Near-Realtime Quantitative Precipitation Estimation and Prediction (RealPEP)

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BAMS
Meeting Summary

Near-Realtime Quantitative Precipitation Estimation and Prediction (RealPEP)

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Precipitation and Flash-Flood Predictions From Minutes to Days

What: 250 participants discussed ideas and recent developments in the fields of quantitative precipitation estimation (QPE) based on the exploitation of measurements of polarimetric radars and microwave backhaul links, observation-based quantitative precipitation nowcasting (QPN), numerical quantitative precipitation forecasting (QPF), flash-flood prediction (FFP), and their organization into seamless prediction systems.

When: 5–7 October 2020

Where: Online (https://indico.scc.kit.edu/e/realpep_conf)

KEYWORDS: Rainfall; Radars/Radar observations; Satellite observations; Nowcasting; Numerical weather prediction/forecasting; Neural networks

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Flash floods in small- to medium-sized catchments and intense precipitation over cities caused by severe local storms pose increasing threats to our society. For the timely prediction of such events, the value of high-resolution and high-quality QPE and corresponding forecasts cannot be overrated. Seamless predictions harmonizing nowcasting and numerical weather prediction (NWP) across forecast lead times from minutes to days would greatly help to improve the value and efficiency of warnings. Organized by the Research Unit on Near-Realtime Precipitation Estimation and Prediction (RealPEP, www2.meteo.uni-bonn.de/realpep) and supported by the Project on Seamless Integrated Forecasting System (SINFONY, www.dwd.de/DE/forschung/forschungsprogramme/sinfony_iafe/sinfony_node.html) of the German Meteorological Service (DWD), an international 3-day online conference was held from 5 to 7 October 2020, dedicated to Precipitation and Flash-Flood Predictions from Minutes to Days (https://indico.scc.kit.edu/event/883/). Most speakers agreed to have their presentations recorded, which we uploaded to YouTube for further distribution (see, e.g., on the conference homepage, https://indico.scc.kit.edu/event/883/page/588-recorded-talks).

The speakers were both invited experts in the respective research fields and researchers from the RealPEP and SINFONY projects. Talks and discussions could be followed on video stream. Interaction between the about 250 participants was enabled by entering written questions and comments via a dedicated tool, which allowed for voting and thus also ranking questions. Registered participants could enter chat rooms from where they could be moved to the speaker room for posing the questions directly to the speakers and the auditorium. On the last day of the conference podium discussions with selected speakers summarized talks and discussions and elaborated on overarching problems, ideas, and developments in the fields of quantitative precipitation estimation (QPE), quantitative precipitation nowcasting (QPN), quantitative precipitation forecasting (QPF), flash-flood prediction (FFP), and their organization into seamless prediction systems, which also constituted the topics of the five sessions during the conference. We report here in particular on the outcomes of the panel discussions.

Quantitative precipitation estimation

Polarimetric weather radars emerged as the most efficient sensors for real-time, high-resolution, and accurate QPE, classification of hydrometeor types, and severe weather warnings; they also constitute an important information source for evaluation and improvement of storm-scale weather forecast models. Since 2013 the atmosphere over the entire United States is monitored by a polarimetric radar network. Germany upgraded its network to polarimetry until 2015 in parallel to other European countries. Three presentations reported on QPE based on estimates of differential phase and specific attenuation, which became available only due to the advent of polarimetry, and their superiority compared to traditional techniques utilizing only the reflectivity factor Z (Chen et al. 2021; Diederich et al. 2015; Zhang et al. 2020). However, polarimetry is only now being used operationally for precipitation estimation in the United States, while it is not yet at that stage in European countries. The use of different radar wavelengths, i.e., S-band in the United States and C-band radars in Europe, is at least partly responsible for the time lag occurring in Europe; C-band radars pose additional challenges due to the characteristics of radiation–hydrometeor interactions, so-called resonance effects, preventing clear rainfall relations at that frequency. The synergistic use of satellite-based estimates is becoming increasingly important to achieve global coverage, because radar networks are not available over most of the land areas and even decreasing in poorer countries.

