BAMS
Meeting Summary

Advancing Precipitation Estimation, Prediction, and Impact Studies

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Twelfth International Precipitation Conference (IPCI2)

What: Scientists from more than 60 countries met at the Twelfth International Precipitation Conference (IPCI2) to discuss the latest advances in precipitation estimation, prediction, and impact assessment and contemplate the challenges and opportunities that lie ahead.

When: 19–21 June 2019

Where: Irvine, California

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Precipitation exhibits a large variability over a wide range of space and time scales: from seconds to years and decades in time and from the millimeter scale of microphysical processes to regional and global scales in space. It also exhibits a large variability in magnitude and frequency, from low extremes resulting in prolonged droughts to high extremes resulting in devastating floods. Improving precipitation estimation and prediction has great societal impact for decision support in water resources management, infrastructure protection and design under accelerating climate extremes, quantifying water and energy balances at the regional to global scales, and predicting hurricanes, tornadoes, floods, and droughts that affect the economy and security around the world (e.g., Blunden and Arndt 2019). Yet, despite significant advances in observations and physical understanding, precipitation still remains one of the most challenging variables to model and predict at local, regional, and global scales with significant implications for our ability to quantify water and energy cycle dynamics, inform decision-making, and predict hydrogeomorphic hazards in response to precipitation extremes (e.g., Maggioni and Massari 2019).

Observations of precipitation from ground-based and satellite sensors are paramount for advancing precipitation science and for monitoring Earth's water cycle, weather, and climate. The Tropical Rainfall Measuring Mission (TRMM) (Kummerow et al. 1998) was the first satellite to be equipped with both an active and a passive sensor dedicated to precipitation measurement forging a new era of developing passive microwave (PMW) retrieval algorithms (Huffman et al. 2007). Currently, the international constellation of satellites of the Global Precipitation Measurement (GPM) mission, including the GPM *Core Observatory* launched in 2014 (Hou et al. 2014; Skofronick-Jackson et al. 2017), offers almost global coverage of precipitation (Tan et al. 2019). However, challenges still exist, among them the detection and estimation of precipitation and snowfall over complex topography, snow- and ice-covered regions, at high latitudes and along land margins (coast lines and lakes), and in estimating heavy precipitation from convective weather systems [e.g., Decadal Survey; National Academies of Science, Engineering, and Medicine (NASEM); NASEM 2018, chapter 6]. The past and future successes of precipitation observation from space rely on the synergy and complementarity with ground and airborne measurements (for calibration and validation in particular, see Kirstetter et al. 2012; Kidd et al. 2018; Houze et al. 2017; Duan et al. 2015).

Over the past decade, significant advances have also been made in numerical weather prediction (NWP) models and global circulation models (GCMs). Yet, accurate prediction of extreme rainfall, quantifying sources of precipitation predictability, and understanding the interactions of large-scale atmosphere–land–ocean dynamics and regional hydroclimate remain important challenges for the research and operational communities. In fact, precipitation with its notorious complexity offers the stringiest quantitative criterion to evaluate climate model advances (Tapiador et al. 2018).

History of international precipitation conferences

The International Precipitation Conferences (IPCs) have a long history of successfully bringing together the international community to discuss the newest research findings, integrate research, discuss challenges and opportunities, and craft new directions on precipitation research within a broad interdisciplinary setting. This conference series has served as the nucleation point for the atmospheric sciences, hydrologic sciences, and applied hydrometeorological research communities to advance a wide range of topics including improved cloud parameterizations for numerical weather prediction models, stochastic and dynamic downscaling from climate models, improving the retrieval of local, regional, and global precipitation from in situ and remote sensors, deriving fused precipitation products for hydrologic applications, uncertainty quantification and extreme value analysis, and applications to flooding and water resources management.

The first IPC (IPC1) was organized in Caracas, Venezuela, in 1986 as an AGU Chapman Conference, and it has since been hosted around the world.[1] IPC12 brought the community back to the United States (18 years later since IPC7 in 2001) to discuss advances and promote collaborations and synergistic activities needed to address the increasing challenges of global precipitation research and applications.

