Radar-based Rainfall Information

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Radar-based rainfall information has been widely used in hydrological and meteorological applications, as it provides data with a high spatial and temporal resolution that improve rainfall representation. However, the broad diversity of studies makes it difficult to gather a condensed overview of the usefulness and limitations of radar technology and its application in particular situations.

Keywords: hydrological modelling ; nowcasting

1. Introduction

Radar technology (an active instrument that operates in a microwave band) was intensively developed for military use in the period before and during World War II. During the war, radar operators noticed echoes on radar screens caused by weather phenomena. After the war, scientists studied how to use radars for detecting precipitation. Since then, weather radars have been used by national weather services and research institutions, since they enable the detection of precipitating clouds, as well as their structure and development. Considerable efforts have also been made to obtain more accurate quantitative precipitation information that can be used in hydrological modelling and numerical weather prediction.

The use of radar-based rainfall data for hydrological modelling was motivated by the need to accurately measure the spatial structure of precipitation fields and to exploit the potential of radar-based rainfall data to generate short-term and very short-term (near real-time) quantitative precipitation forecasts. One of the first uses of weather radar precipitation data in hydrological applications was as an input to rainfall-runoff models. Therefore, effective derivation of precipitation from radar retrievals has been a subject of interest from the beginning of radar meteorology and hydrology and still remains one of the most important areas of research.

In terms of the estimation of quantitative precipitation, the well-known Marshall–Palmer formula[1] for converting radar reflectivity into precipitation intensity is still often used today. It is one of the most cited papers in the field of radar hydrology. The literature on this topic is extensive, and various reviews exist, e.g., Wilk and Kessler[2], Wilson and Brandes[3], Zawadzki[4], Joss and Waldvogel[5], and Krajewski and Smith[6].

Other areas of application of weather radar networks in operational hydrology include storm hazard assessment and flood forecasting, warning, and management[7][8]. The current interest in land surface hydrological processes has stimulated research into the spatial and temporal variability of precipitation. A potential area for the application of weather radar in this context is in the validation and verification of sub-grid rainfall parameterizations for atmospheric mesoscale models and global circulation models [9].

Weather radar measurements are obviously connected with non-negligible and sometimes even large errors; hence, radar can be referred to as a semi-quantitative measurement device [10]. The errors are due to measuring techniques and their extent depends on weather conditions, in particular on precipitation processes and the size distribution of precipitation particles. Nevertheless, radar provides very useful information, i.e., real-time coverage at high spatiotemporal resolution, with data being available after a very short time from being observed. Thus, the quality control procedures can be carried out simultaneously for a proper quantitative precipitation estimation.

2. Using Radar Rainfall Data in Flash Flood Modeling

The benefits of using rainfall radar data in hydrological applications were not reached effortlessly as one could have expected when this new spatially distributed data source became available[11]. Berne and Krajewski [12] discussed several aspects of the challenges of using weather radar in hydrological modelling while arguing that the evidence pointed to contradicting results regarding the improvements achieved by using radar-based rainfall data on rainfall-runoff distributed models. Whereas many studies reported an added value of the high resolution of radar rainfall data on hydrological applications, some others did not find a significant improvement. Currently, many more investigations have come to light and an updated overview of the use of radar rainfall on hydrology can be provided. Hereafter, the major radar-related topics on rainfall-runoff modelling and streamflow forecasting will be covered to highlight the main approaches and concerns that have been tackled in relation to the use of radar rainfall estimates. This section does not entail an intensive documentation of all studies in the field of radar hydrology, but rather a comprehensive review of the main topics that are discussed in the literature while providing some relevant examples. Therefore, it aims to provide a general outline of current investigations and challenges when dealing with radar data for hydrological applications with a focus on rainfall-runoff modelling, particularly flash-flood forecasting.

2.1. Flash Flood Modelling Approaches Using Radar Data

There are three different approaches for rainfall-runoff modelling, including flood forecasting, that have explored the usefulness of radar rainfall estimates. Those are process-based, machine learning-based, and data-based mechanistic models.

Process-based models can represent the hydrological processes with different degrees of detail, from small detail in lumped models (e.g., reservoir or tank models) to highly detailed, physically based, distributed models. When radar data became available, lumped models were preferred due to the low computational cost[13]. However, semi-distributed and distributed models have become more attractive due to the enormous increase in high computer power. Additionally, it is clear that the distributed nature of radar rainfall can be better exploited with a distributed model[14]. Nevertheless, distributed models are complex and have a large number of parameters that need to be calibrated in each model cell, which produces a large uncertainty in modelling estimates (i.e., the equifinality problem). Since all hydrological processes are represented in detail, distributed models demand large amounts of distributed data sets: vegetation, topography, soils, land use, and geology, to name a few. These data are seldom available at the scale of interest, which limits the applicability of these models.

