



Editorial

An Editorial for the Special Issue “Processing and Application of Weather Radar Data”

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In 2019, the World Meteorological Organization (WMO) pointed out the following based on the statistics from 2007 to 2019: in natural disasters, 90% of losses are related to meteorology, of which heavy storms and floods account for more than 70%. Heavy precipitation plays a very important role in the early warning of meteorological, hydrological, and geological disasters. Therefore, accurate monitoring and early warning and forecasting of heavy rainfall induced by strong convection are the basis for improving our ability to prevent natural disasters, such as floods, landslides, and mudslides.

Currently, the most powerful technique for monitoring natural hazards induced by heavy rainstorms is to use weather radars (e.g., ground-based radars, profiling radars, and space-borne radars) [1,2]. Dual-polarization or dual-frequency radar data are used to derive water mixing ratios and number concentrations as well as to improve the capability of the convection-permitting numerical weather prediction (NWP) models to forecast severe storms at scales varying from a few hundred meters to kilometers. Advanced quantitative precipitation forecast (QPF) products are of great assistance in short-term weather and hydrological forecasting. Associated surface in situ observations, such as from rain gauges, runoff gauges, and disdrometers, are also required for calibrating radar observational variables and products [3,4].

In this Special Issue, studies covered several important topics, involving the development of radar signal processing methods; characterization of errors/uncertainties in remote sensing precipitation products and retrieval algorithm functions of different conditions; new sensing techniques as well as attenuation correction and calibration techniques; applications of radar data in data assimilation to improve the performance of NWP models; development of new analysis methods (e.g., machine learning and data assimilation) to maximize the benefits of using extensive datasets, multi-scale remote sensing data, and in situ data fusion; and application of radar data in disastrous weather (e.g., heavy rain, hail, and tornado) analysis and radar observations of hydrometeorological extremes. All of which improve the skills of QPF, radar signal processing methods, etc.

Routinely, operational weather radars could suffer from many difficulties that limit their data quality and applications. Efforts are made in proposing new bin-by-bin approximation methods employing the European Centre for Medium-Range Weather Forecasts (ECMWF) re-analysis data trying to address the attenuation caused by atmospheric gases and stratiform clouds [5], training the dilated and self-attentional UNet model to improve the completion of weather radar missing data [6], developing novel optimization strategy to mitigate the effects of sidelobes in strong convection weather process [7], and developing techniques for noise cancelation and recovery of radial velocity to improve the quality of three-dimensional radar wind fields [8].



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Understanding the characteristics of the raindrop size distribution (DSD) is crucial to improve our knowledge of the microphysical processes of precipitation and to improve the accuracy of radar quantitative precipitation estimation (QPE). Topics in this Special Issue presented the spatial variability of DSD in different geographic regions and its influence on radar QPE [3], performance differences in the QPE relationship of dual-polarization radars under different schemes, radar wavelengths, and rainfall rates R classes in typical arid areas of China [9]. A new uniformity index for the axis ratios derived from dual-polarization weather radar data was proposed for raindrop area identification and analysis [10]. Microphysics schemes were also tested to depict the contrast between convective and stratiform regions in terms of the DSD [11]. Aircraft observations were analyzed to gain insights in the vertical distribution of cloud microphysical properties in different parts of stratocumulus clouds [12].

Weather forecasting plays a pivotal role in modern society, aiding individuals and decision makers in making informed choices and preparations. Recent advancements in weather radar technology and Blending forecast have propelled meteorological research and forecasting capabilities to new heights. For example, the prediction abilities of the Radar Extrapolation Forecast (REF), Wuhan Rapid Update Cycle (WHRUC), GRAPES_3 km, and Blending are compared and analyzed. It is shown that Blending is obviously better than the single forecast, especially in the heavy precipitation echo forecast, and plays a positive role in the convective forecast [13]. Another notable area of progress lies in the field of nowcasting and QPF. Traditionally, radar echo extrapolation methods have been used for nowcasting, but they often suffer from spatial inaccuracies. However, recent studies have showcased the efficacy of deep learning techniques in improving nowcasting performance. Despite their success, current deep learning-based models face challenges in accurately representing spatial variability, leading to a “blurry” effect in forecasts. To address this issue, researchers have proposed novel approaches, such as the Spatial Variability Representation Enhancement (SVRE) loss function and the Attentional Generative Adversarial Network (AGAN) model [14]. These innovations offer promising solutions for achieving high-precision radar nowcasting applications.

Moreover, the integration of multiscale representations (MSRs) of the atmosphere holds immense potential for advancing model–data fusion techniques in weather forecasting [15]. By reconstructing radar echoes from weather model simulations and satellite products, researchers have unveiled stratified features within the atmosphere, providing valuable insights into small-scale patterns and larger-scale information. This holistic understanding of atmospheric dynamics paves the way for more accurate and reliable forecasts, transcending conventional limitations in nowcasting.

In parallel, advancements in precipitation forecasting have been significant, particularly in addressing the challenges on sub-seasonal to seasonal scales. The development of the Quantile Mapping of Matching Precipitation Threshold by Time Series (MPTT-QM) method represents a breakthrough in precipitation bias correction, offering improved spatial distribution and temporal consistency in forecasts [16]. Furthermore, innovations, such as the nonlinear grid transformation (NGT) method, show promise in enhancing convective echo extrapolation prediction, thereby refining precipitation forecasts and mitigating potential inaccuracies [17].

Beyond forecasting techniques, studies on weather systems, such as mesovortices (MVs) during the rainy season, provide valuable insights into their spatiotemporal distributions and environmental influence [18]. Additionally, the utilization of machine learning algorithms for retrieving temperature and relative humidity profiles demonstrates the interdisciplinary nature of meteorological research [19], offering new avenues for enhancing data accuracy and reliability. Despite the significant progress in radar technology, challenges persist in radar processing and applications. Efforts are under way to improve data quality and maximize the utility of operational weather radars.

In summary, the continuous advancements in weather radar technology hold immense promise for revolutionizing meteorological forecasting and disaster preparedness. As we

navigate an increasingly volatile climate, investing in these innovations is essential for safeguarding lives and livelihoods. By harnessing the full potential of weather forecasting technology, one can better anticipate and mitigate the impact of extreme weather events, ensuring a safer and more resilient future for us all.

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