3. Emerging directions

3.1. Toward the new generation of products

George Huffman[1] and Pierre-Emmanuel Kirstetter[2]

[1] NASA Goddard Space Flight Center

[2] University of Oklahoma, Norman, OK

The fine time interval provided in modern precipitation products is only possible by combining estimates from many individual high-quality satellite sensors, and even then, additional approximations are needed to fill numerous gaps in the mosaic of short-interval segments from the various sensors. As such, the future directions of global observationally-based precipitation products involve improvements in the individual retrievals, improvements and operationalization of additional sensor estimates and innovations in assembling the merged products, including the intercalibration and homogenization of the data record. One major challenge is to both provide consistent estimates in any particular epoch of the constellation and to provide consistent estimates across generations of sensors with differing capabilities.

3.1.1. Passive microwave retrievals

3.1.1.1. Outstanding problems

Passive microwave (PMW) retrievals form the mainstay of modern global precipitation estimates. Improvements over 3+ decades of development have expanded their utility, but challenges remain, including orographic precipitation, snowfall and the performance of the estimates in specific weather regimes as discussed in Chapter 1. These topics critically impact detection and rate estimation (see Chapter 1), and are best addressed at the sensor level, as opposed to the merger process, because that allows detailed sensor information to be applied to the issues, in combination with ancillary data, such as atmospheric temperature and moisture profiles, generally drawn from numerical reanalyses/forecasts. The diversity of channels, resolutions and scanning patterns that sensors "see" considerably complicates efforts to make uniform retrievals as well.

3.1.1.2. Machine learning

Recent work on precipitation retrievals has focused on applying current concepts in machine learning algorithms. For example, recent work has shown encouraging results in applying machine learning approaches to PMW data (Adhikari et al., 2020). Importantly, machine learning techniques require quality training data. Uncertainties in satellite precipitation estimation often transfer from the calibration data set, for example, from PMW to Geostationary Earth Orbit Infrared (GEO-IR) estimates (Upadhyaya et al., 2020). A training precipitation set with properties improperly matching the capabilities of the satellite sensor and its observed information content can negatively impact precipitation detection and quantification retrievals and propagate systematic and random errors (Chapter 1.2).

3.1.1.3. Probabilistic QPE

The uncertainty structure of satellite-based quantitative precipitation estimation (QPE) is largely unknown at fine spatio-temporal scales and requires more than just one deterministic "best precipitation estimate" to adequately cope with the intermittent, highly skewed distribution that characterizes precipitation. Because satellite retrievals are underdetermined, uncertainty

DOI: 10.13021/gewex.precip.3.1

should be an integral part of QPE (Kirstetter et al., 2018; Chapter 1.2). Precipitation probability mapping has been shown to outperform deterministic estimates by mitigating systematic biases in the deterministic retrievals, quantifying uncertainty and advancing the monitoring of precipitation extremes.

3.1.1.4. Surface-based calibrators

While satellite retrievals have almost exclusively been calibrated by precipitation gauges, the installed base of surface radars in the U.S., Europe, Australia, Japan and elsewhere seems to invite use if questions of quality control, access and archive record can be overcome (Chapter 1.2). The proliferation of communications microwave link-base precipitation estimates holds similar promise as well (Leijnse et al., 2007; Messer et al., 2006), with the same caveats.

3.1.2. Other estimates

Besides PMW retrievals, a number of other satellite sensor families provide precipitation estimates. In the grand tradition of precipitation estimation, none of these sensors provides totally new data band, but (except for GEO-IR), little or no use has been made of them.