Another source of uncertainty comes from the selection of the initial conditions, mainly the soil moisture conditions (SMC). To account for correct SMC, the model needs to include a detailed soil map, the soils' hydrological properties, and also distributed soil depths. Since soils and their properties are highly variable in mountain catchments, and very difficult and expensive to collect, the application of distributed models in mountain environments faces a big challenge. The problem of SMC initialization in the model is more complex for flash flood forecasting than for general rainfall-runoff modelling (as for hydrological design or post-event analyses), as the model needs to have good initial conditions for obtaining good results. Thus, each time the forecast is initialized (every few hours), the forecasting system has to update its SMC, which can be highly demanding and subject to uncertainty [15], although soil moisture assimilation strategies have proved successful in distributed models [16]. Using distributed models remains challenging, although they can benefit more from radar data. On the other hand, lumped models are used when there is scarce spatially-distributed data and/or computer power is limited. In this case, radar rainfall is aggregated at the basin scale (e.g., area-weighted mean of the overlaying radar grid cells), losing the details of the rainfall fields. This can be slightly avoided when applied in small catchments. Therefore, semi-distributed models are considered as a compromise between lumped and distributed models, where it is still possible to capture some details of the spatial variability while maintaining accessible data requirements. Here, the basin is divided into subbasins, and in each of them a lumped model is used[17]. While there are difficulties in the application of distributed models, there are modelling objectives that can only be answered with them: hydrological impact of land use changes or discharge forecasting in rapidly evolving catchments[18].

With the advent of artificial intelligence, the use of models based on machine learning (ML) models for rainfall-runoff mapping and discharge forecasting has dramatically increased. These models are known for their outstanding performance, but also for their complex training process and for being considered as black box models. Thus, model parameters lack physical interpretation regarding the runoff processes. A comprehensive review of several ML algorithms used for flood forecasting using radar rainfall data is provided by Mosavi et al. [19]. Besides the use of support vector machines, the authors highlighted the use of a variety of Artificial Neural Networks (ANN) derived models, such as neuro-fuzzy, adaptive neuro-fuzzy inference systems (ANFIS), wavelet neural networks (WNN), and multilayer perceptron (MLP), as the more frequent models in the literature. More sophisticated ML-based models such as genetic programming[20] have also been explored with satisfactory results. Nonetheless, other ML-based models as those based on decision trees (DT) are less complex algorithms that have just recently been explored by using radar rainfall[21]. Even though many ML algorithms serve as black box models, deep learning (DL) approaches have been demonstrated that are able to provide some insights about the relations of the inputs that fed the model towards the discharge. It should be of great advantage and interest to extract some knowledge of the rainfall-runoff process by using these techniques as a reverse engineering strategy. Kratzert et al. [22] performed a study using Long Short Term Memory (LSTM) ANN over 241 catchments and showed the ability of this DL approach to learn long-term dependencies between the inputs and the output of the model (e.g., those related to modelling storage effects) along with the possibility to transfer process understanding from the regional to the local scale. Recently, Xiang and Demir [23] proposed the use of DL for extending the forecast horizon until five days on an hourly basis with promising results. Because there is a very recent interest on the application of DL for discharge forecasting, it has been tested by using only spatially distributed rainfall derived from dense rain gauges. Therefore, the benefits of applying DL on radar rainfall for streamflow forecasting remain unknown.

Finally, data base mechanistic (DBM) models are another type of hydrological model that combines a statistical definition of the rainfall-runoff model with a supervised optimization of its parameters that ensures that the model parameters have a physical meaning. DBM models have been less explored for rainfall-runoff modelling, but have also proven to be efficient when using radar rainfall forecasts in small mountain catchments[24]. In DBM models, radar data is aggregated as in a lumped model; thus, the distributed rainfall fields are lost. On the whole, there is a major need for research on developing smart model structures that are able to properly incorporate, as far as possible, the distributed nature of radar rainfall data. Thus, taking advantage of radar data comes from a combined strategy as a result of expert knowledge and the individual strengths of a hydrological model.

2.2. Uncertainty in Radar Estimates for Hydrological Modeling

Although radar-based precipitations estimates are known to provide significant spatially distributed rainfall information, they are still subject to errors, which can notoriously reduce hydrological model performances[25]. Radar rainfall estimation is a necessary step for the use of spatially distributed rainfall on physically-based hydrological models. Thus, as weather radar provides an indirect measurement of rainfall (i.e., reflectivity), the transformation from reflectivity to rainfall implies many processes that add uncertainty to the estimations. Despite the nature of ML-based models that would allow the mapping of any input (independently of its physical meaning or interpretation) to an output, the vast majority of studies that applied ML-based models for streamflow modelling or forecasting also performed a radar rainfall retrieval process as a previous step to the modelling itself in order to guarantee a proper quantitative representation of rainfall[19].

Quantification of uncertainty of radar estimates is of main importance, particularly when using physically-based models. It is because the quantitative estimation of the radar rainfall retrievals strongly influences model results. Studies with physically-based models have focused on two main sources of uncertainty: uncertainty in rainfall input[26][27][28] originated from the systematic errors produced in the process of *Z–R* transformation, and uncertainty in model parameters[29][30]. Investigations on radar hydrology are more frequently focused on rainfall input uncertainty.

In a trade-off between the added error of the radar rainfall derivation chain and the improvement on the radar rainfall estimates, the bias adjustment by means of rain gauge networks has been extensively accepted for applications on radar hydrology, while efforts have been made to reduce the negative effects of relative calibration on radar composites, as in Seo et al. [31]. For instance, uncertainty in radar rainfall estimates was evaluated by Seo et al.[24] using different radar rainfall products that differ on the data composition (i.e., only radar-based product vs. rain gauge bias-adjusted radar product). The study demonstrated the need for bias-adjusted radar estimates related to the Iowa Flood Studies (IFloodS) experiment. Nonetheless, according to Paz et al.[32], the heterogeneous distributions of rain gauge networks for radar bias adjustment strongly affect the quality of adjusted rainfall fields because of the fractality of the rain gauge network.