Opportunistic sensors such as commercial microwave links (CMLs), personal weather stations (PWS), or crowd-sourcing techniques produce a wealth of additional information and complement dedicated sensor networks. The presentations showed the recent promising results for hydrometeorological observations by CMLs and PWS from a dense urban sensor network (de Vos et al. 2020) and the application of CML-derived rainfall data for urban drainage modeling (Pastorek et al. 2019). Discussions made clear that the information from these sensors is very valuable for QPE, not only in regions with scarce rain gauge networks. But assuring a constant high-level data quality still is a scientific challenge (Polz et al. 2020), in particular when working toward real-time applications. Hence, it was stressed that opportunistic sensors should not replace dedicated sensor networks. With the ever growing digital infrastructure (5G and beyond) their potential for hydrometeorological applications will, however, continue to increase. The discussion showed that the two major obstacles for a future operational usage of opportunistic sensor data are 1) to deal with the continuously evolving network structure and unknown data quality and 2) finding and implementing sustainable business or cooperation models for data providers of opportunistic sensors and national meteorological services.

The conference contributions and discussions have shown that artificial intelligence (AI) and deep learning (DL) approaches, combined with increasingly powerful high-performance computers and massively increased amounts of data are boosting, e.g., for data quality detection. The missing database to tackle especially the extreme cases of relevance in flash-flood forecasting hampers the operational application of AI/DL approaches.

Quantitative precipitation nowcasting

For the first, up to 2 h of lead-time observation-based nowcasting of precipitation beats NWP. This time period is required to manage the data streams between observations and data assimilation (DA) systems, to do the DA, and to let the numerical model recover from the shocks inflicted by DA. The conventional radar-based extrapolation nowcasting has a limited forecast skill as it cannot model the evolution of precipitation, mainly its growth and decay processes. Atencia et al. (2017) demonstrate that resulting errors show a systematic bias depending on the time of day, which is related to the solar cycle resulting in increased average rainfall in the afternoon. To address uncertainties due to growth and decay of precipitation cells and their location, the probabilistic nowcasting method STEPS (Bowler et al. 2006; Pulkkinen et al. 2019) is in widespread use. STEPS builds upon SPROG (Seed 2003), which exploits the scale-dependent movements of precipitation, and creates an ensemble of QPN fields. These approaches are computationally fast, simple to implement, and hard to beat in the scale of 1 h or less by other approaches. Further extensions and/or alternative approaches are currently emerging taking the life cycle of events into account. The latter use either statistical approaches based on climatologies or diurnal cycles or try to exploit process signatures for growth or decay in the observations for modifications in the projected life cycles (e.g., columns of enhanced differential reflectivity Z_{DR}; Ilotoviz et al. 2018; Kumjian et al. 2014). In most studies precipitation is extrapolated in time using gridded radar data. However, in areas with poor radar coverage, the inclusion and merging of other data sources such as rain gauges, microwave links, and satellite observations comes handy as it can better capture the precipitation system. To capture the uncertainties in precipitation data, a stochastic space–time model of the input errors is required when generating ensembles members (Seed et al. 2013). Some studies also let state information from

NWP forecasts influence the tendencies of the nowcasts fields. State-of-the-art nowcasting algorithms aim at a synergistic use of multiple data sources such as, ordered in decreasing level of importance, 1) radar, 2) NWP, 3) satellite (MSG/SEVIRI), and 4) lightning data. Lightning information did not seem to help a lot in improving nowcasting, as lead times are most probably too small for exploitation.

Current and future challenges include the improvement of radar data quality, a more progressive use of information content inherent in 3D polarimetric observations such as microphysical retrievals [liquid water content (LWC); Reimann et al. 2021], process descriptors (dendritic growth signatures for new snow generation; Trömel et al. 2019), and especially the generation of new precipitation cells during the lead time. Since the skill of current methods is restricted to already existing precipitation objects, discussions during the conference stressed the high demand for a full exploitation of convective initiation signals in the observations. Accordingly, satellite-based information on water vapor fields is seen as very important and promising, especially when they become available with the high temporal and spatial resolution provided, e.g., by Meteosat Third Generation (MTG). Methods based on refraction index estimates derived from clutter signals in radar observations, however, have not yet shown operational potential.