3.1.2.1. GEO

GEO-IR estimates pre-date the start of PMW data, and present the interesting dilemma that they are plentiful, but tend to be of lower quality due to reliance on relating cloud-top structure to surface precipitation. As such, these data are used as backup information in multi-satellite products that depend on PMW data. Nonetheless, this use is a key and ongoing need, meaning continued advancement is important. Following on the discussion of machine learning approaches above, researchers are specifically applying machine learning to GEO-IR data (including Tao et al., 2018). Research has already demonstrated that using multi-channel GEO data can provide improved precipitation estimates, including Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Multispectral Analysis (PERSIANN-MSA; Behrangi et al., 2009). Machine learning techniques should be beneficial here as well, but a primary barrier to operational use of multiple channels is the need to access the global collection of the requisite channels, and in some cases handling the differences among similar channels on different sensors. At present, only the GEO-IR is available in an archived and current source of uniformly formatted global datasets, including the CPC Global 4-km Merged IR dataset (CPC, 2020) and the Gridded Satellite (GridSat) collection (Knapp et al., 2011). The long-term (and current) record of GEO precipitation estimates would be significantly improved by creating global datasets for the GEO-Visible and GEO-Water Vapor channels as companions to the GEO-IR.

Succeeding generations of GEO satellites carry progressively more-capable sensors, exemplified by NOAA's Advanced Baseline Imager (ABI) sensor on board the latest Geostationary Operational Environmental Satellites (GOES-R Series). ABI provides three times more spectral channels, four times the resolution and five times faster scanning when compared to its predecessor imager on board previous-generation GOES (Schmit et al., 2017). The GOES-R series also carries a lightning sensor that potentially provides additional input for estimating precipitation. This new generation of GEO sensors opens new opportunities in quantifying precipitation rates, and makes it imperative to provide easy, analysis-ready access to the multiple channels provided across the various satellites, including developing analysis schemes that account for the different channel frequencies. One clear requirement is that the precipitation research community needs to demonstrate the skill of multi-channel GEO versus single-channel GEO-IR versus PMW, all using modern algorithms, to determine the costbenefit analysis of the three-channel (and even-more-channel) GEO retrievals against the development effort and expense for the requisite input datasets.

3.1.2.2. Advanced Very High Resolution Radiometer (AVHRR)

One limitation to GEO observations is that the footprints are sufficiently distorted above the 60° latitude circle in both hemispheres that the data are not used at higher latitudes, as exemplified by the CPC Global 4-km Merged IR dataset covering the latitude band 60°N-S. In addition, current GEO-IR schemes tend to confuse surface ice and snow with cloudiness, leading to low skill in polar regions. Recently, Xie et al. (2019) introduced the use of AVHRR IR data for precipitation estimates. These sensors have a history back to 1979 on the NOAA-series polar orbiters, are uniformly processed and include cloudiness estimates that allow the (approximate) separation of surface snow and ice from clouds. Ehsani et al. (2020) provide another example of this concept. Despite flying on only a few polar orbiters, the convergence of orbital swaths near the poles allows relatively frequent observations of any given location. Going forward, the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor will provide equivalent data.

3.1.2.3. Cloud volume

The series of the old Television-Infrared Operational Sounder (TIROS) Operational Vertical Sounder (TOVS), current Advanced Infrared Sounder (AIRS) and relatively new Cross-track Infrared Sounder (CrIS) instruments have been used to provide precipitation estimates based on cloud volume parameters [and the same could be done with the Infrared Atmospheric Sounding Interferometer (IASI)]. Even though the original (Susskind and Pfaendtner, 1989; Susskind et al., 1997) estimates are fairly approximate, they have proved useful as a basis for providing high-latitude estimates for most of the GPCP Versions 1, 2, and 3 products (Huffman et al., 2001; Adler et al., 2018; Huffman et al., 2020a). Improvements with the Smith and Barnet (2019) Version 7 products are expected to refine the AIRS and CrIS estimates, and the advent of an equivalently-long timeseries of AVHRR/CrIS implies that the two approaches should be evaluated for use together at the high latitudes for both GPCP and other multi-satellite products. The MODIS instruments on Terra and Aqua have 16 IR “cloud” channels that might be used in a similar way, but are not presently.