One strategy for evaluating the uncertainty of rainfall estimates is to use ensemble models. Here, some changes in the configuration of the model (input source, model parameters, or both) are carried out, and the corresponding model evaluation is performed, as in Pomeón et al. [32]. A radar rainfall ensemble is the result of the application of an error model, which may account for observed errors (i.e., as compared with rain gauges), spatial and temporal dependences, and their marginal distribution, that reflects several possible realizations on the rainfall field [27][28]. Thus, through the application of a hydrological model by using different radar rainfall ensembles, it is possible to evaluate the radar input uncertainty. Error models range from simple schemes that add a fixed Gaussian random error and evaluate the radar rainfall ensembles on different hydrological models[33] to more refined but also complex error models that include geostatistical approaches for the generation of synthetic error fields [27] and non-Gaussian distributions[28].

Another approach that has been explored for quantifying the precipitation data uncertainty when using spatial distributed rainfall is a Bayesian analysis that accounts for influence of the length of the rainfall time series. For instance, Sikorska and Seibert[34] evaluated different rainfall data sources: only gauge station, interpolated gauge station, and radar-based precipitation in an alpine catchment by using different time series lengths for the model calibration process. The authors found the radar-based precipitation was more informative for the model, which derived in the higher accuracy. Thus, the evaluation of ensemble models towards several realizations of probability distributions allow uncertainty bands to be obtained, which exhibits the robustness of the model under induced errors on the input radar data. Therefore, this is a powerful tool not only for researchers, but also mainly for decision-makers using flood forecasting, which needs to be transferred to early-warning operational systems.

Even though the measurement error of weather radar retrievals cannot be avoided, the systematic error that comes from the *Z*–*R* transformation could be disregarded when using raw reflectivity records as inputs for ML-based models. Very recently, Orellana-Alvear et al. [21] demonstrated the suitability of using the native radar variable (reflectivity) as input for a random forest model for discharge forecasting. Performance of the model was comparable with the use of radar rainfall estimates, and therefore the authors concluded that differences should be overlooked. It opened a new alternative for performing discharge forecasting by using native radar data, which is extremely beneficial in regions with sparse and uneven distributed rain gauge networks, that would reduce the uncertainty of systematic errors.

2.3. Radar Spatial Resolution and Catchment Scale

The added value of a finer spatial resolution of radar imagery for hydrological models is usually taken for granted. Thus, many studies have been conducted with the objective to identify the best radar spatial resolution for hydrological applications (e.g., Shakti et al. [35]). Results suggested that higher rainfall resolutions are relevant at smaller catchment scales and mainly when rainfall events of high variability occur. For instance, Thorndahl et al. [18], in their review, identified a reduced need of high resolution radar rainfall for bigger urban catchments. As illustration, a comparison of the use of C-band and X-band radar data as rainfall inputs for rainfall-runoff models was performed by Paz et al.[36] in an urbanized catchment (3 km^2) close to Paris. Results pointed to a better representation of X-band radar rainfall with a spatial resolution of 250 × 250 m^2 at 3.41 min frequency in contrast to the 1 × 1 km^2 spatial resolution of the C-band radar data at 5 min frequency. Evaluation on a small (64 km^2) mountainous catchment in the Italian Alps confirmed the benefits on X-band spatial resolution data for peak simulation [37]. A review paper of the effects of spatial and temporal variability on hydrological response in urban areas was performed by Cristiano et al.[38]. The authors concluded from the literature that physically-based models have become more specialized, and high-resolution spatial rainfall data is of utmost need to take advantage of the models.

Furthermore, Cristiano et al.[39] introduced dimensionless scaling factors that reflect the interactions between rainfall, its input resolution, and catchment on the hydrological response in urban areas. The novelty of these scaling factors is that they allow the identification of the needed rainfall resolution in order to reach a given level of accuracy in model performance. Most studies (e.g., Anagnostou et al.[37]; Paz et al.[36]) in the literature have performed an evaluation of the impact of the radar rainfall resolution (i.e., spatial and temporal) in the hydrological response over a specific catchment, which impedes the generalization of their results. In this context, it is still difficult to assess if the findings in these studies respond to the size of the catchment, the variability of the rainfall event in time and space, the particularities of the terrain, etc. Nonetheless, those that have been able to reproduce their analysis on a wider scope have concluded that sensitivity of the hydrological models to different rainfall resolutions decreased when the size of the catchment increased. For instance, Ochoa-Rodriguez et al. [40] performed an analysis of the impact of different rainfall spatial (100–3000 m) and temporal (1–10 min) resolutions at seven urban catchments that differ on the geomorphological characteristics of their locations by using X-band polarimetric radar data. The authors found that a temporal resolution lower than 5 min is needed for performing an adequate hydrological modelling, whereas a spatial resolution of 3 km (cartesian grid size) does not properly work for urban catchments.

