hersbach, H. (2013). On the exchange of momentum over the open ocean. *Journal of Physical Oceanography, 43*(8), 1589-1610. https://doi.org/10.1175/JPO-D-12-0173.1

Eghdami, M., Bhushan, S., & Barros, A.P. (2018). Direct numerical simulations to investigate energy transfer between meso-and synoptic scales. *Journal of the Atmospheric Sciences, 75*(4), 1163-1171. https://doi.org/10.1175/JAS-D-17-0216.1

Fairall, C.W., Bradley, E.F., Godfrey, J.S., Wick, G.A., Edson, J.B., & Young, G.S. (1996a). Cool-skin and warm-layer effects on sea surface temperature. *Journal of Geophysical Research: Oceans, 101*(C1), 1295-1308. https://doi.org/10.1029/95JC03190

Fairall, C.W., Bradley, E.F., Hare, J.E., Grachev, A.A., & Edson, J.B. (2003). Bulk parameterization of air–sea fluxes: Updates and verification for the COARE algorithm. *Journal of Climate, 16*(4), 571-591. https://doi.org/10.1175/1520-0442(2003)016<0571:BPOASF>2.0.CO;2

Fairall, C.W., Bradley, E.F., Rogers, D.P., Edson, J.B., & Young, G.S. (1996b). Bulk parameterization of air-sea fluxes for tropical ocean-global atmosphere coupled-ocean atmosphere response experiment. *Journal of Geophysical Research: Oceans, 101*(C2), 3747-3764. https://doi.org/10.1029/95JC03205

Feng, Z., Houze, R.A., Leung, L.R., Song, F., Hardin, J.C., Wang, J., ... & Homeyer, C. R. (2019). Spatiotemporal characteristics and large-scale environments of mesoscale convective systems east of the Rocky Mountains. *Journal of Climate, 32*(21), 7303-7328. https://doi.org/10.1175/JCLI-D-19-0137.1

Ferraro, R., Waliser, D.E., Gleckler, P., Taylor, K.E., & Eyring, V. (2015). Evolving Obs4MIPs to support phase 6 of the coupled model Intercomparison project (CMIP6). *Bulletin of the American Meteorological Society, 96*(8), ES131-ES133. https://doi.org/10.1175/BAMS-D-14-00216.1

Henderson, S.A., Maloney, E.D., & Son, S.W. (2017). Madden–Julian oscillation Pacific teleconnections: The impact of the basic state and MJO representation in general circulation models. *Journal of Climate, 30*(12), 4567-4587. https://doi.org/10.1175/JCLI-D-16-0789.1

Houze Jr, R.A., McMurdie, L.A., Petersen, W.A., Schwaller, M.R., Baccus, W., Lundquist, J.D., ... & Chandrasekar, V. (2017). The Olympic Mountains Experiment (OLYMPEX). *Bulletin of the American Meteorological Society, 98*(10), 2167-2188. https://doi.org/10.1175/BAMS-D-16-0182.1

Infanti, J.M., & Kirtman, B.P. (2016). North American rainfall and temperature prediction response to the diversity of ENSO. *Climate Dynamics, 46*(9-10), 3007-3023. https://doi.org/10.1007/s00382-015-2749-0

Jiang, X., Lau, N.C., & Klein, S.A. (2006). Role of eastward propagating convection systems in the diurnal cycle and seasonal mean of summertime rainfall over the US Great Plains. *Geophysical Research Letters, 33*(19). https://doi.org/10.1029/2006GL027022

Kim, G., & Barros, A.P. (2001). Quantitative flood forecasting using multisensor data and neural networks. *Journal of Hydrology, 246*(1-4), 45-62. https://doi.org/10.1016/S0022-1694(01)00353-5

Kim, H., Caron, J.M., Richter, J.H., & Simpson, I.R. (2020). The lack of QBO-MJO connection in CMIP6 models. *Geophysical Research Letters, 47*(11), e2020GL087295. https://doi.org/10.1029/2020GL087295

Kim, H., Vitart, F., & Waliser, D.E. (2018). Prediction of the Madden–Julian oscillation: A review. *Journal of Climate, 31*(23), 9425-9443. https://doi.org/10.1175/JCLI-D-18-0210.1

King, A.D., Butler, A.H., Jucker, M., Earl, N.O., & Rudeva, I. (2019). Observed relationships between sudden stratospheric warmings and European climate extremes. *Journal of Geophysical Research: Atmospheres, 124*(24), 13943-13961. https://doi.org/10.1029/2019JD030480

Ma, H.Y., Zhou, C., Zhang, Y., Klein, S.A., Zelinka, M.D., Zheng, X., ... & Wu, C.M. (2021). A multi-year short-range hindcast experiment with CESM1 for evaluating climate model moist processes from diurnal to interannual timescales. *Geoscientific Model Development, 14*(1), 73-90. https://doi.org/10.5194/gmd-2020-39

Maher, P., Vallis, G.K., Sherwood, S.C., Webb, M.J., & Sansom, P.G. (2018). The impact of parameterized convection on climatological precipitation in atmospheric global climate models. *Geophysical Research Letters, 45*(8), 3728-3736. https://doi.org/10.1002/2017GL076826

Mariotti, A., E.A. Barnes, E.K.-M. Chang, A. Lang, P.A. Dirmeyer, K. Pegion, D. Barrie, and C. Baggett. (2019). Bridging the weather-to-climate prediction gap, *Eos,* 100. https://doi.org/10.1029/2019EO115819.