3.1.2.4. Assimilation/forecast

An additional data source that warrants consideration is numerical assimilation/model estimates of precipitation. While not “observational”, many end-users are less concerned about the origin of the estimates and more about having the “best” estimates. Most numerical schemes have known problems in “convective” weather regimes, which typifies much of the tropics and sub-tropics. However, it has long been the case that numerical products prove better than observations in “stratiform” weather regimes that typify higher latitudes (Ebert et al., 2007). These considerations suggest that the merged products should have data fields that incorporate such numerical assimilation/forecast estimates in locations/times for which they are competitive with the observational estimates. Such a combination can naturally incorporate improvements in both retrievals and assimilations as enhanced versions are released. This discussion raises the point that the relative performance of each is a worthy research topic on an ongoing basis, and of considerable interest to end-users.

3.1.2.5. Soil moisture

Another approach to estimating precipitation is to work backwards from satellite estimates of soil moisture. In summary, given local soil, vegetation and previous rainfall conditions, changes in soil moisture sensed by satellites can be approximately related to current rainfall. The Soil

Moisture Analysis Rainfall Tool (SMART; Crow et al., 2011) and Soil Moisture to Rain (SM2Rain; Brocca et al., 2014) are examples, with the former focusing on creating adjusted satellite datasets to obtain the timeseries of rainfall that is most consistent with the record of soil moisture changes. The relatively infrequent soil moisture observations make operational use a challenge that is a matter of current research.

3.1.3. Merged products

3.1.3.1. Outstanding problems

Most users focus on merged precipitation data products, as noted previously, and Chapter 1 has discussed known issues intrinsic to the merger schemes. First, it is helpful to recall that some merged datasets prioritize homogeneity in the data record, usually by severely down-selecting the choice of input data. These are said to follow Climate Data Record (CDR) standards, and include GPCP (Adler et al., 2018) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR). High-Resolution Precipitation Products (HRPP), on the other hand, try to enforce homogeneity, but include “all possible” data. These include CMORPH (Joyce et al., 2004), GSMaP (Kubota et al., 2007), and IMERG (Huffman et al., 2020b), among others. All of these datasets choose some intercalibration, with CDRs usually picking a PMW standard, and HRPPs tending to use a calibrator that incorporates spaceborne radar. Homogeneity for the calibrator across sensors is key, and one main reason that continued access to a reasonably wide-swath spaceborne radar in future missions is considered a high priority. A second outstanding issue is how best to fill the numerous gaps that exist when PMW data are segmented to a short-interval time grid (typically 30–60 minutes), discussed in Chapter 1 as “revist-gap mitigation.” As a first approximation, the “morphing” concept pioneered in Joyce et al. (2004) is used in CMORPH, GSMaP and IMERG. The best choice for how to compute the propagation vectors is a matter of current research, and the IMERG team plans to introduce the Scheme for Histogram Adjustment of Ranked Precipitation Estimates in the Neighborhood (SHARPEN; Tan et al., 2020) to counteract some of the averaging effects implicit in morphing. The grand challenge is to develop and operationalize a better “storm development” algorithm that estimates the lifecycle stages of precipitation systems. For example, Rain Estimation Using Forward-Adjusted Advection of Microwave Estimates (REFAME; Behrangi et al., 2010) uses time series of local GEO-IR brightness temperatures to better track the evolution of the precipitation between PMW overpasses.

