IMPROVING HYDROLOGIC ANALYSIS AND APPLICATIONS USING QUALITY WEATHER RADAR DATA AND THE STORM PRECIPITATION ANALYSIS SYSTEM

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ABSTRACT

The use of radar estimated precipitation is among the most important technological advancements improving the accuracy and reliability of hydrologic models in recent years. Not surprisingly, the use of radar estimated precipitation is a significant area of research and is applied operationally in a number of practical applications, such as reservoir inflow monitoring, water resources management, stormwater management, and flood warning systems.

Radar data far exceeds the spatial densities of rain gauge networks and has a finer temporal scale (as frequent as 5-minutes) than traditional rain gauges, therefore allowing precipitation estimates to be made at all ungauged locations. While radar estimated precipitation provides a great improvement in temporal and spatial scales for hydrologic modelling, the radar precipitation estimates require correction adjustments to account for under/over estimations, radar beam blockage, hail contamination and radar-precipitation relationships.

The Storm Precipitation Analysis System (SPAS) includes state-of-the-science advances in spatial and temporal radar-aided precipitation analysis. Utilizing Weather Decision Technology’s (WDT) quality controlled Level-II radar data, SPAS utilizes hourly algorithms and correction adjustments to improve the accuracy and reliability of radar-estimated precipitation for use in many applications, including civil infrastructure design and operational hydrology.

For many years, SPAS operated as a post-storm analysis tool, providing hydrologic models the necessary high-resolution precipitation data for calibration and validation. However, SPAS has evolved to have near real-time capabilities using innovative, state-of-the-science techniques. An overview of SPAS real-time (SPASRT), WDT’s radar processing, and a comparison of precipitation using different radar inputs and Z-R algorithms are provided.

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INTRODUCTION

Grounded on years of scientific research with a demonstrated reliability in post-storm rainfall analyses, the Storm Precipitation Analysis System (SPAS) has evolved into a near real-time hydrometeorological tool that provides accurate spatial precipitation data for use in a variety of hydrologic applications. SPAS is a state-of-the-science meteorological tool used to characterize the temporal and spatial details of rainfall events (Parzybok and Tomlinson, 2006). Real-time SPAS (SPASRT), coupled with a real-time hydrologic model, can provide inflow/flood monitoring information.

SPAS was originally designed in 2002 to produce storm depth-area-duration (DAD) analyses for making objective comparisons of rainfall associated with extreme rainfall storms in Probable Maximum Precipitation (PMP) studies, but has evolved to support a number of other applications (Faulkner et al., 2004, Tomlinson et al., 2006 and 2008). SPAS/SPASRT output applications include runoff model calibration/validation, flood event reconstruction, storm water runoff analysis and reservoir/lake inflow monitoring. Detailed rainfall data allow hydrologists to more accurately model runoff from basins, particularly when the rainfall is unevenly distributed over the drainage basin.

During the last several years, SPASRT output has been increasingly used in a greater variety of applications. The added variety of applications has prompted scientific advancements in SPAS, including the use of NEXRAD weather radar data. The coupling of SPASRT with NEXRAD provides accurate spatially and temporally distributed rainfall products for hydrologic applications (Hultstrand et al., 2008). Hourly rainfall observations are generally limited to a small number of locations, with many basins lacking observational rainfall data entirely. While NEXRAD data provides valuable spatial and temporal information over data sparse basins, it has historically lacked reliability for determining rainfall rates and quantitative rainfall amounts.

New techniques have been developed in SPASRT to incorporate NEXRAD radar data together with observed rainfall gauge data, to compute accurate hourly and sub-hourly spatially distributed rainfall. The improved reliability is made possible by calibrating the NEXRAD data each hour with rain gauge observations. The SPASRT computed precipitation provide reliable hourly and sub-hourly estimates over a region and/or individual watersheds with spatial scales down to approximately 1.0 square kilometres (one third of a square mile) and temporal scales as frequent as 5-minute. The high spatial and temporal resolution of the SPASRT rainfall data allows for accurate determination of rainfall volumes over basins and sub-basins for runoff model calibration.