Another relevant study that provided streamflow simulation evaluation by using a quite diverse dataset of 3620 flood events that occurred over 181 catchments of a variety of sizes and climate conditions was carried out by Lobligeois et al. [41]. Rather than focusing on the evaluation of a combination of spatial and temporal resolutions or radar data, this study used radar-based data with a fixed 1 km, 1-h resolution over a 10-year period in France as input for a lumped and a distributed model. Results were analyzed by considering catchment location and types of rainfall events (i.e., spatial variability of rainfall). The authors found that both models, lumped and distributed, performed similarly on the catchments in western France that are under oceanic climate conditions and thus exhibit fairly uniform precipitation fields. In contrast, the spatially distributed rainfall data was greatly beneficial to the model accuracy in southern France, where mountain catchments with highly variable precipitation in space are located. Interestingly, in certain regions, distributed models can outperform simpler models in certain periods of the year (e.g., when rainfall fields are complex), while in other periods they do not; thus, Loritz et. al. [14] propose the development of adaptive models as a way to exploit the information of distributed rainfall while reducing the computational costs of modelling.

All in all, studies suggest that the combination of catchment biophysical characteristics (e.g., land use, topography, soils), rainfall types (orographic, convective, stratiform), rainfall variability in time and space, and modelling objectives (flash flood forecasting, hydrologic design) determine the required radar spatio-temporal resolution and model complexity.

2.4. Usefulness of Blending Data and Ancillary Data

With the aim of improving the accuracy of rainfall-runoff modelling and discharge forecasting, ancillary data that relates to the physical runoff processes are usually included. Regularly, semi-distributed and distributed models already need additional geomorphological variables for an adequate model calibration. Nonetheless, additional information that comes from rainfall forecasts, NWP, and more sophisticated blending techniques of rainfall data have proven to enhance the performance of rainfall-runoff models and discharge forecasting by allowing the extension of the forecast horizon while using different modelling strategies. Ochoa-Rodriguez et al. [42] provided an in-depth review of radar–rain gauge merging techniques by proposing an application-oriented categorization. This classification accounted for radar bias adjustment methods, geostatistical methods such as kriging techniques, and finally integration methods where neither radar nor rain gauge data are considered as a primary data source, but a combination of both that extracts the best information from each instrument is produced as a final result. From those, mean field bias adjustment, kriging with external drift, and Bayesian merging were found the most relevant techniques. These methods were reviewed by considering their use in urban hydrology applications, and therefore they are a good starting point for evaluating their effectiveness on rainfall-runoff modelling. Likewise, McKee and Binns [43] performed a similar review but with a focus on near real-time application of gauge radar merging methods in operational systems. Moreover, the inclusion of satellite-based soil moisture estimations [15] or a related representation (e.g., a proxy based on rainfall accumulation) in addition to the radar-based rainfall information, has satisfactorily improved runoff modelling and discharge forecasting with distributed models[44].

Besides the blending of radar–rain gauge data, the inclusion of short-term radar rainfall forecasts is an important strategy that has improved streamflow forecasting. For instance, Heuvelink et al.[45] demonstrated that the use of radar rainfall nowcasting improves the hydrological response, but also comes with the highest uncertainty in smaller catchments. It was an expected result, since rainfall forecasts were found to diminish its accuracy with increasing lead time. This effect also responded to other studies previously mentioned where smaller catchments are usually associated with higher spatial variability of rainfall. Heuvelink et al.[45] found that the best scenario of discharge forecasting showed a gain of almost three hours more in advance than without rainfall nowcasting.

Finally, the use of Numerical Weather Predictions (NWP) as inputs for rainfall-runoff modelling has gained much attention on the last years. Radar rainfall data can be used for assimilation, thus forcing the generation of NWP, which would enhance its accuracy. As NWP provide longer-term rainfall forecast, its use as input for discharge forecasting has allowed not only the improvement the model performance, but also the increase of the lead time forecasts. More sophisticated techniques may involve blending data dynamically with changing weight functions. For instance, the combination of NWP and radar-based predictions with corrections for orographic rainfall whose weights are computed according to their expected skills can be found in Yu et al. [46]. A relevant illustration of three operational early warning systems for flash flood forecasting in Europe that showed the advantage of using a combination of different data sources is documented in Alfieri et al.[47].

2.5. Post-Event Flash Flood Analyses

Radar data has been extensively used in studies of flash flood processes understanding. Since heavy rainfall events—particularly in mountain areas—cannot be captured by conventional rain gauge networks, radar data opened a whole new dimension to the study of flash floods. Post-event analyses (e.g., Bouilloud et al.[48]; Marchi et al.[49]) or forensic hydrological (e.g., Bronstert et al. [50]; Borga et al. [51]) are studies that reconstruct (flash) floods in an attempt to understand the triggering mechanisms and the development of these extreme events; this new knowledge is then later used for developing forecasting models. Under this scheme, forecast models can be improved or developed further as to effectively simulate the flash flood processes given the detailed precipitation input, but hydrological models can also serve as test beds to identify adjustments to radar rainfall data (Borga et al. [52]; Seo et al. [30]). As an example, Javelle et al.[53] analyzed the forecasting performance of a distributed model for different lead times in absence of quantitative precipitation forecasting. Radar data was able to improve simulations for short lead times; main limitations were attributed to both rainfall underestimation and the modelling uncertainty.

In summary, studying the combination of meteorological aspects, rainfall fields, hydrological processes, hydrological modelling, and human activities (e.g., land use change in floodplains) allows for an in-depth comprehension of flood events[50]. This knowledge—together with social and infrastructure data—is crucial for flash flood risk management [54]. Here, radar data has been key to understanding the impact of spatial distribution of rainfall and its evolution along the event.