3.1.3.2. Short-interval combinations with surface data

One modification to satellite-only merged products that seems attractive is to use submonthly precipitation gauge data to adjust multi-satellite estimates, since gauges are generally considered the gold standard for actual amounts. It would be nice to do this at the finest-possible time interval, but even daily gauges tend to be representative of relatively small regions (i.e., short correlation distances), meaning rather dense gauge networks are required. Clearly, oceans and many land areas lack the necessary station coverage. Xie and Xiong (2011) developed a scheme that used probability density functions (PDFs) of dense gauge data to both bias-correct CMORPH and create a combination with the de-biased CMORPH. The University of California Santa Barbara/Climate Hazards Center generates gauge-enhanced 0.05°x0.5° precipitation estimates by blending Global Telecommunication Systems station observations with bias-corrected cold cloud duration imagery in GEO-IR (Funk et al., 2015). The time interval is chosen to provide gauge estimates that are representative of larger regions than the typical daily gauge reports. The same research group is considering applying this approach to IMERG.

Other candidate surface-based precipitation datasets for possible merger with or routine calibration of merged datasets includes surface radar networks, microwave links for telecommunications, lightning-detection networks and citizen science data, such as from the Global Learning and Observations to Benefit the Environment (GLOBE) program (https://www.globe.gov/). All of these sources present challenges in terms of availability in real or post-real time, accessible archives of both the Level 1 (that is, sensor) and Level 2 (product) data and quality control. Note well that the potential for using surface data should not obscure the fact that many regions lack adequate surface data for routine use in merged products, or even for confident validation.

3.1.3.3. Weighted merger

As quasi-global precipitation products have proliferated, Beck et al. (2017) took advantage of the diversity of estimates to develop regionally-varying weights for each dataset to build a "best" average global dataset, MSWEP. This approach should score better than any individual estimate, but it depends critically on what the standard is for choosing the weights, and paradoxically only maintains a strong, stable advantage as long as the individual datasets continue to be produced and included. Additionally, the weighting should be recomputed any time any of the inputs is upgraded to a new version, although it could be a matter of judgment whether any particular change requires the effort of computing new weights.

3.1.4. Uncertainty estimates

A final unmet need is for precipitation datasets to provide estimates of uncertainty, starting with the individual sensors, and carrying through to the merged products (Chapter 1). While Chapter 1 contains a discussion of sources of uncertainty, here, the future development work is to turn these concepts into gridbox-by-gridbox estimates. The focus has to be on using globally available inputs for this error computation, which excludes detailed use of surface data, except where those data are being merged into the product.

One potential approach is for the individual sensor estimates to provide probabilistic QPE, as described in Chapters 1.1.4 and 3.1.1, and then carry that entire set of information through the merged datasets. It is an open question whether specifying a set of quantiles or giving coefficients of a fitted function is best. There is also a critical need for methods to aggregate the gridbox-level uncertainties to larger space/time data averaging, such as daily and/or 1°x1°. At these scales, the work of the Megha-Tropiques team has paved the way for a more systematic evaluation of the uncertainty associated with sampling (Roca et al., 2018; Chambon et al., 2012). Whatever form these "expert" error estimates take, it is important that the merged datasets provide a "simple" error statement for non-expert users. For example, the IMERG team has prototyped a "Quality Index" that maps from a quantitative estimate of correlation to a simple "stoplight" chart (Huffman et al., 2020b), but much research remains. Regardless of the approach, it is a best practice that the simple error index should be traceable to a quantitative error statement. Chapter 3.2 addresses this topic in more detail.

3.1.5. Recommendations

i. Address orographic and snowfall regimes at the single-sensor level.
ii. Match training datasets for machine learning to the satellite sensor capabilities.
iii. Pursue scientific, technical and administrative issues to unlock the promise that surface-based datasets such as radar and communication microwave links hold as calibration and validation information.

iv. Assemble analysis-ready multi-channel GEO datasets; IR, visible and water vapor cover the long record, while more channels, as well as lightning data, are available in recent years.
v. Pursue retrievals from AVHRR, VIIRS, TOVS, AIRS, CrIS and IASI to provide useful estimates at high latitudes.
vi. Upgrade merged products to provide data fields that incorporate numerical assimilation/forecast estimates where they are useful, and provide routine reports on the relative skill of retrievals and assimilations/forecasts.
vii. Pursue the use of soil moisture observations in satellite precipitation estimates.
viii. Address the grand challenge of making detailed observational estimates of storm lifecycle development for use in merged products.
ix. Pursue incorporating short-interval surface data, including gauges, radar, telecommunications microwave links, lightning-detection networks and citizen science, recognizing that deficiencies in data coverage are severe limitations on global application.
x. Continue to develop skill-weighted mergers of datasets.
xi. Prioritze advancing uncertainty estimates at the gridbox level, and developing a methodology for aggregating these estimates to larger time/space scales.