Merryfield, W.J., Baehr, J., Batté, L., Becker, E.J., Butler, A.H., Coelho, C.A., ... & Yeager, S. (2020). Current and emerging developments in subseasonal to decadal prediction. *Bulletin of the American Meteorological Society, 101*(6), E869-E896. https://doi.org/10.1175/BAMS-D-19-0037.1

Morrison, H., van Lier-Walqui, M., Fridlind, A.M., Grabowski, W.W., Harrington, J.Y., Hoose, C., ... & Xue, L. (2020). Confronting the challenge of modeling cloud and precipitation microphysics. *Journal of Advances in Modeling Earth Systems, 12*(8), e2019MS001689. https://doi.org/10.1029/2019MS001689

NASA. (2020). IMPACTS. https://espo.nasa.gov/sites/default/files/documents/Executive_Summary_IMPACTS_Final.pdf

Nishant, N., & Sherwood, S.C. (2021). How strongly are mean and extreme precipitation coupled?. *Geophysical Research Letters,* e2020GL092075. https://doi.org/10.1029/2020GL092075

National Science and Technology Council (NSTC). (2020). Earth System Predictability Research and Development Strategic Framework and Roadmap. Office of Science and Technology Policy. https://www.icams-portal.gov/organization/researchandinnovation/esp_randd_strategic_framework_roadmap.pdf

Phillips, T.J., Potter, G.L., Williamson, D.L., Cederwall, R.T., Boyle, J.S., Fiorino, M., ... & Yio, J.J. (2004). Evaluating parameterizations in general circulation models: Climate simulation meets weather prediction. *Bulletin of the American Meteorological Society, 85*(12), 1903-1916. https://doi.org/10.1175/BAMS-85-12-1903

Satoh, M., Stevens, B., Judt, F., Khairoutdinov, M., Lin, S.J., Putman, W.M., & Düben, P. (2019). Global cloud-resolving models. *Current Climate Change Reports, 5*(3), 172-184. https://doi.org/10.1007/s40641-019-00131-0

Serreze, M.C., Clark, M.P., Armstrong, R.L., McGinnis, D.A., & Pulwarty, R.S. (1999). Characteristics of the western United States snowpack from snowpack telemetry (SNOTEL) data. *Water Resources Research, 35*(7), 2145-2160. https://doi.org/10.1029/1999WR900090

Shin, S.I., Sardeshmukh, P.D., Webb, R.S., Oglesby, R.J., & Barsugli, J.J. (2006). Understanding the mid-Holocene climate. *Journal of Climate, 19*(12), 2801-2817. https://doi.org/10.1175/JCLI3733.1

Skofronick-Jackson, G., Petersen, W.A., Berg, W., Kidd, C., Stocker, E.F., Kirschbaum, D.B., ... & Wilheit, T. (2017). The Global Precipitation Measurement (GPM) mission for science and society. *Bulletin of the American Meteorological Society, 98*(8), 1679-1695. https://doi.org/10.1175/BAMS-D-15-00306.1

# References (continued)


Stevens, B., Satoh, M., Auger, L., Biercamp, J., Bretherton, C.S., Chen, X., ... & Zhou, L. (2019). DYAMOND: the DYnamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains. *Progress in Earth and Planetary Science, 6,* 61. https://doi.org/10.1186/s40645-019-0304-z

Swann, A.L., Hoffman, F. M., Koven, C.D., & Randerson, J.T. (2016). Plant responses to increasing CO2 reduce estimates of climate impacts on drought severity. *Proceedings of the National Academy of Sciences, 113*(36), 10019-10024. https://doi.org/10.1073/pnas.1604581113

Tao, K., & Barros, A.P. (2010). Using fractal downscaling of satellite precipitation products for hydrometeorological applications. *Journal of Atmospheric and Oceanic Technology, 27*(3), 409-427. https://doi.org/10.1175/2009JTECHA1219.1

Teng, H., Branstator, G., Tawfik, A.B., & Callaghan, P. (2019). Circumglobal response to prescribed soil moisture over North America. *Journal of Climate, 32*(14), 4525-4545. https://doi.org/10.1175/JCLI-D-18-0823.1

Williams, K.D., Bodas-Salcedo, A., Déqué, M., Fermepin, S., Medeiros, B., Watanabe, M., ... & Williamson, D.L. (2013). The Transpose-AMIP II experiment and its application to the understanding of Southern Ocean cloud biases in climate models. *Journal of Climate, 26*(10), 3258-3274. https://doi.org/10.1175/JCLI-D-12-00429.1

Xiong, Y., & Ren, X. (2021). Influences of Atmospheric Rivers on North Pacific Winter Precipitation: Climatology and Dependence on ENSO Condition. *Journal of Climate, 34*(1), 277-292. https://doi.org/10.1175/JCLI-D-20-0301.1

Yu L. (2019). Global Air-Sea Fluxes of Heat, Fresh Water, and Momentum: Energy Budget Closure and Unanswered Questions. *Annual Review of Marine Science. 11,* 227-248. https://doi.org/10.1146/annurev-marine-010816-060704

Zarakas, C.M., Swann, A.L., Laguë, M.M., Armour, K.C., & Randerson, J.T. (2020). Plant Physiology Increases the Magnitude and Spread of the Transient Climate Response to CO2 in CMIP6 Earth System Models. *Journal of Climate, 33*(19), 8561-8578. https://doi.org/10.1175/JCLI-D-20-0078.1

Zarzycki, C.M., Jablonowski, C., Thatcher, D.R., & Taylor, M.A. (2015). Effects of localized grid refinement on the general circulation and climatology in the Community Atmosphere Model. *Journal of Climate, 28*(7), 2777-2803. https://doi.org/10.1175/JCLI-D-14-00599.1

Zhang, K., Wan, H., Liu, X., Ghan, S.J., Kooperman, G.J., Ma, P.L., ... & Lohmann, U. (2014). On the use of nudging for aerosol–climate model intercomparison studies. *Atmospheric Chemistry and Physics, 14*(16), 8631-8645. https://doi.org/10.5194/acp-14-8631-2014

Zhao, M. (2020). Simulations of Atmospheric Rivers, Their Variability, and Response to Global Warming Using GFDL's New High-Resolution General Circulation Model. *Journal of Climate, 33*(23), 10287-10303. https://doi.org/10.1175/JCLI-D-20-0241.1