3. Conclusions

Weather radar measurements have enormous potential in hydrological applications, though they are still not fully utilized. The main direction of current research is the effective use of their high temporal and spatial resolution—it is assumed that the desired resolution for small catchments, in particular the urbanized ones, should be up to 1 km (cartesian grid size) and up to 5 min in space and time, respectively, and weather radar is the only device that can provide such a high resolution.

However, the biggest limitation of the use of weather radar data for hydrological applications is in their quality. More and more effective quality control algorithms are being developed thanks to more advanced image processing techniques related to increasing computing possibilities, including those based on machine learning. At the same time, however, there are new challenges, such as those resulting from the increasing presence of RLAN signals particularly disrupting weather radars operating in the most popular C-band and those resulting from the negative impact of wind farms on radar measurements. The radar errors are hard to diagnose and thus hard to remove completely. Thereby, data from other measuring systems, rain gauge networks in particular, are used to improve the radar-based quantitative precipitation estimation through either its adjustment or the multi-source combination.

New perspectives appear with the increasingly better availability of weather radar data from on board meteorological satellites in low Earth orbits, since such radars have a completely different error structure than the common ground-based weather radars. Moreover, crowdsourcing measurements become more and more popular, especially those from private meteorological stations, as the data from private meteorological stations can be a valuable supplement to national rain gauge networks and can be used for adjustment of weather radar data or generation of multi-source estimates.

Methods for precipitation nowcasting for early warning against dangerous precipitation are commonly used by meteorological services. These methods use current data and process it using statistical methods and/or artificial intelligence methods, thus avoiding the high time consumption of complex mathematical models used for medium-term weather forecasts. The nowcasting models are computationally undemanding and do not require large data sets. They usually give reasonable predictions for lead times up to 2 h with a high frequency of calculations (e.g., every 10 min). The basic limitation of the nowcasting methods is their limited accuracy for longer lead times, i.e., after a certain time, the nowcasting methods can no longer compete with standard NWP models. The accuracy of nowcasts depends strongly on the type of meteorological situation. For instance, in the case of severe convection, nowcasting can give a reasonable forecast for 10 to 20 min only.

Various nowcasting procedures can be used, which differ in the kind of prediction: (i) quantitative, (ii) categorical, (iii) probabilistic, and (iv) ensemble. Each kind of prediction has its own advantages and disadvantages, but there is a clear tendency of considering the uncertainty of methods in the development of methods, which leads to a preference of ensemble or probabilistic prediction. Nevertheless, every user of a nowcasting method should be aware that the parameters are determined subjectively, i.e., they are not of general validity. Therefore, each nowcasting model should be tuned specifically for the area of interest, and its properties should be considered if the model outputs are further used, e.g., in hydrological applications. All in all, despite fundamental shortcomings, the nowcasting models are currently irreplaceable.

Assimilation of data into NWP models is an important way to refine forecasts. Radar data are very important for the forecast, as they contain detailed and spatially dense information on hydrometeors in the atmosphere. It is obvious that both types of radar data, i.e., radar reflectivity and Doppler radial velocity, are important for prediction of cloud development and precipitation; however, it is not entirely clear whether the Doppler radial velocity or the radar reflectivity is more important for assimilation. Recent studies have suggested that assimilation of a particular type of data refines the prediction of only certain processes. Therefore, it can be recommended to assimilate both types of radar data, which appears to have complementary effect.

Several assimilation methods for radar data assimilation differ for radar reflectivity and Doppler radial velocity. The difference is mainly due to the fact that the Doppler radial velocity is a model quantity, while the reflectivity is a derived variable from model quantities. The general tendency in data assimilation is the use of sophisticated methods, which include features of the 4D variation method, but also the use of simplifications that allow fast enough assimilation of the data. In parallel to these methods, techniques based on the application of an ensemble Kalman filter are used and developed. Nevertheless, applications of the nudging technique in conjunction with the assimilation of radar reflectivity, such as latent heat nudging, have still occasionally appeared in literature, since they are very efficient in terms of computational demands.

The use of radar rainfall data for flash flood modelling needs to be further exploited by strategies that combine expert knowledge and the specific advantages and strengths of different hydrological models. This would allow the development of smart model structures that leverage the spatially distributed nature of radar data. Nonetheless, radar imagery has proven to be already a key component to improve the understanding of flash flood events and their development when used as reverse engineering. This knowledge is of utmost importance for risk management related to the reduction of social and infrastructure impacts of flash flood events.