3.1.6. References

Adhikari, A., M.R. Ehsani, Y. Song and A. Behrangi, 2020: Comparative Assessment of Snowfall Retrieval from Microwave Humidity Sounders Using Machine Learning Methods. *Earth and Space Science*, early release e2020EA001357, 65 pp., doi:10.1029/2020ea001357.

Adler, R.F., M. Sapiano, G.J. Huffman, J.-J. Wang, G. Gu, D.T. Bolvin, L. Chiu, U. Schneider, A. Becker, E.J. Nelkin, P. Xie, R. Ferraro and D.-B. Shin, 2018: The Global Precipitation Climatology Project (GPCP) Monthly Analysis (New Version 2.3) and a Review of 2017 Global Precipitation. *Atmosphere*, 9, 14 pp., doi:10.3390/atmos9040138.

Beck, H.E., N. Vergopolan, M. Pan, V. Levizzani, A.I.J.M. van Dijk, G. Weedon, L. Brocca, F. Pappenberger, G.J. Huffman and E.F. Wood, 2017: Global-Scale Evaluation of 22 Precipitation Datasets Using Gauge Observations and Hydrological Modeling. *Hydrology and Earth System Sciences*, 21(12), 6201–6217, doi:10.5194/hess-21-6201-2017.

Behrangi, A., K.-L. Hsu, B. Imam, S. Sorooshian, G.J. Huffman and R.J. Kuligowski, 2009: PERSIANN-MSA: A Precipitation Estimation Method from Satellite-Based Multispectral Analysis. *Journal of Hydrometeorology*, 10, 1414–1429, doi:10.1175/2009JHM1139.1.

Behrangi, A., B. Imam, K. Hsu, S. Sorooshian, T.J. Bellerby and G.J. Huffman, 2010: REFAME: Rain Estimation Using Forward Adjusted-Advection of Microwave Estimates. *Journal of Hydrometeorology*, 11, 1305–1321, doi:10.1175/2010JHM1248.1.

Brocca, L., L. Ciabatta, C. Massari, T. Moramarco, S. Hahn, S. Hasenauer, R. Kidd, W. Dorigo, W. Wagner and V. Levizzani, 2014: Soil as a Natural Rain Gauge: Estimating Global Rainfall from Satellite Soil Moisture Data. *Journal of Geophysical Research: Atmospheres*, 119, 5128–5141, doi:10.1002/2014JD021489.

Chambon, P., I. Jobard, R. Roca, and N. Viltard, 2012: An Investigation of the Error Budget of Tropical Rainfall Accumulation Derived from Merged Passive Microwave and Infrared Satellite Measurements. *Quarterly Journal of the Royal Meteorological Society*, 139, 879–893, doi:10.1002/qj.1907.

CPC, 2020: CPC Global 4-km Merged IR dataset. Posted at https://catalog.data.gov/dataset/climate-prediction-center-ir-4km-dataset and archived at https://disc.gsfc.nasa.gov/datasets/GPM_MERGIR_1/summary?keywords=cpc%20ir.

Crow, W.T., M.J. van den Berg, G.J. Huffman and T. Pellarin, 2011: Correcting Rainfall Using Satellite-Based Surface Soil Moisture Retrievals: The Soil Moisture Analysis Rainfall Tool (SMART). *Water Resources Research*, 47, W08521, doi:10.1029/2011WR010576.