# Appendix A – Abbreviations and Acronyms

| | |
|---|---|
| **3D** | three-dimensional |
| **AI4ESP** | Artificial intelligence for Earth system predictability |
| **AMV** | Atlantic Multidecadal Variability |
| **AR Recon** | Atmospheric River Reconnaissance |
| **AR-AFS** | Atmospheric River Analysis and Forecast System |
| **ARM** | Atmospheric Radiation Measurement |
| **ASR** | Atmospheric System Research |
| **BNL** | Brookhaven National Laboratory |
| **CESM** | Community Earth System Model |
| **CLIVAR** | Climate Variability and Predictability Program |
| **CMIP6** | Coupled Model Intercomparison Project Phase 6 |
| **CONUS** | continental United States |
| **CPC** | Climate Prediction Center |
| **CPO** | Climate Program Office |
| **DOD** | US Department of Defense |
| **DOE** | U.S. Department of Energy |
| **DYAMOND** | DYnamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains |
| **E3SM** | Energy Exascale Earth System Model |
| **ECMWF** | European Centre for Medium-Range Weather Forecasts |
| **EESSD** | Earth and Environmental Systems Sciences Division |
| **ENSO** | El Niño-Southern Oscillation |
| **ESMs** | Earth System Models |
| **ESP** | Earth System Predictability |
| **FTAC** | Fast Track Action Committee |
| **GEMS** | Global Environmental Monitoring System |
| **GEWEX** | Global Energy and Water Exchanges |
| **GFDL** | Geophysical Fluid Dynamics Laboratory |
| **GPM** | Global Precipitation Measurement |
| **GSRMs** | global storm-resolving models |
| **HAFS** | Hurricane Analysis and Forecast System |
| **hPa** | hectopascal |
| **HWRF** | Hurricane Weather Research and Forecasting |
| **ICAMS** | Interagency Council for Advancing Meteorological Services |
| **IGIM** | Interagency Group on Integrative Modeling |
| **IMPACTS** | Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms |
| **IPCC** | Intergovernmental Panel on Climate Change |
| **IRI** | International Research Institute for Climate and Society |
| **km** | kilometer(s) |
| **LBL** | Lawrence Berkeley National Laboratory |
| **LES** | Large Eddy Simulation |
| **LLNL** | Lawrence Livermore National Laboratory |
| **m** | meter(s) |
| **MCS** | mesoscale convective system |
| **MJO** | Madden-Julian Oscillation |

# Abbreviations and Acronyms (continued)

| | |
|---|---|
| **ML/AI** | machine learning and artificial intelligence |
| **MRW** | Medium Range Weather |
| **NAO** | North Atlantic Oscillation |
| **NASA** | National Aeronautics and Space Administration |
| **NCAR** | National Center for Atmospheric Research |
| **NCEP** | National Centers for Environmental Prediction |
| **NOAA** | National Oceanic and Atmospheric Administration |
| **NSF** | National Science Foundation |
| **NSTC** | National Science and TecÙology Council |
| **NWS** | National Weather Service |
| **Obs IWG** | Integrated Observations Interagency Working Group |
| **obs4MIPs** | Observations for Model Intercomparisons Project |
| **OLYMPEX** | Olympic Mountains Experiment |
| **OSTP** | Office of Science and TecÙology Policy |
| **PDO/PDV** | Pacific Decadal Oscillation/Variability |
| **PMEL** | Pacific Marine Environmental Laboratory |
| **PNNL** | Pacific Northwest National Laboratory |
| **PPGC** | Precipitation Prediction Grand Challenge |
| **PPGC WG** | Precipitation Prediction Grand Challenge Working Group |
| **PSL** | Physical Sciences Laboratory |
| **QBO** | Quasi-Biennial Oscillation |
| **RRFS** | Rapid Refresh Forecast System |
| **S2D** | seasonal to decadal |
| **S2S** | sub-seasonal to seasonal |
| **SNOTEL** | Snow Telemetry |
| **SRW** | Short Range Weather |
| **SST** | sea surface temperature |
| **SSWs** | Sudden Stratospheric Warmings |
| **TRACER** | TRacking Aerosol Convection interactions ExpeRiment |
| **UFS** | Unified Forecast System |
| **US** | United States |
| **US CLIVAR** | U.S. Climate Variability and Predictability Program |
| **USDA** | United States Department of Agriculture |
| **USGCRP** | U.S. Global Change Research Program |
| **USGEWEX** | US Global Energy and Water Exchanges |
| **USGS** | United States Geological Survey |
| **WCRP** | World Climate Research Programme |
| **West-WRF** | West Weather Research and Forecasting |
| **WoF** | Warn of Forecast |
| **WWRP** | World Weather Research Programme |