Hydrologists and local water management authorities request reliable predictions up to 6 h ahead motivating further research on the combined use of especially radar and satellite-based information. Also the use of artificial neural networks (ANNs) for learning growth and decay dependent on multiple inputs (orography, flow, diurnal cycle, freezing level heights, etc.) or learning the dynamics from NWPs to enhance radar-based extrapolation was stressed (Foresti et al. 2019).

Quantitative precipitation forecasting and seamless prediction

Most talks in this session addressed data assimilation schemes and the preparation of the NWP models for adequately dealing with the complex remotely sensed information on clouds and precipitation. Getting the NWP models to accept such observations—without getting rid of the information again by gravity waves—was considered an important requisite for extending the lead time of forecasts.

There were only a few tries to directly assimilate polarimetric radar observations, which contain potentially a wealth of information on the overall state of precipitation systems. For example, Putnam et al. (2019) for the first time directly assimilated real polarimetric radar observations using the ensemble Kalman filter (EnKF) for a supercell case from 20 May 2013 in Oklahoma and provided a proof of concept by demonstrating the value of polarimetric measurements. But the limited capabilities of NWP models to sufficiently reproduce the processes, which generate the hydrometeor compositions leading to the polarimetric signals (Schinagl et al. 2019), seems to remain a major obstacle. Thus, intermediate steps are currently favored, such as the assimilation of state information retrieved from polarimetry or the exploitation of that information in more general terms by the "translation" of polarimetry-observed system development states (e.g., updraft regions identified by Z_{DR}-columns) into equivalent model states, which are then assimilated (Carlin et al. 2017).

Latent heat nudging, which was declared dead already a decade ago, seems to be still a workhorse for operational radar data assimilation. While the method is currently in the process of being replaced by the assimilation of reflectivities (e.g., Bick et al. 2016), latent heat nudging may still play a role for very short-term predictions because of its computational ease and for guiding or configuring spread in ensemble prediction methods (e.g., Milan et al. 2014; Vobig et al. 2021, manuscript submitted to *Quart. J. Roy. Meteor. Soc.*).

A problem was identified in the objective determination of the impact of the different data sources on quantitative precipitation prediction related to the use of regional models, because these might carry already—possibly biased—uncertainty for the global models with which they are driven.

The assimilation of nowcasted states in NWP was discussed as a potential method for achieving seamless predictions between nowcasts and NWP, but the correct quantification of the error of the nowcasted information given the double use of observed information when both the observation itself and the nowcast derived from the observations remains to be determined (Potthast et al. 2021, manuscript submitted to *Mon. Wea. Rev.*). Currently an appropriate merging of model predictions and nowcasted states is preferably pursued for seamless prediction. A major problem remains, however, how to appropriately weigh both components, which must be dynamic and probably also situation-dependent.

Flash flood prediction

Despite promising national and international projects and decades of research in hydrology and hydrometeorology, societies are still caught unguarded worldwide and surprised by flash floods, resulting in significant losses and damages. In this context, the discussions explored the key missing scientific and technical breakthroughs to achieve better flood forecasts.

The current theories to describe hydrological processes at the catchment scale still fail to explain complex behaviors, neglecting multiscale heterogeneities and relevant impacts of dynamical geomorphological changes (Amponsah et al. 2016). The lack of accurate peak flow measurements, particularly in case of flash floods, is also one of the crucial missing pieces of this puzzle. Two presentations focused on the importance of post-flood surveys and proposed methods to improve extreme flood discharge estimates and the associated uncertainties (Lumbroso and Gaume 2012).

Despite rapid technological advances in processing power, computational capacity is still one of the limitations to achieve the high resolution required for flash floods. The lack of national centers with large computing resources dedicated for flood forecasting systems was questioned, as this strategy has proven successful for significant advances in weather predictions (Bauer et al. 2015).

The application of models based on physics equations in high resolution would be feasible when computational limits are unlocked for operational flood forecast, improving flood predictions, especially for ungauged catchments (Poméon et al. 2020).

The final debate benefited from the perspectives of both researchers and practitioners from operational flood forecasting services, highlighting the importance of a co-constructive approach for the development of efficient flood warning systems. The communication and interpretation of uncertainties for the end users remain the main challenges for achieving an efficient operational flood forecast (Silvestro et al. 2017; Speight et al. 2021).