Focus of IPC12 and challenges ahead

IPC12 focused on three main themes: 1) global precipitation estimation from multiple sensors, 2) water cycle dynamics and predictive modeling at local to regional to global scales, and 3) hydrologic impacts of precipitation extremes and anticipated change. Given the challenges of climate variability and change, especially changes in precipitation extremes and seasonality, specific emphasis was placed on subseasonal to seasonal (S2S) forecasting (the gap between weather forecasts and seasonal climate predictions) using models and observations and assessment of uncertainty propagation to impact studies such as floods, droughts and ecological changes. IPC12 also aimed to provide a forum to explore new data analytic and machine learning (ML) methodologies, taking advantage of the unprecedented explosion of Earth observations from space and climate model outputs, for improved estimation and prediction. It also brought together scientists and operational managers in an effort to bridge the gap from research to operations (R2O) and operations to research (O2R).

[1] IPC2: 1988, Cambridge, Massachusetts; IPC3: 1991, College Station, Texas; IPC4: 1993, Iowa City, Iowa; IPC5: 1995, Elounda, Greece; IPC6: 1998, Waimea, Hawaii; IPC7: 2001, Rockport, Maine; IPC8: 2004, Vancouver, Canada; IPC9: 2007, Marnes la Vallée, France; IPC10: 2010, Coimbra, Portugal; and IPC11: 2013, Wageningen, Netherlands.

Estimation of precipitation from multiple sensors. Despite notable advances in multisensor retrieval techniques, numerous challenges continue to be of central importance (Levizzani et al. 2020a,b). Among these are (i) deficiencies in properly recovering light and extreme precipitation, hail, and snowfall, especially over radiometrically complex land surfaces such as mountainous regions and coastal areas; (ii) deficiencies in recovering submesoscale variability from passive instruments; (iii) optimal integration of multisatellite radiometric retrievals with distinct temporal samplings, spatial resolutions, and error structures across different instruments and frequency channels; and (iv) characterization and quantification of the retrieval uncertainty at multiple scales.

IPC12 focused on several of the above challenges. Winter precipitation was emphasized by noting that snowfall is important to measure in the context of climate change for accurate accounting of the resulting snowpack that provides the source of water for millions of people. Specific winter challenges include the retrieval of precipitation phase (liquid rain, hail, graupel, snow, and mixed-phased precipitation) and accurate estimation of precipitation over snow- or ice-covered areas from passive instruments (Eghdami and Barros 2019; Rysman et al. 2018; Ebtehaj and Kummerow 2017; Tian et al. 2015). Measuring the properties of frozen hydrometeors remains challenging with current and new sensing methodologies, both active and PMW sensors (Ringerud et al. 2019). The development of three-frequency radars for retrieving the hydrometeor phase and particle size distribution is a promising area that requires further investigation (Tridon et al. 2019). Beyond snow, "opportunistic sensing" using cellular communication networks (Overeem et al. 2013) and indirect estimations of rain from satellites through soil moisture gravimetry (e.g., the GRACE satellite) (Behrangi et al. 2018) and microwave scatterometers (Brocca et al. 2014) are promising areas of research and development.

In the context of the unprecedented wealth of observations with diverse information content, the use of data analytics and ML concepts to learn complex relationships from large precipitation datasets was discussed (Sadeghi et al. 2019), along with the need for physically based dimensionality reduction methods of the inherently high-dimensional precipitation retrieval problems (e.g., Petty 2013). Precipitation validation at multiple scales involves the continuous improvement of "reference ground products" over well instrumented areas with ground observation networks [e.g., see Kirstetter et al. (2012) for the United States]. Outstanding issues discussed during the conference include the validation over poorly instrumented areas by extrapolating validation statistics from a few well-instrumented validation sites. The integration and quantification of uncertainty is necessary in the reference and the retrieved products (Kirstetter et al. 2018) along with the development of techniques for comparing products within their specified uncertainties and codependencies at multiple scales (e.g., Guilloteau and Foufoula-Georgiou 2020).