# Appendix B – Workshop Agenda

| Day 1 – November 30, 2020 | | |
|---|---|---|
| **Opening Session: Overview & Scope** | | |
| **Start Time (EST)** | **Topic** | **Speaker** |
| 10:00 AM | Workshop Introduction, Slack Channel, and Agenda Overview | Jin Huang (NOAA/CPO), Renu Joseph (DOE/EESSD/EESM), Co-chairs |
| 10:05 AM | NOAA's Precipitation Prediction Grand Challenge (PPGC) | Wayne Higgins (NOAA/CPO) |
| 10:15 AM | DOE's Water Cycle Predictability and Precipitation Priorities | Gerald Geernaert (DOE/EESSD) |
| 10:25 AM | Overview of Earth System Predictability R&D Workshop | Jim Hurrell (Colorado State University) |
| **Session 1: Limits and Sources of Predictability Part I** | | |
| 10:40 AM | Session Introduction | Ben Kirtman (U. Miami), Magdalena Balmaseda (ECMWF), Samson Hagos (DOE/PNNL), Co-chairs |
| 10:42 AM | Keynote: Signal, Noise and Predictability in North Atlantic Regime Systems | Kristian Strommen (Oxford) and Tim Palmer (Oxford) |
| 11:07 AM | Introduction of Panel | Co-chairs |
| 11:10 AM | Mechanisms of S2S Precipitation Predictability | Andrew Robertson (IRI, Columbia University) |
| 11:15 AM | S2S Prediction of Precipitation | Frederic Vitart (ECMWF) |
| 11:20 AM | Observing Air-Sea Interactions Strategy (OASIS) for 2030 | Meghan Cronin (NOAA/PMEL) |
| 11:25 AM | MJO-ENSO Teleconnection Interference and Impacts on Blocking | Stephanie Henderson (Univ. of Wisconsin) |
| 11:30 AM | Open Discussion: Speaker & Panel (Part 1 of 2) | |
| **LUNCH –** Slide Reel: Current Capabilities and Systems Relevant to Precipitation Processes and Predictability | | |
| **Session 1: Limits and Sources of Predictability Part II** | | |
| 1:00 PM | Session Introduction | Co-chairs |
| 1:05 PM | Keynote: Sub-seasonal and Seasonal Precipitation: from Predictability to Prediction | Kathy Pegion (GMU) |
| 1:35 PM | Introduction of Panel | Co-chairs |
| 1:40 PM | Thoughts on Exciting Directions to Explore Towards Improving Prediction Skill of Precipitation | Aneesh Subramanian (Univ. of CO) |
| 1:45 PM | Panelist Remarks | Ruby Leung (PNNL) |
| 1:50 PM | Limits and Sources of Predictability – Seasonal to Multidecadal Scale | Tom Delworth (NOAA/GFDL) |
| 1:55 PM | Panelist Remarks | Russ Schumacher (CSU) |
| 2:00 PM | Open Discussion: Speaker & Panel (Part 2 of 2) | |

| Day 2 – December 1, 2020 | | |
|---|---|---|
| **Session 2: Key Processes Critical to Precipitation Biases** | | |
| **Start Time (EST)** | **Topic** | **Speaker** |
| 10:00 AM | Session Introduction | Hsi-Yen Ma (DOE/LLNL), Yi Ming (NOAA/GFDL), Co-chairs |
| 10:05 AM | Keynote: Are Global Storm-Resolving Models a Path to Reduce Precipitation Biases in Climate Projections? | Chris Bretherton (UW) |
| 10:35 AM | Introduction of Panel | Co-chairs |
| 10:40 AM | Identifying and Improving Key Physical Processes Critical to Precipitation Biases – Hierarchy Modeling and Field Observations | Shaocheng Xie (DOE/LLNL) |
| 10:45 AM | A Model Study of Precipitation and its Extremes Using a Weather Phenomena-Based Model | Ming Zhao (NOAA/GFDL) |
| 10:50 AM | Insights from Spaceborne Precipitation Measurements on Model Representations of Convective Systems | Steve Nesbitt (UIUC) |
| 10:55 AM | GPM Radar Observations and CAM5 Depictions of Convective and Stratiform Rain over CONUS | Courtney Schumacher (TAMU) |
| 11:00 AM | Open Discussion: Speaker & Panel | |
| **LUNCH** – Slide Reel: Current Capabilities and Systems Relevant to Precipitation Processes and Predictability | | |
| **Session 3: Interdisciplinary Processes** | | |
| **Start Time (EST)** | **Topic** | **Speaker** |
| 1:00 PM | Session Introduction | Sandy Lucas (NOAA/CPO), Sally McFarlane (DOE/EESSD), Co-chairs |
| 1:05 PM | Keynote: Ocean-Atmosphere Interactions Related to Precipitation Predictability and Bias | Elizabeth Thompson (NOAA/ESRL/PSL) |
| 1:35 PM | Introduction of Panel | Co-chairs |
| 1:40 PM | How NOT to Represent Aerosol-Cloud-Precipitation Interactions | Andrew Gettelman (NCAR) |
| 1:45 PM | Prediction vs Predictability | Ana Barros (Duke) |
| 1:50 PM | Quantifying the Role that Terrestrial Ecosystems Play in Earth's Climate | Abigail Swann (UW) |
| 1:55 PM | Stratosphere-troposphere Interactions and Precipitation | Yaga Richter (NCAR) |
| 2:00 PM | Open Discussion: Speaker & Panel | |

| Day 3 – December 2, 2020 | | |
|---|---|---|
| **Session 4: Reginal Precipitation** | | |
| **Start Time (EST)** | **Topic** | **Speaker** |
| 10:00 AM | Session Introduction | Angie Pendergrass (NCAR), Ana Barros (Duke), Vijay Tallapragada (NOAA/NWS), Co-chairs |
| 10:05 AM | Keynote: Operational Forecasting of Precipitation: Regional Aspects | Dave Novak (NCEP/WPC) |
| 10:35 AM | Introduction of Panel | Co-chairs |
| 10:40 AM | Precipitation Processes in Midlatitude Cyclones: Results from recent Field Campaigns | Lynn McMurdie (U Washington) |
| 10:45 AM | Atmospheric Rivers and Their Impact on Precipitation Forecasts on the US West Coast | Marty Ralph (CW3E/Scripps) |
| 10:50 AM | Observational Perspectives from the Upcoming TRACER Campaign | Anita Rapp (TAMU) |
| 10:55 AM | Model Biases in Southeastern US Precipitation | Johnna Infanti (NOAA/CPC) |
| 11:00 AM | Open Discussion: Speaker & Panel | |
| **LUNCH –** Slide Reel: Current Capabilities and Systems Relevant to Precipitation Processes and Predictability | | |
| **Wrap-up Session: Agencies/Programs Inputs** | | |
| **Start Time (EST)** | **Topic** | **Speaker** |
| 1:00 PM | Session Introduction | Jin Huang (NOAA/CPO), Renu Joseph (DOE/EESSD/EESM), Co-chairs |
| 1:05 PM | NSF Overview | Anjuli Bamzai (NSF) |
| 1:15 PM | Space-Based Precipitation Activities Enabled by NASA Headquarters | Gail Skofronick-Jackson (NASA) |
| 1:25 PM | Agency – DOD | Mike Farrar (USAF) |
| 1:35 PM | OSTP – Earth System Predictability; ICAMS | Annarita Mariotti (OSTP) |
| 1:45 PM | US CLIVAR Program Perspectives | Mike Patterson, Director |
| 2:00 PM | Session Summaries<br>– Session 1<br>– Session 2<br>– Session 3<br>– Session 4 | Session Chairs |
| 2:50 PM | Next Steps & Report Preparation | Renu Joseph (DOE/ESSMD), Jin Huang (NOAA/CPO), Co-chairs |