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References

Amponsah, W., and Coauthors, 2016: Hydrometeorological characterization of a flash flood associated with major geomorphic effects: Assessment of peak discharge uncertainties and analysis of the runoff response. *J. Hydrometeor.*, **17**, 3063–3077, https://doi.org/10.1175/JHM-D-16-0081.1.

Atencia, A., I. Zawadzki, and M. Berenguer, 2017: Scale characterization and correction of diurnal cycle errors in MAPLE. *J. Appl. Meteor. Climatol.*, **56**, 2561–2575, https://doi.org/10.1175/JAMC-D-16-0344.1.

Bauer, P., A. Thorpe, and G. Brunet, 2015: The quiet revolution of numerical weather prediction. *Nature*, **525**, 47–55, https://doi.org/10.1038/nature14956.

Bick, T., and Coauthors, 2016: Assimilation of 3D radar reflectivities with an ensemble Kalman filter on the convective scale. *Quart. J. Roy. Meteor. Soc.*, **142**, 1490–1504, https://doi.org/10.1002/qj.2751.

Bowler, N. E. H., C. E. Pierce, and A. W. Seed, 2006: STEPS: A probabilistic precipitation forecasting scheme which merges an extrapolation nowcast with downscaled NWP. *Quart. J. Roy. Meteor. Soc.*, **132**, 2127–2155, https://doi.org/10.1256/qj.04.100.

Carlin, J. T., J. Gao, J. C. Snyder, and A. V. Ryzhkov, 2017: Assimilation of ZDR columns for improving the spinup and forecast of convective storms in storm-scale models: Proof-of-concept experiments. *Mon. Wea. Rev.*, **145**, 5033–5057, https://doi.org/10.1175/MWR-D-17-0103.1.

Chen, J.-Y., S. Trömel, A. V. Ryzhkov, and C. Simmer, 2021: Assessing the benefits of specific attenuation for quantitative precipitation estimation with a C-band radar network. *J. Hydrometeor.*, https://doi.org/10.1175/JHM-D-20-0299.1, in press.

de Vos, L. W., A. M. Droste, M. J. Zander, A. Overeem, H. Leijnse, B. G. Heusinkveld, G. J. Steeneveld, and R. Uijlenhoet, 2020: Hydrometeorological monitoring using opportunistic sensing networks in the Amsterdam metropolitan area. *Bull. Amer. Meteor. Soc.*, **101**, E167–E185, https://doi.org/10.1175/BAMS-D-19-0091.1.

Diederich, M., A. Ryzhkov, C. Simmer, P. Zhang, and S. Trömel, 2015: Use of specific attenuation for rainfall measurement at X-band radar wavelengths. Part II: Rainfall estimates and comparison with rain gauges. *J. Hydrometeor.*, **16**, 503–516, https://doi.org/10.1175/JHM-D-14-0067.1.

Foresti, L., I. Sideris, D. Nerini, L. Beusch, and U. Germann, 2019: Using a 10-year radar archive for nowcasting precipitation growth and decay—A probabilistic machine learning approach. *Wea. Forecasting*, **34**, 1547–1569, https://doi.org/10.1175/WAF-D-18-0206.1.

Ilotoviz, E., A. Khain, A. V. Ryzhkov, and J. C. Snyder, 2018: Relation between aerosols, hail microphysics, and ZDR columns. *J. Atmos. Sci.*, **75**, 1755–1781, https://doi.org/10.1175/JAS-D-17-0127.1.

Kumjian, M. R., A. P. Khain, N. Benmoshe, E. Ilotoviz, A. V. Ryzhkov, and V. T. J. Phillips, 2014: The anatomy and physics of ZDR columns: Investigating a polarimetric radar signature with a spectral bin microphysical model. *J. Appl. Meteor. Climatol.*, **53**, 1820–1843, https://doi.org/10.1175/JAMC-D-13-0354.1.

Lumbroso, D., and E. Gaume, 2012: Reducing the uncertainty in indirect estimates of extreme flash flood discharges. *J. Hydrol.*, **414–415**, 16–30, https://doi.org/10.1016/j.jhydrol.2011.08.048.