Water cycle dynamics and predictive modeling at local to regional to global scales. Recent decades have produced important physical insights into ocean–atmosphere–land dynamics. Despite our increased understanding of climate modes of variability, less is known about how these modes affect precipitation predictability at seasonal and subseasonal scales (NASEM 2016). The massive availability of satellite observations and climate model outputs (Overpeck et al. 2011) along with new advances in data analysis and improvements in climate modeling in the past decade have created new opportunities to advance hydrometeorology research and to address specific challenges related to water availability and extremes under climate change. Four important challenges discussed during IPC12 were (i) assess sources of predictability of seasonal precipitation, by discovering and quantifying known and emergent climate modes and teleconnections; (ii) quantify how the climate system and resulting precipitation are anticipated to change in magnitude and frequency under different climate scenarios; (iii) validate and improve climate and Earth system models (ESMs) in terms of physical representations and parameterizations (Kuo et al. 2020); and (iv) utilize precipitation observations from multiple sensors and climate model outputs to improve the accuracy and reliability of S2S precipitation forecasts (defined as those made 2 weeks to 12 months in advance; see NASEM 2016 Box 1.1 for discussion of definitions) for a range of applications in hydrology, water resources, hazard prevention and control, and decision-making (DeFlorio et al. 2019).

Precipitation (together with upper winds and outgoing solar radiation) is a key variable for detecting changes in the location of the intertropical convergence zone (ITCZ). Projected shifts in the ITCZ location (e.g., Byrne et al. 2018) will have significant implications for water cycle dynamics and regional precipitation and requires further study. Also, recent evidence suggests a weakening of the ENSO signal and the emergence of the western Pacific as an important contributor to the hydrometeorology of the southwestern United States and other regions of the world (e.g., Kohyama et al. 2018; Mamalakis et al. 2018). Such findings emphasize the importance of using precipitation both as a diagnostic and a prognostic variable for climate studies and the need for the continuity and high quality of precipitation records (measurements and integrated measurements and observations) for robust estimates of change (Park et al. 2017).

IPC12 emphasized the need for research in understanding the complex interactions between large-scale climate modes and precipitation, unraveling new dynamical mechanisms responsible for major climate shifts affecting regional and global hydroclimate, the use of advanced methodologies of dimensionality reduction and pattern detection (such as spectral and nonlinear principal component analysis) applied to spatiotemporal climate variables (e.g., Ghil et al. 2002), and the use of information theory, network theory, and ML methods to extract knowledge and infer causality and predictability of precipitation at a range of space and time scales.

Hydrologic impacts of precipitation extremes and anticipated change. The way that space–time variability of precipitation interacts with the spatial heterogeneity of soils, topography, vegetation, and stream networks to produce spatially and temporally variable runoff and soil moisture is a question that impacts many areas of hydrologic and climate research, and most importantly applied water resource management decisions. As precipitation shows variability over a wide range of scales, the processes at the interface between the atmosphere and land surface also operate at multiple scales. Sensitivity to spatial variability and hydrological response times are then radically different for urban drainage networks compared to continental-scale basins.

IPC12 discussed several pressing problems at the intersection of precipitation research and hydrologic/geomorphologic impacts, including tracking extreme precipitation to reduce disaster risk such as flooding and landslides (Gourley et al. 2017); quantifying phase and rates of precipitation at convective and orographic scales suitable to capture flash floods; quantifying rates of snow accumulation, snowmelt, ice melt, and sublimation from snow and ice at scales driven by topographic variability; improving drought monitoring to forecast short-term impacts more accurately and to assess potential mitigations; and characterizing the microphysical processes and interactions of hydrometeors for improving weather and climate models (Chen et al. 2020). It was concluded that assessing these challenges requires improvement in understanding and modeling the universality and scalability of hydrological processes, as well as the use of an adapted statistical framework for the analysis of extremes in nonstationary and often nonlinear settings.

Soroosh Sorooshian Hydrometeorology Symposium

A special feature of IPC12 was the "Soroosh Sorooshian Hydrometeorology Symposium" to honor the pioneering career of Professor Sorooshian in advancing hydrometeorology research and applications, providing community leadership, and mentoring a cadre of colleagues over the past four decades. As the founder of the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California Irvine, he has built global capacity for monitoring, forecasting, and mitigation of hydrologic disasters through the development of precipitation products, leveraging and extending the benefits of space and weather agencies' technological resources into applications that assist hydrologists and water resource managers worldwide with equitable access to relevant information.