# Appendix C – Workshop Participants

| Participant | Affiliation |
|---|---|
| Vesta Afzali Gorooh | University of California, Irvine |
| Fiaz Ahmed | University of California, Los Angeles |
| Min-Seop Ahn | Lawrence Livermore National Laboratory |
| Ghassan Alaka | NOAA |
| John Albers | NOAA |
| Noel Aloysius | University of Missouri |
| Valentine Anantharaj | Not Provided |
| Michael Anderson | California Department of Water Resources |
| Nathan Anderson | NOAA |
| H. Annamalai | University of Hawai'i |
| Jennifer Arrigo | DOE |
| Bob Atlas | NOAA |
| Alyssa Atwood | Florida State University |
| Cory Baggett | NOAA |
| Magdalena Balmaseda | ECMWF |
| Anjuli Bamzai | NSF |
| Katelyn Barber | Pacific Northwest National Laboratory |
| Dan Barrie | NOAA |
| Ana Barros | Duke University |
| Sean Bath | NOAA |
| Emily Becker | University of Miami |
| Nancy Beller-Simms | NOAA |
| Alex Belochitski | NOAA |
| Stan Benjamin | NOAA |
| Dhruv Bhagtani | Australian National University |
| Uma Bhatt | University of Alaska |
| Peter Black | NOAA |
| Robert Black | NOAA |
| Mike Bodner | NOAA |
| Celine Bonfils | Lawrence Livermore National Laboratory |
| William Boos | University of California, Berkeley |
| James Booth | The City College of New York |
| Paloma Borque | Pacific Northwest National Laboratory |
| Jared Bowden | North Carolina State University |
| Marcia Branstetter | Oak Ridge National Laboratory |
| Melissa Breeden | NOAA |
| Victoria Breeze | NOAA |
| Chris Bretherton | University of Washington |

| Participant | Affiliation |
|---|---|
| Laura Briley | University of Michigan |
| Maureen Brooks | NOAA |
| Bonnie Brown | NOAA |
| John Brown | NOAA |
| Robert Burgman | Florida International University |
| Patrick Burke | NOAA |
| Michelle Bushman | Western States Water Council |
| Courtney Byrd | NOAA |
| Forest Cannon | Not Provided |
| Antonietta Capotondi | NOAA |
| Jessie Carman | NOAA |
| Julie Caron | UCAR |
| Theo Carr | Massachusetts Institute of Technology |
| Christopher Castellano | University of California, San Diego |
| Paul Chan | Not Provided |
| Kim Channell | University of Michigan |
| William Chapman | Not Provided |
| Randy Chase | University of Illinois |
| Di Chen | University of California, Los Angeles |
| Haonan Chen | NOAA |
| Jingyi Chen | Pacific Northwest National Laboratory |
| Shuyi Chen | University of Washington |
| Tse-Chun Chen | NOAA |
| Christine Chiu | Colorado State University |
| Maya Chung | Princeton University |
| Laura Ciasto | NOAA |
| Adam Clark | NOAA |
| John Coggins | NOAA |
| William Collins | Lawrence Berkeley National Laboratory |
| Emil Constantinescu | Argonne National Laboratory |
| James Correia | NOAA |
| William Crawford | US Naval Research Laboratory |
| Juan Crespo | NASA |
| Meghan Cronin | NOAA |
| Wenjun Cui | University of Arizona |
| Arlindo da Silva | NASA |
| Katie Dagon | UCAR |
| LuAnn Dahlman | NOAA |

| Participant | Affiliation |
|---|---|
| Ni Dai | University of Miami |
| Shannon Davis | DOE |
| Xujing Davis | DOE |
| Nick Dawson | Idaho Power |
| Benjamin DeAngelo | NOAA |
| Mike DeFlorio | University of California, San Diego |
| Andrew DeLaFrance | University of Washington |
| Luca Delle Monache | University of California, San Diego |
| Timothy DelSole | George Mason University |
| Tom Delworth | NOAA |
| Charlotte DeMott | Colorado State University |
| Sachin Deshpande | Indian Institute of Tropical Meteorology |
| Eric DeWeaver | NSF |
| David DeWitt | NOAA |
| Howard Diamond | NOAA |
| Juliana Dias | NOAA |
| Ty Dickinson | University of Oklahoma |
| Paul Dirmeyer | George Mason University |
| Kalyn Dorheim | Pacific Northwest National Laboratory |
| James Doyle | Naval Research Laboratory |
| Shiheng Duan | University of California, Davis |
| George Duffy | Jet Propulsion Laboratory |
| Timothy Dunkerton | NorthWest Research Associates |
| Lena Easton-Calabria | RAND |
| Azhar Ehsan | Not Provided |
| Michael Ek | UCAR |
| Gregory Elsaesser | Columbia University |
| Christopher Fairall | NOAA |
| Jiwen Fan | Pacific Northwest National Laboratory |
| Michael Farrar | USAF |
| Yan Feng | Argonne National Laboratory |
| Zhe Feng | Pacific Northwest National Laboratory |
| Robert Ferraro | Jet Propulsion Laboratory |
| Eric Fetzer | Jet Propulsion Laboratory |
| Joseph Finlon | University of Washington |
| Evan Fishbein | NASA |
| Gregory Frost | NOAA |
| Rong Fu | University of California, Los Angeles |
| Jay Fuhrman | University of Virginia |
| Jason Furtado | University of Oklahoma |