Milan, M., D. Schüttemeyer, T. Bick, and C. Simmer, 2014: A sequential ensemble prediction system at convection permitting scales. *Meteor. Atmos. Phys.*, **123**, 17–31, https://doi.org/10.1007/s00703-013-0291-3.

Pastorek, J., M. Fencl, J. Rieckermann, and V. Bareš, 2019: Commercial microwave links for urban drainage modelling: The effect of link characteristics and their position on runoff simulations. *J. Environ. Manage.*, **251**, 109522, https://doi.org/10.1016/j.jenvman.2019.109522.

Polz, J., C. Chwala, M. Graf, and H. Kunstmann, 2020: Rain event detection in commercial microwave link attenuation data using convolutional neural networks. *Atmos. Meas. Tech.*, **13**, 3835–3853, https://doi.org/10.5194/amt-13-3835-2020.

Poméon, T., N. Wagner, C. Furusho, S. Kollet, and R. Reinoso-Rondinel, 2020: Performance of a PDE-based hydrologic model in a flash flood modeling framework in sparsely-gauged catchments. *Water*, **12**, 2157, https://doi.org/10.3390/w12082157.

Pulkkinen, S., D. Nerini, A. A. Pérez Hortal, C. Velasco-Forero, A. Seed, U. Germann, and L. Foresti, 2019: Pysteps: An open-source Python library for probabilistic precipitation nowcasting (v1.0). *Geosci. Model Dev.*, **12**, 4185–4219, https://doi.org/10.5194/gmd-12-4185-2019.

Putnam, B., M. Xue, Y. Jung, N. Snook, and G. Zhang, 2019: Ensemble Kalman filter assimilation of polarimetric radar observations for the 20 May 2013 Oklahoma tornadic supercell case. *Mon. Wea. Rev.*, **147**, 2511–2533, https://doi.org/10.1175/MWR-D-18-0251.1.

Reimann, L., C. Simmer, and S. Trömel, 2021: Dual-polarimetric radar estimators of liquid water content over Germany. *Meteor. Z.*, **30**, 237–249, https://doi.org/10.1127/metz/2021/1072.

Schinagl, K., P. Friederichs, S. Trömel, and C. Simmer, 2019: Gamma drop size distribution assumptions in model bulk parameterizations and radar polarimetry and their impact on polarimetric radar moments. *J. Appl. Meteor. Climatol.*, **58**, 467–478, https://doi.org/10.1175/JAMC-D-18-0178.1.

Seed, A., 2003: A dynamic and spatial scaling approach to advection forecasting. *J. Appl. Meteor.*, **42**, 381–388, https://doi.org/10.1175/1520-0450(2003)042<0381:ADASSA>2.0.CO;2.

—, C. E. Pierce, and K. Norman, 2013: Formulation and evaluation of a scale decomposition-based stochastic precipitation nowcast scheme. *Water Resour. Res.*, **49**, 6624–6641, https://doi.org/10.1002/wrcr.20536.

Silvestro, F., N. Rebora, G. Cummings, and L. Ferraris, 2017: Experiences of dealing with flash floods using an ensemble hydrological nowcasting chain: Implications of communication, accessibility and distribution of the results. *J. Flood Risk Manage.*, **10**, 446–462, https://doi.org/10.1111/jfr3.12161.

Speight, L. J., M. D. Cranston, C. J. White, and L. Kelly, 2021: Operational and emerging capabilities for surface water flood forecasting. *Wiley Interdiscip. Rev.: Water*, **8**, e1517, https://doi.org/10.1002/wat2.1517.

Trömel, S., A. V. Ryzhkov, B. Hickman, K. Mühlbauer, and C. Simmer, 2019: Polarimetric radar variables in the layers of melting and dendritic growth at X band—implications for a nowcasting strategy in stratiform rain. *J. Appl. Meteor. Climatol.*, **58**, 2497–2522, https://doi.org/10.1175/JAMC-D-19-0056.1.

Zhang, J., L. Tang, S. Cocks, P. Zhang, A. Ryzhkov, K. Howard, C. Langston, and B. Kaney, 2020: A dual-polarization radar synthetic QPE for operations. *J. Hydrometeor.*, **21**, 2507–2521, https://doi.org/10.1175/JHM-D-19-0194.1.