A trademark of CHRS is the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) products (Hsu et al. 1997; Hong et al. 2004;

Ashouri et al. 2015; Nguyen et al. 2020) used worldwide for hydrologic prediction and water resources applications. The PERSIANN Climate Data Record (PERSIANN-CDR) product provides an important dataset to detect global changes in climate and hydroclimate patterns. CHRS have developed various data and information systems for its global users, including integrated system for satellite precipitation and information (RainSphere, http://rainsphere.eng.uci.edu), real-time high-resolution satellite and crowdsourced rainfall observations for hydrologic and natural disaster management applications (iRain, http://irain.eng.uci.edu), and on-demand data processing system for CHRS's satellite precipitation products (DataPortal, http://chrsdata.eng.uci.edu). Currently the PERSIANN products are used all over the world (http://chrsdata.eng.uci.edu/statistics) to inform water management decisions at the local and regional levels, to address needs in hydrological modeling and to study climatic trends and extreme events. For example, they have been demonstrated to be especially useful in the data-sparse region of the Tibetan Plateau (Miao et al. 2015; Liu et al. 2017).

Training early career scientists

A series of workshops and tutorials for graduate students and early career scientists were organized during IPC12. These included the following: 1) Quantitative Precipitation Estimation (QPE): Observations from Radar, Gauges and Satellites for Flood Prediction (instructor: Pierre Kirstetter, University of Oklahoma/NOAA National Severe Storms Laboratory). This course focused on precipitation information that can be obtained from various sensors and specifically from weather radars and satellites. It discussed the uncertainties and spatial and temporal resolutions in which various techniques can capture precipitation patterns such that product combination can be successfully achieved. It also provided case studies of the impact of precipitation accuracy on watershed response and hydrological modeling at local to continental scales; 2) Hands-On Workshop on Extreme Value Analysis (instructors: Amir AghaKouchack and Charlotte Love, UC Irvine, and Mojtaba Sadegh, Boise State University). This hands-on workshop introduced stationary and nonstationary extreme value analysis methods used in hydrology and climate research. Specifically, it discussed extreme weather events; extreme value distributions; univariate and multivariate extreme value analysis; change detection methods; stationary versus nonstationary extreme value analysis; and temporal versus process-based nonstationary analysis; 3) CHRS PERSIANN: Algorithms, Data Products and Applications (instructors: Kuolin Hsu and Phu Nguyen, UC Irvine). This course provided fundamental knowledge about the PERSIANN algorithms, developed at the CHRS in collaboration with the UNESCO Intergovernmental Hydrological Programme (IHP) Global Network on Water and Development Information for Arid Lands (G-WADI) over the past two decades. The three main data products [PERSIANN, PERSIANN Cloud Classification System (CCS), and PERSIANN-CDR], were introduced with utility of each of the datasets as well as the recently developed systems [iRain, RainSphere, and Data Portal]; and 4) A deep dive into the configuration and features of the National Water Model (Instructor: David Gochis, NCAR). This course provided an in-depth description of the operational National Water Model (NWM) configuration of the Weather Research and Forecasting-Hydro modeling system. The core physics components and model architecture were discussed as was the workflow comprising the operational model. Aspects of foundational dataset development, verification activities, and model calibration were also presented in detail and version-over-version changes in model configurations and in model simulation performance were reviewed.

Future outlook

The three days of intense discussions during IPC12 clearly demonstrated that substantial progress has been made over the past decade on precipitation estimation, modeling, and prediction and that the International Precipitation Conferences provide a valuable forum for global exchange of ideas and collaboration toward accelerating progress. The precipitation community now benefits from multiple long-term satellite-based precipitation records from both visible/infrared and PMW sensors [e.g., PERSIANN, Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS) (Funk et al. 2015), CMORPH (Xie et al. 2017), IMERG (Tan et al 2019), and GSMaP (Ushio et al. 2009)]. These records, combined with advances in ground-based measurement technologies and models, have provided tremendous insight into hydrometeorological processes and have enabled routine application of these datasets in hydrological forecasting and hydrological hazard detection and monitoring. They have also enabled better quantification and understanding of the water cycle and its global and regional changes.

As we enter the next decade of precipitation research, we look forward to achieving exciting new milestones by continued advances in measurement technologies combined with physics and rigorous mathematical methodologies for large-data analysis to bring the accuracy and resolution of global precipitation products to a new level, increase the fidelity of climate model projections for regional precipitation at scales that matter, quantify with certainty future changes in precipitation and extremes, and provide the much-needed decision support for water resources management and rainfall-induced hazards.

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