| Participant | Affiliation |
| --- | --- |
| Murielle Gamache | NOAA |
| Jidong Gao | NOAA |
| Ned Gardiner | NOAA |
| Piyush Garg | University of Illinois |
| Omar Gates | University of Michigan |
| Patrick Gatlin | NASA |
| Sagar Gautam | Lawrence Berkeley National Laboratory |
| Gerald Geernaert | DOE |
| Charlette Geffen | Pacific Northwest National Laboratory |
| Andrew Gettelman | UCAR |
| Scott Giangrande | Brookhaven National Laboratory |
| Sundararaman Gopalakrishnan | NOAA |
| Virendra Goswami | Not Provided |
| Jon Gottschalck | NOAA |
| Garrett Graham | NOAA |
| Geneva Gray | U.S. Environmental Protection Agency |
| Mircea Grecu | NASA |
| Jorge Guerra | NOAA |
| Ismail Gultepe | Environment Canada |
| William Gutowski | Iowa State University |
| Ziad Haddad | Jet Propulsion Laboratory |
| Samson Hagos | Pacific Northwest National Laboratory |
| Mike Halpert | NOAA |
| Tom Hamil | NOAA |
| Jongil Han | NOAA |
| Joseph Hardin | Not Provided |
| Daniel Harnos | NOAA |
| Bryce Harrop | Pacific Northwest National Laboratory |
| Feng He | University of Wisconsin, Madison |
| Jie He | Georgia Institute of Technology |
| Stephanie Henderson | University of Wisconsin, Madison |
| Jacob Hendrickson | University of California, Irvine |
| David Herring | NOAA |
| Wayne Higgins | NOAA |
| Paul Hirschberg | NOAA |
| Justin Hnilo | DOE |
| Forrest Hoffman | Climate Modeling.org |
| Stephen Holden | Environment and Climate Change Canada |
| Matthew Horan | University of Tennessee, Knoxville |
| Fiona Horsfall | NOAA |

| Participant | Affiliation |
|---|---|
| Svetla Hristova-Veleva | Jet Propulsion Laboratory |
| Grace Hu | Office of Management and Budget |
| I-Kuan Hu | NOAA |
| Junjun Hu | NOAA |
| Junjun Hu | University of Oklahoma |
| Huanping Huang | Lawrence Berkeley National Laboratory |
| Jin Huang | NOAA |
| Xingying Huang | University of California, Santa Barbara |
| Yongjie Huang | Not Provided |
| Jim Hurrell | Colorado State University |
| Margaret Hurwitz | NOAA |
| Johnna Infanti | NOAA |
| Jay Jasperse | Sonoma County Water Agency |
| Shantanu Jathar | Colorado State University |
| Michael Jensen | Brookhaven National Laboratory |
| Jonghoon Jeong | University of California, Los Angeles |
| Lihui Ji | Duke University |
| Xianan Jiang | University of California, Los Angeles |
| Aaron Johnson | University of Oklahoma |
| Jeanine Jones | California Department of Water Resources |
| Renu Joseph | DOE |
| Erika Jozwiak | City of New York |
| Youngsun Jung | NOAA |
| Jonghunj Kam | Pohang University of Science and Technology |
| Daehyun Kang | University of Washington |
| Brian Kawzenuk | University of California, San Diego |
| Daehyun Kim | University of Washington |
| Dongmin Kim | NOAA |
| Hyemi Kim | Stony Brook University |
| Jim Kinter | George Mason University |
| Ben Kirtman | University of Miami |
| Petra Klein | University of Oklahoma |
| Stephen Klein | Lawrence Livermore National Laboratory |
| Doug Kluck | NOAA |
| Mu-Chieh Ko | NOAA |
| John Kochendorfer | NOAA |
| Pavlos Kollias | Stony Brook University |
| Monika Kopacz | NOAA |
| Matthew Koszuta | Oregon State University |
| Sujith Krishnakumar | Pacific Northwest National Laboratory |

| Participant | Affiliation |
|---|---|
| V. Krishnamurthy | George Mason University |
| Sayali Kulkarni | Not Provided |
| Jitendra Kumar | Oak Ridge National Laboratory |
| Sanjiv Kumar | Auburn University |
| Yi-Hung Kuo | University of California, Los Angeles |
| Young-Oh Kwon | Woods Hole Oceanographic Institution |
| Alfonso Ladino | University of Illinois |
| Emerson LaJoie | NOAA |
| Bjorn Lambrigtsen | Jet Propulsion Laboratory |
| Kathleen Lantz | NOAA |
| Matthew Lebsock | Jet Propulsion Laboratory |
| Chia-Ying Lee | Columbia University |
| Jiwoo Lee | Lawrence Livermore National Laboratory |
| Jungmin Lee | Lawrence Livermore National Laboratory |
| Sang-Ki Lee | NOAA |
| Sukyoung Lee | The Pennsylvania State University |
| Hua Leighton | NOAA |
| Chiara Lepore | Lamont-Doherty Earth Obs./Columbia University |
| Kyle Lesinger | Auburn University |
| L. Ruby Leung | Pacific Northwest National Laboratory |
| Michelle L'Heureux | NOAA |
| Hui Li | UCAR |
| Jianfeng Li | Pacific Northwest National Laboratory |
| Laifang Li | The Pennsylvania State University |
| Yue Li | University of California, Irvine |
| Zhiying Li | Ohio State University |
| Mochi Liao | Not Provided |
| Hyunggyu Lim | NOAA |
| Varavut Limpasuvan | NSF |
| Maofeng Liu | University of Miami |
| Nana Liu | Pacific Northwest National Laboratory |
| Wei Liu | Not Provided |
| Ye Liu | Pacific Northwest National Laboratory |
| Hosmay Lopez | NOAA |
| Dan Lu | Oak Ridge National Laboratory |
| Sandy Lucas | NOAA |
| Lifeng Luo | Michigan State University |
| Hsi-Yen Ma | Lawrence Livermore National Laboratory |
| Cristielen Machado | Not Provided |
| Gavin D. Madakumbura | University of California, Los Angeles |