References

1. Marshall, J.S.; Langille, R.C.; Palmer, W.M.K. Measurement of Rainfall by Radar. J. Meteor. 1947, 4, 186–192, doi:10.1175/1520-0469(1947)004<0186:MORBR>2.0.CO;2.
2. Wilk, K.E.; Kessler, E. Quantitative Radar Measurements of Precipitation. In Meteorological Observations and Instrumentation; Teweles, S., Giraytys, J., Eds.; American Meteorological Society: Boston, MA, USA, 1970; pp. 315–329, ISBN 978-1-935704-35-5.
3. Wilson, J.W.; Brandes, E.A. Radar Measurement of Rainfall—A Summary. Bull. Amer. Meteor. Soc. 1979, 60, 1048–1060, doi:10.1175/1520-0477(1979)060<1048:RMORS>2.0.CO;2.
4. Zawadzki, I. Factors Affecting the Precision of Radar Measurements of Rain. In Proceedings of the 22nd Conference on Radar Meteorology, Boston, MA, USA, 1 January 1984; pp. 251–256.
5. Joss, J.; Waldvogel, A.; Collier, C.G. Precipitation Measurement and Hydrology. In Radar in Meteorology: Battan Memorial and 40th Anniversary Radar Meteorology Conference; Atlas, D., Ed.; American Meteorological Society: Boston, MA, USA, 1990; pp. 577–606, ISBN 978-1-935704-15-7.
6. Krajewski, W.F.; Smith, J.A. Radar Hydrology: Rainfall Estimation. Adv. Water Resour. 2002, 25, 1387–1394, doi:10.1016/S0309-1708(02)00062-3.
7. Collier, C.G. Applications of Weather Radar Systems: A Guide to Uses of Radar Data in Meteorology and Hydrology, 2nd ed.; Wiley: Chichester, UK; New York, NY, USA, 1996; ISBN 978-0-471-96013-3.
8. Zappa, M.; Beven, K.J.; Bruen, M.; Cofiño, A.S.; Kok, K.; Martin, E.; Nurmi, P.; Orfila, B.; Roulin, E.; Schröter, K.; et al. Propagation of Uncertainty from Observing Systems and NWP into Hydrological Models: COST-731 Working Group 2. Atmospheric Science Letters 2010, 11, 83–91, doi:https://doi.org/10.1002/asl.248.
9. Zhang, Y.; Xie, S.; Klein, S.A.; Marchand, R.; Kollias, P.; Clothiaux, E.E.; Lin, W.; Johnson, K.; Swales, D.; Bodas-Salcedo, A.; et al. The ARM cloud radar simulator for global climate models: Bridging field data and climate models. Bull. Am. Meteorol. Soc. 2018, 99, 21–26, doi:10.1175/BAMS-D-16-0258.1.
10. Joss, J. Operational Use of Radar for Precipitation Measurements in Switzerland; Vdf Hochschulverl. an der ETH Zürich: Zürich, Switherlands, 1998; ISBN 978-3-7281-2501-9.
11. Seo, D.-J.; Habib, E.; Andrieu, H.; Morin, E. Hydrologic Applications of Weather Radar. J. Hydrol. 2015, 531, 231–233, doi:10.1016/j.jhydrol.2015.11.010.
12. Berne, A.; Krajewski, W.F. Radar for Hydrology: Unfulfilled Promise or Unrecognized Potential? Adv. Water Resour. 2013, 51, 357–366, doi:10.1016/j.advwatres.2012.05.005.
13. Loumagne, C.; Normand, M.; Riffard, M.; Weisse, A.; Quesney, A.; Hégarat-Mascle, S.L.; Alem, F. Integration of Remote Sensing Data into Hydrological Models for Reservoir Management. Hydrol. Sci. J. 2001, 46, 89–102, doi:10.1080/02626660109492802.
14. Loritz, R.; Hrachowitz, M.; Neuper, M.; Zehe, E. The Role and Value of Distributed Precipitation Data for Hydrological Models. Hydrol. Earth Syst. Sci. 2020, 25, 147–167.
15. Li, Y.; Grimaldi, S.; Walker, J.P.; Pauwels, V.R.N. Application of Remote Sensing Data to Constrain Operational Rainfall-Driven Flood Forecasting: A Review. Remote Sens. 2016, 8, 456, doi:10.3390/rs8060456.
16. Ridler, M.-E.; Madsen, H.; Stisen, S.; Bircher, S.; Fensholt, R. Assimilation of SMOS-Derived Soil Moisture in a Fully Integrated Hydrological and Soil-Vegetation-Atmosphere Transfer Model in Western Denmark. Water Resour. Res. 2014, 50, 8962–8981, doi:10.1002/2014WR015392.
17. Gabriele, S.; Chiaravalloti, F.; Procopio, A. Radar–Rain-Gauge Rainfall Estimation for Hydrological Applications in Small Catchments. In Proceedings of the Advances in Geosciences, Fargau-Pratjau, Germany, 12 July 2017; Volume 44, pp. 61–66.
18. Delrieu, G.; Braud, I.; Berne, A.; Borga, M.; Boudevillain, B.; Fabry, F.; Freer, J.; Gaume, E.; Nakakita, E.; Seed, A.; et al. Weather Radar and Hydrology. Adv. Water Resour. 2009, 32, 969–974, doi:10.1016/j.advwatres.2009.03.006.

19. Mosavi, A.; Ozturk, P.; Chau, K. Flood Prediction Using Machine Learning Models: Literature Review. Water 2018, 10, 1536, doi:10.3390/w10111536.

20. Dinu, C.; Drobot, R.; Pricop, C.; Blidaru, T.V. Genetic Programming Technique Applied for Flash-Flood Modelling Using Radar Rainfall Estimates. Math. Model. Civ. Eng. 2017, 13, 27–38, doi:10.1515/mmce-2017-0012.

21. Orellana-Alvear, J.; Célleri, R.; Rollenbeck, R.; Muñoz, P.; Contreras, P.; Bendix, J. Assessment of Native Radar Reflectivity and Radar Rainfall Estimates for Discharge Forecasting in Mountain Catchments with a Random Forest Model. Remote Sens. 2020, 12, 1986, doi:10.3390/rs12121986.