Ebert, E.E., J.E. Janowiak and C. Kidd, 2007: Comparison of Near-Real-Time Precipitation Estimates from Satellite Observations and Numerical Models. *Bulletin of the American Meteorological Society*, 88, 47–64, doi:10.1175/BAMS-88-1-47.

Ehsani, M.R., A. Behrangi, A. Adhikari, Y. Song, G.J. Huffman and D.T. Bolvin, 2020: Assessment of the Advanced Very High-Resolution Radiometer for Snowfall Retrieval in High Latitudes Utilizing CloudSat and Machine Learning. *Journal of Hydrometeorology*, in review.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell and Michaelsen, 2015: The Climate Hazards Infrared Precipitation with Stations—a New Environmental Record for Monitoring Extremes. *Science Data*, 2, 150066, doi:10.1038/sdata.2015.66.

Huffman, G.J., R.F. Adler, M. Morrissey, D.T. Bolvin, S. Curtis, R. Joyce, B. McGavock, J. Susskind, 2001: Global Precipitation at One-Degree Daily Resolution from Multi-Satellite Observations. *Journal of Hydrometeorology*, 2, 36–50, doi:10.1175/1525-7541(2001)002<0036:GPAODD>2.0.CO;2.

Huffman, G.J., R.F. Adler, A. Behrangi, D.T. Bolvin, E.J. Nelkin and Y. Song, 2020a: Algorithm Theoretical Basis Document (ATBD) for Global Precipitation Climatology Project Version 3.1 Precipitation Data, 31 pp, https://docserver.gesdisc.eosdis.nasa.gov/public/project/MEaSUREs/GPCP/GPCP_ATBD_V3.1.pdf.

Huffman, G.J., D.T. Bolvin, D. Braithwaite, K. Hsu, R. Joyce, C. Kidd, E.J. Nelkin, S. Sorooshian, E.F. Stocker, J. Tan, D.B. Wolff and P. Xie, 2020b: Integrated Multi-satellitE Retrievals for the Global Precipitation Measurement (GPM) mission (IMERG). In: Advances in Global Change Research, Vol. 67, *Satellite Precipitation Measurement* (V. Levizzani, C. Kidd, D. Kirschbaum, C. Kummerow, K. Nakamura, F.J. Turk, eds.). Springer Nature, Dordrecht, ISBN 978-3-030-24567-2 / 978-3-030-24568-9 (eBook), 343–353, doi:10.1007/978-3-030-24568-9_19.

Joyce, R.J., J.E. Janowiak, P.A. Arkin and P. Xie, 2004: CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *Journal of Hydrometeorology*, 5, 487–503, https://doi.org/10.1175/1525-7541(2004)005<0487%3ACAMTPG>2.0.CO%3B2.

Kirstetter, P.-E., N. Karbalaee, K. Hsu and Y. Hong, 2018: Probabilistic Precipitation Rate Estimates with Space-Based Infrared Sensors. *Quarterly Journal of the Royal Meteorological Society*, 144, 191–205, doi:10.1002/qj.3243.

Knapp, K.R., S. Ansari, C.L. Bain, M.A. Bourassa, M.J. Dickinson, C. Funk, C.N. Helms, C.C. Hennon, C.D. Holmes, G.J. Huffman, J.P. Kossin, H.-T. Lee, A. Loew and G. Magnusdottir, 2011: Globally Gridded Satellite Observations for Climate Studies. *Bulletin of the American Meteorology Society*, 92, 893–907, doi:10.1175/2011BAMS3039.1.

Kubota, T., S. Shige, H. Hashizume, K. Aonashi, N. Takahashi, S. Seto, M. Hirose, Y.N. Takayabu, K. Nakagawa, K. Iwanami, T. Ushio, M. Kachi and K. Okamoto, 2007: Global precipitation map using satellite-borne microwave radiometers by the GSMaP project: Production and validation. *IEEE Transactions on Geoscience and Remote Sensing*, 45, 2259–2275, https://doi.org/10.1109/TGRS.2007.895337.