| Participant | Affiliation |
|---|---|
| Gudrun Magnusdottir | University of California, Irvine |
| Salil Mahajan | Oak Ridge National Laboratory |
| Naser Mahfouz | NOAA |
| Eric Maloney | Colorado State University |
| Jiafu Mao | Oak Ridge National Laboratory |
| Annarita Mariotti | Office of Science and Technology Policy |
| Frank Marks | NOAA |
| Elinor Martin | University of Oklahoma |
| Dave McCarren | NOAA |
| Sally McFarlane | DOE |
| Greg McFarquhar | University of Oklahoma |
| Lynn McMurdie | University of Washington |
| Avichal Mehra | NOAA |
| Karen Metchis | Not Provided |
| Tilden Meyers | NOAA |
| Art Miller | University of California, San Diego |
| Samar Minallah | University of Michigan |
| Yi Ming | NOAA |
| Vasubandhu Misra | Florida State University |
| Yumin Moon | Not Provided |
| Mary Morris | NASA |
| Maruti Kumar Mudunuru | Pacific Northwest National Laboratory |
| Johannes Muelmenstaedt | Pacific Northwest National Laboratory |
| Esther Mullens | University of Florida |
| Louisa Nance | UCAR |
| Bala Narapusetty | NOAA |
| Richard Neale | UCAR |
| David Neelin | University of California, Los Angeles |
| Stephen Nesbitt | University of Illinois |
| Phu Nguyen | University of California, Irvine |
| Wenfei Ni | NOAA |
| Jesse Norris | University of California, Los Angeles |
| David Novak | NOAA |
| Omon Obarein | Kent State University |
| Mega Octaviani | Pacific Northwest National Laboratory |
| Luke Odell | University of California, San Diego |
| Rigo Olivera | Florida International University |
| Mark Olsen | NOAA |
| Joseph Olson | NOAA |
| Evan Oswald | Not Provided |

| Participant | Affiliation |
|---|---|
| Melissa Ou | NOAA |
| Sujan Pal | University of Illinois |
| Robert Palmer | University of Oklahoma |
| Timothy Palmer | University of Oxford |
| Baoxiang Pan | Lawrence Livermore National Laboratory |
| Danahé Paquin-Ricard | Environment Canada |
| Linsey Passarella | University of Tennessee, Knoxville |
| Mike Patterson | US CLIVAR |
| Kathy Pegion | George Mason University |
| Yannick Peings | University of California, Irvine |
| Angie Pendergress | UCAR |
| Thomas Phillips | SBC Global |
| James Pinto | UCAR |
| Diego Pons | Colorado State University |
| Derek Posselt | Jet Propulsion Laboratory |
| Abhnil Prasad | University of New South Wales |
| Andreas Prein | UCAR |
| Roger Pulwarty | NOAA |
| Bryony Puxley | University of Oklahoma |
| Yun Qian | Pacific Northwest National Laboratory |
| Hongchen Qin | Lawrence Livermore National Laboratory |
| Yi Qin | Lawrence Livermore National Laboratory |
| Patricia Quinn | NOAA |
| Mani Rajagopal | University of Utah |
| Marty Ralph | University of California, San Diego |
| Venkatachalam Ramaswamy | NOAA |
| Varis Ransi | NOAA |
| Douglas Rao | Texas A&M University |
| Anita Rapp | Texas A&M University |
| Colin Raymond | Columbia University |
| Kevin Reed | Stony Brook University |
| Jessica Reimer | Western States Water Council |
| Viktor Reshniak | Oak Ridge National Laboratory |
| Carolyn Reynolds | Naval Research Laboratory |
| Yaga Richter | UCAR |
| Lina Rivelli-Zea | University of Illinois |
| Andrew Robertson | IRI/Columbia University |
| Deje Robi | NSF |
| Erika Roesler | Sandia National Laboratories |
| Robert Rogers | NOAA |

| Participant | Affiliation |
|---|---|
| Jacola Roman | NASA |
| Angela Rowe | University of Wisconsin, Madison |
| Stephanie Rushley | Not Provided |
| Eri Saikawa | Emory University |
| Naoko Sakaeda | University of Oklahoma |
| Koichi Sakaguchi | Pacific Northwest National Laboratory |
| Venkadesh Samykannu | Not Provided |
| Scott Sandgathe | University of Washington |
| Clayton Sasaki | University of Washington |
| Rick Saylor | NOAA |
| Michael Schichtel | NOAA |
| Kathleen Schiro | University of Virginia |
| Raymond Schmitt | Woods Hole Oceanographic Institution |
| Carl Schreck | North Carolina State University |
| Mathias Schreier | NASA |
| Melanie Schroers | University of Oklahoma |
| Siegfried Schubert | NASA |
| Courtney Schumacher | Texas A&M University |
| Russ Schumacher | Colorado State University |
| Virginia Selz | NOAA |
| Retish Senan | ECMWF |
| Yolande Serra | University of Washington |
| Eric Shearer | University of California, Irvine |
| Elena Shevliakova | NOAA |
| Hui Shi | Farallon Institute |
| Christine Shields | UCAR |
| Chul-Su Shin | George Mason University |
| Jacob Shpund | Pacific Northwest National Laboratory |
| Israel Silber | Penn State University |
| Bohar Singh | IRI/Columbia University |
| Gail Skofronick-Jackson | NASA |
| Abhishekh Srivastava | University of California, Davis |
| Cristiana Stan | George Mason University |
| Bill Stern | NOAA |
| Alison Stevens | NOAA |
| Cheyenne Stienbarger | NOAA |
| Drew Story | USGCRP |
| Kristian Strommen | University of Oxford |
| Hui Su | Jet Propulsion Laboratory |
| Aneesh Subramanian | University of Colorado, Boulder |