22. Kratzert, F.; Klotz, D.; Brenner, C.; Schulz, K.; Herrnegger, M. Rainfall–Runoff Modelling Using Long Short-Term Memory (LSTM) Networks. Hydrol. Earth Syst. Sci. 2018, 22, 6005–6022, doi:10.5194/hess-22-6005-2018.

23. Xiang, Z.; Demir, I. Distributed Long-Term Hourly Streamflow Predictions Using Deep Learning—A Case Study for State of Iowa. Environ. Model. Softw. 2020, 131, 104761, doi:10.1016/j.envsoft.2020.104761.

24. Smith, P.J.; Panziera, L.; Beven, K.J. Forecasting Flash Floods Using Data-Based Mechanistic Models and NORA Radar Rainfall Forecasts. Hydrol. Sci. J. 2014, 59, 1403–1417, doi:10.1080/02626667.2013.842647.

25. Borga, M. Accuracy of Radar Rainfall Estimates for Streamflow Simulation. J. Hydrol. 2002, 267, 26–39, doi:10.1016/S0022-1694(02)00137-3.

26. Seo, B.-C.; Krajewski, W.F.; Quintero, F.; ElSaadani, M.; Goska, R.; Cunha, L.K.; Dolan, B.; Wolff, D.B.; Smith, J.A.; Rutledge, S.A.; et al. Comprehensive Evaluation of the IFloodS Radar Rainfall Products for Hydrologic Applications. J. Hydrometeor. 2018, 19, 1793–1813, doi:10.1175/JHM-D-18-0080.1.

27. Cecinati, F.; Rico-Ramirez, M.A.; Heuvelink, G.B.M.; Han, D. Representing Radar Rainfall Uncertainty with Ensembles Based on a Time-Variant Geostatistical Error Modelling Approach. J. Hydrol. 2017, 548, 391–405, doi:10.1016/j.jhydrol.2017.02.053.

28. Dai, Q.; Han, D.; Zhuo, L.; Huang, J.; Islam, T.; Srivastava, P.K. Impact of Complexity of Radar Rainfall Uncertainty Model on Flow Simulation. Atmos. Res. 2015, 161–162, 93–101, doi:10.1016/j.atmosres.2015.04.002.

29. Beven, K.; Binley, A. The Future of Distributed Models: Model Calibration and Uncertainty Prediction. Hydrol. Process. 1992, 6, 279–298, doi:10.1002/hyp.3360060305.

30. Seo, B.-C.; Cunha, L.K.; Krajewski, W.F. Uncertainty in Radar-Rainfall Composite and Its Impact on Hydrologic Prediction for the Eastern Iowa Flood of 2008. Water Resour. Res. 2013, 49, 2747–2764, doi:10.1002/wrcr.20244.

31. Paz, I.; Tchiguirinskaia, I.; Schertzer, D. Rain Gauge Networks' Limitations and the Implications to Hydrological Modelling Highlighted with a X-Band Radar. J. Hydrol. 2020, 583, 124615, doi:10.1016/j.jhydrol.2020.124615.

32. Poméon, T.; Wagner, N.; Furusho, C.; Kollet, S.; Reinoso-Rondinel, R. Performance of a PDE-Based Hydrologic Model in a Flash Flood Modeling Framework in Sparsely-Gauged Catchments. Water 2020, 12, 2157, doi:10.3390/w12082157.

33. Zhu, D.H.; Peng, D.Z.; Cluckie, I.D. Statistical Analysis of Error Propagation from Radar Rainfall to Hydrological Models. Hydrol. Earth Syst. Sci. Discuss. 2012, 9, 10277–10302, doi:10.5194/hessd-9-10277-2012.

34. Sikorska, A.E.; Seibert, J. Value of Different Precipitation Data for Flood Prediction in an Alpine Catchment: A Bayesian Approach. J. Hydrol. 2018, 556, 961–971, doi:10.1016/j.jhydrol.2016.06.031.

35. Shakti, P.C.; Tsuyoshi, N.; Ryohei, M. The Role of the Spatial Distribution of Radar Rainfall on Hydrological Modeling for an Urbanized River Basin in Japan. Water 2019, 11, 1703, doi:10.3390/w11081703.

36. Paz, I.; Willinger, B.; Gires, A.; Alves de Souza, B.; Monier, L.; Cardinal, H.; Tisserand, B.; Tchiguirinskaia, I.; Schertzer, D. Small-Scale Rainfall Variability Impacts Analyzed by Fully-Distributed Model Using C-Band and X-Band Radar Data. Water 2019, 11, 1273, doi:10.3390/w11061273.

37. Anagnostou, M.N.; Nikolopoulos, E.I.; Kalogiros, J.; Anagnostou, E.N.; Marra, F.; Mair, E.; Bertoldi, G.; Tappeiner, U.; Borga, M. Advancing Precipitation Estimation and Streamflow Simulations in Complex Terrain with X-Band Dual-Polarization Radar Observations. Remote Sens. 2018, 10, 1258, doi:10.3390/rs10081258.

38. Cristiano, E.; ten Veldhuis, M.-C.; van de Giesen, N. Spatial and Temporal Variability of Rainfall and Their Effects on Hydrological Response in Urban Areas—a Review. Hydrol. Earth Syst. Sci. 2017, 21, 3859–3878, doi:10.5194/hess-21-3859-2017.

39. Cristiano, E.; Veldhuis, M.; Wright, D.B.; Smith, J.A.; Giesen, N. van de The Influence of Rainfall and Catchment Critical Scales on Urban Hydrological Response Sensitivity. Water Resour. Res. 2019, 55, 3375–3390, doi:10.1029/2018WR024143.