Leijnse, H., R. Uijlenhoet and J.N.M. Stricker, 2007: Rainfall Measurement Using Radio Links from Cellular Communication Networks. *Water Resources Research*, 43, W03201, 6 pp., doi:10.1029/2006WR005631.

Messer, H., A. Zinevich and P. Alpert, 2006: Environmental Monitoring by Wireless Communication Networks. *Science*, 312, 713, doi:10.1126/science.1120034.

Roca, R., N. Taburet, E. Lorant, P. Chambon, M. Alcoba, H. Brogniez, S. Cloché, C. Dufour, M. Gosset and C. Guilloteau, 2018: Quantifying the Contribution of the Megha-Tropiques Mission to the Estimation of Daily Accumulated Rainfall in the Tropics. *Quarterly Journal of the Royal Meteorological Society*, 144, 49–63, doi:10.1002/qj.3327.

Schmit, T.J., P. Griffith, M.M. Gunshor, J.M. Daniels, S.J. Goodman and W.J. Lebair, 2017: A Closer Look at the ABI on the GOES-R Series. *Bulletin of the American Meteorological Society*, 98, 4. 681–698, doi:10.1175/BAMS-D-15-00230.1.

Smith, N., and C.D. Barnet, 2019: Uncertainty Characterization and Propagation in the Community Long-Term Infrared Microwave Combined Atmospheric Product System (CLIMCAPS). *Remote Sensing*, 11, 1227, 25 pp, doi:10.3390/rs11101227.

Susskind, J., and J. Pfaendtner, 1989: Impact of interactive physical retrievals on NWP. *Report on the Joint ECMWF/EUMETSAT Workshop on the Use of Satellite Data in Operational Weather Prediction: 1989–1993*, Vol. 1, (T. Hollingsworth, ed.). ECMWF, Shinfield Park, Reading RG2 9AV, U.K., 245–270.

Susskind, J., P. Piraino, L. Rokke, L. Iredell and A. Mehta, 1997: Characteristics of the TOVS Pathfinder Path A Dataset. *Bulletin of the American Meteorological Society*, 78, 1449–1472, doi:10.1175/1520-0477(1997)078<1449:COTTPP>2.0.CO;2.

Tan, J., G.J. Huffman, D.T. Bolvin, E.J. Nelkin and M. Rajagopal, 2020: SHARPEN: A Scheme to Restore the Distribution of Averaged Precipitation Fields. *Journal of Hydrometeorology*, submitted.

Tao, Y., K.L. Hsu, A. Ihler, X.G. Gao and S. Sorooshian, 2018: A Two-Stage Deep Neural Network Framework for Precipitation Estimation from Bispectral Satellite Information. *Journal of Hydrometeorology*, 19, 393–408, doi:10.1175/JHM-D-17-0077.1.

Upadhyaya, S.A., P.-E. Kirstetter, J.J. Gourley and R.J. Kuligowski, 2020: On the Propagation of Satellite Precipitation Estimation Errors: From Passive Microwave to Infrared Estimates. *Journal of Hydrometeorolgy*, 21, 1367–1381, doi:10.1175/JHM-D-19-0293.1.

Xie, P., R. Joyce, S. Wu, L. Ren and B. Katz, 2019: *A Preliminary Examination of the Second Generation CMORPH Satellite Precipitation Estimates*. 44th NOAA Annual Climate Diagnostics and Prediction Workshop, held in Durham, NC, USA, 22–24 October 2019.

Xie, P., and A.-Y. Xiong, 2011: A Conceptual Model for Constructing High-Resolution Gauge-Satellite Merged Precipitation Analyses. *Journal of Geophysical Research: Atmospheres*, 116, 14 pp., doi:10.1029/2011JD016118.