| Participant | Affiliation |
|---|---|
| Alex Sun | University of Texas, Austin |
| Jielun Sun | NSF |
| Yongqiang Sun | NOAA |
| Abigail Swann | University of Washington |
| James Taggart | NOAA |
| Sheng-Lun Tai | Pacific Northwest National Laboratory |
| Vijay Tallapragada | NOAA |
| Simone Tanelli | Jet Propulsion Laboratory |
| Qi Tang | Lawrence Livermore National Laboratory |
| Shuaiqi Tang | Pacific Northwest National Laboratory |
| Cheng Tao | Lawrence Livermore National Laboratory |
| Francisco Tapiador | University of Castilla-La Mancha |
| Haiyan Teng | Pacific Northwest National Laboratory |
| Christopher Terai | Lawrence Livermore National Laboratory |
| Sarah Tessendorf | UCAR |
| Chad Thackeray | University of California, Los Angeles |
| Elizabeth Thompson | NOAA |
| LuAnne Thompson | University of Washington |
| Baijun Tian | Jet Propulsion Laboratory |
| Di Tian | Auburn University |
| Jingjing Tian | Lawrence Livermore National Laboratory |
| Yang Tian | Harvard University |
| Michael Tippett | Columbia University |
| Jim Todd | NOAA |
| Daniel Tong | George Mason University |
| Mingjing Tong | NOAA |
| Joe Turk | Jet Propulsion Laboratory |
| Paul Ullrich | University of California, Davis |
| Shruti Upadhyaya | University of Oklahoma |
| Marcus van Lier-Walqui | Columbia University |
| Adam Varble | Pacific Northwest National Laboratory |
| Gabriele Villarini | University of Iowa |
| Augustin Vintzileos | University of Maryland |
| Frederic Vitart | ECMWF |
| Haruko Wainwright | Lawrence Berkeley National Laboratory |
| Hui Wan | Pacific Northwest National Laboratory |
| Chenggong Wang | Princeton University |
| Die Wang | Brookhaven National Laboratory |
| Fang Wang | Auburn University |
| Hailan Wang | NASA |

| Participant | Affiliation |
|---|---|
| Hailong Wang | Pacific Northwest National Laboratory |
| Jingyu Wang | University of Arizona |
| Xuguang Wang | University of Oklahoma |
| Yuan Wang | California Institute of Technology |
| Zhuo Wang | University of Illinois |
| Tony Willardson | Western States Water Council |
| Eric Williams | NOAA |
| Anna Wilson | University of California, San Diego |
| Brandon Wolding | Not Provided |
| Sun Wong | Jet Propulsion Laboratory |
| Stan Wullschleger | Oak Ridge National Laboratory |
| Shaocheng Xie | Lawrence Livermore National Laboratory |
| Lulin Xue | UCAR |
| Yan Xue | NOAA |
| Takanobu Yamaguchi | NOAA |
| Cheng-En Yang | University of Tennessee, Knoxville |
| Da Yang | University of California, Davis |
| Fanglin Yang | NOAA |
| Qiu Yang | Pacific Northwest National Laboratory |
| Zhao Yang | Not Provided |
| Jiacheng Ye | University of Illinois |
| Srikanth Yoginath | Oak Ridge National Laboratory |
| Ryuji Yoshida | NOAA |
| Sungduk Yu | Yale University |
| Jing Yuan | IRI/Columbia University |
| Qing Yue | NASA |
| Nusrat Yussouf | NOAA |
| Colin Zarzycki | Penn State University |
| Jonathan Zawislak | NOAA |
| Xubin Zeng | University of Arizona |
| Bosong Zhang | University of Miami |
| Dongxiao Zhang | NOAA |
| Jian Zhang | NOAA |
| Jill Zhang | Lawrence Livermore National Laboratory |
| Kai Zhang | Pacific Northwest National Laboratory |
| Likun Zhang | Lawrence Berkeley National Laboratory |
| Minghua Zhang | Stony Brook University |
| Rudong Zhang | Not Provided |
| Shixuan Zhang | Pacific Northwest National Laboratory |
| Wei Zhang | NOAA |

| Participant | Affiliation |
|---|---|
| Wei Zhang | Oak Ridge National Laboratory |
| Yingxiao Zhang | University of Michigan |
| Yunyan Zhang | Lawrence Livermore National Laboratory |
| Yuwei Zhang | Pacific Northwest National Laboratory |
| Yuying Zhang | Lawrence Livermore National Laboratory |
| Zhibo Zhang | University of Maryland, Baltimore County |
| Ming Zhao | NOAA |
| Xue Zheng | Lawrence Livermore National Laboratory |
| Jiayu Zhou | NOAA |
| Linjiong Zhou | NOAA |
| Xiaoli Zhou | NOAA |
| Yang Zhou | Lawrence Berkeley National Laboratory |
| Zeen Zhu | Stony Brook University |

## For More Information

**Regional & Global Model Analysis**

climatemodeling.science.energy.gov/rgma | Renu Joseph, renu.joseph@science.doe.gov

**Earth System Science and Modeling Division**

https://cpo.noaa.gov/Meet-the-Divisions/Earth-System-Science-and-Modeling | Jin Huang, jin.huang@noaa.gov