40. Ochoa-Rodriguez, S.; Wang, L.-P.; Gires, A.; Pina, R.D.; Reinoso-Rondinel, R.; Bruni, G.; Ichiba, A.; Gaitan, S.; Cristiano, E.; van Assel, J.; et al. Impact of Spatial and Temporal Resolution of Rainfall Inputs on Urban Hydrodynamic Modelli

ng Outputs: A Multi-Catchment Investigation. J. Hydrol. 2015, 531, 389–407, doi:10.1016/j.jhydrol.2015.05.035.

41. Lobligeois, F.; Andréassian, V.; Perrin, C.; Tabary, P.; Loumagne, C. When Does Higher Spatial Resolution Rainfall Information Improve Streamflow Simulation? An Evaluation Using 3620 Flood Events. Hydrol. Earth Syst. Sci. 2014, 18, 575–594, doi:10.5194/hess-18-575-2014.
42. Ochoa-Rodriguez, S.; Wang, L.-P.; Willems, P.; Onof, C. A Review of Radar-Rain Gauge Data Merging Methods and Their Potential for Urban Hydrological Applications. Water Resour. Res. 2019, 55, 6356–6391, doi:10.1029/2018WR023332.
43. McKee, J.L.; Binns, A.D. A Review of Gauge–Radar Merging Methods for Quantitative Precipitation Estimation in Hydrology. Can. Water Resour. J. / Rev. Can. Des Ressour. Hydr. 2016, 41, 186–203, doi:10.1080/07011784.2015.1064786.
44. Jadidoleslam, N.; Mantilla, R.; Krajewski, W.F.; Goska, R. Investigating the Role of Antecedent SMAP Satellite Soil Moisture, Radar Rainfall and MODIS Vegetation on Runoff Production in an Agricultural Region. J. Hydrol. 2019, 579, 124210, doi:10.1016/j.jhydrol.2019.124210.
45. Heuvelink, D.; Berenguer, M.; Brauer, C.C.; Uijlenhoet, R. Hydrological Application of Radar Rainfall Nowcasting in the Netherlands. Environ. Int. 2020, 136, 105431, doi:10.1016/j.envint.2019.105431.
46. Yu, W.; Nakakita, E.; Kim, S.; Yamaguchi, K. Improvement of Rainfall and Flood Forecasts by Blending Ensemble NWP Rainfall with Radar Prediction Considering Orographic Rainfall. J. Hydrol. 2015, 531, 494–507, doi:10.1016/j.jhydrol.2015.04.055.
47. Alfieri, L.; Berenguer, M.; Knechtl, V.; Liechti, K.; Sempere-Torres, D.; Zappa, M. Flash Flood Forecasting Based on Rainfall Thresholds. In Handbook of Hydrometeorological Ensemble Forecasting; Duan, Q., Pappenberger, F., Thielen, J., Wood, A., Cloke, H.L., Schaake, J.C., Eds.; Springer: Berlin/Heidelberg, Germany, 2016; pp. 1–38, ISBN 978-3-642-40457-3.
48. Bouilloud, L.; Delrieu, G.; Boudevillain, B.; Kirstetter, P.-E. Radar Rainfall Estimation in the Context of Post-Event Analysis of Flash-Flood Events. J. Hydrol. 2010, 394, 17–27, doi:10.1016/j.jhydrol.2010.02.035.
49. Marchi, L.; Borga, M.; Preciso, E.; Gaume, E. Characterisation of Selected Extreme Flash Floods in Europe and Implications for Flood Risk Management. J. Hydrol. 2010, 394, 118–133, doi:10.1016/j.jhydrol.2010.07.017.
50. Bronstert, A.; Agarwal, A.; Boessenkool, B.; Crisologo, I.; Fischer, M.; Heistermann, M.; Köhn-Reich, L.; López-Tarazón, J.A.; Moran, T.; Ozturk, U.; et al. Forensic Hydro-Meteorological Analysis of an Extreme Flash Flood: The 2016-05-29 Event in Braunsbach, SW Germany. Sci. Total Environ. 2018, 630, 977–991, doi:10.1016/j.scitotenv.2018.02.241.
51. Borga, M.; Comiti, F.; Ruin, I.; Marra, F. Forensic Analysis of Flash Flood Response. Wires Water 2019, 6, e1338, doi:10.1002/wat2.1338.
52. Borga, M.; Gaume, E.; Creutin, J.D.; Marchi, L. Surveying Flash Floods: Gauging the Ungauged Extremes. Hydrol. Process. 2008, 22, 3883–3885, doi:10.1002/hyp.7111.
53. Javelle, P.; Demargne, J.; Defrance, D.; Pansu, J.; Arnaud, P. Evaluating Flash-Flood Warnings at Ungauged Locations Using Post-Event Surveys: A Case Study with the AIGA Warning System. Hydrol. Sci. J. 2014, 59, 1390–1402, doi:10.1080/02626667.2014.923970.
54. Borga, M.; Stoffel, M.; Marchi, L.; Marra, F.; Jakob, M. Hydrogeomorphic Response to Extreme Rainfall in Headwater Systems: Flash Floods and Debris Flows. J. Hydrol. 2014, 518, 194–205, doi:10.1016/j.jhydrol.2014.05.022.