The increased spatial and temporal accuracy of the rainfall analyses has eliminated the need for commonly made assumptions about rainfall characteristics (such as uniform rainfall over a watershed), thereby greatly improving the precision and reliability of hydrologic analyses.
DATA

Rainfall

The coupling of SPASRT with NEXRAD provides accurate spatially and temporally distributed rainfall for hydrologic applications. For the coupling to be effective however, hourly rainfall observations must be obtained for calibrating the radar reflectivity (Z) to rain rate (R) (Z-R relationship). The rainfall observations are often referred to as "ground truth". Hourly rainfall data are identified, acquired, and quality controlled. Since it is imperative to have good, quality rain gauge data, SPASRT imposes four tiers of quality control to the gauge data. The first tier is a gross error check which is actually imposed by the Meteorological Assimilation Data Ingest System (MADIS), the data provider. MADIS eliminates values that are outside pre-set limits (i.e. negative precipitation or precipitation that is grossly too high). The second tier is a spatial check. The spatial check identifies and eliminates values that are not consistent with surrounding values. The spatial check utilizes climatological information for resolving spatial consistency in complex terrain. The third tier is a simple check between the radar reflectivity and reported rainfall. If the radar reflectivity is very high, yet no precipitation was reported, the precipitation is flagged as suspect and not used. The final tier is a statistical check. Utilizing the Z-R relationship, precipitation values that differ more than a pre-defined set of standard deviations from the Z-R relationship are identified and eliminated from the analysis. Figure 1 shows an example Z-R relationship and the color-coded QC flags (except the first tier).
Z-R Relationship SPASRT

03/29/2010 14 (UTC) Radar Scan: 12 R2 = 0.37 IWIs

Figure 1. SPASRT Z-R relationship and gauge QC depiction. Red dots = spatial outlier, yellow dots = high Z-no precipitation outlier, brown = statistical outlier. The green dot represents the maximum Z and its associated precipitation based on the default Z-R relationship (blue line).

Radar

A fundamental requirement for high quality radar-estimated precipitation is a high quality radar mosaic. Weather radar data have been in use by meteorologists since the 1960’s to estimate rainfall depths, but it was not until the early 1990’s that a new, more accurate NEXRAD Doppler radar (WSR88D) was placed into service across the United States. Today NEXRAD coverage of the contiguous United States contains 158 operational stations and 30 in Canada; each radar covers an approximate 463 km (250 nautical miles) radial extent over which the radar can detect precipitation (Figures 2 and 3). Weather Decision Technology (WDT) accesses real-time NEXRAD Level-II radar data from radars across the U.S. and Canada. WDT hosts a computer cluster architecture for radar data processing that includes automated quality control, and sophisticated techniques to combine data from all available radars, resulting in a seamless mosaic (Lakshmanan and Valente, 2006).
Figure 2. Radar locations and 463 km (250 nautical miles) radar extent in the United States.

Figure 3. Radar locations and 463 km (250 nautical miles) radar extent in Canada.

A significant source of error in hydrologic products is low quality precipitation input. Radar clutter or “false echoes in radar data can lead to considerable overestimation of reflectivity–based precipitation. The WDT and National Severe Storms Lab (NSSL) Radar Data Quality Control Algorithm (RDQC) removes non-precipitation artefacts from base Level–II radar data. These artefacts include ground clutter, sea clutter, anomalous propagation, sun strobes,
clear air returns, chaff, biological targets, electronic interference and hardware test patterns. The RDQC algorithm uses sophisticated data processing and a Quality Control Neural Network (QCNN) to delineate the precipitation echoes from those echoes caused by radar artefacts (Lakshmanan and Valente, 2004). Beam blockages due to terrain are mitigated by using 30m DEM data to compute and then discard data from a radar beam that clears the ground by less than 50m and incurs more than 50% power blockage. A clear-air echo removal scheme is applied to radars in clear-air mode when there is no precipitation reported from observation stations within the vicinity of the radar and the observed surface temperature at all stations are above a dynamic threshold. In areas of radar coverage overlap, a distance weighting scheme is applied to assign reflectivity to each 1 km grid, for multiple vertical levels. This scheme is applied to data from the nearest radar that is unblocked by terrain.

Although the radar QC algorithms were developed and tailored for use in the U.S., they have been modified for use in Canada as well. (Zhang et. al. 2008) From the manufacturers of the radar itself to the radar data, Canadian radar is completely different than the U.S. radar data, however WDT has overcome these differences which has allowed seamless, real-time radar data to exist across the U.S. and Canada. See figure 4.

![Map of U.S.-Canada radar mosaic](image)

Figure 4. Sample U.S.-Canada radar mosaic created by Weather Decision Technologies, Inc.

Once the data from individual radars have passed through the RDQC, they are merged to create a seamless mosaic for the United States and southern Canada as shown in Figure 4 and 5. A novel multi-sensor quality control can be applied by post-processing the mosaic to remove any remaining “false echoes”. This technique uses observations of infra-red cloud top temperatures by GOES satellite and surface temperature to create a precipitation/no-precipitation mask. Figure 5 shows the impact of WDT’s quality control measures in the U.S.
Figure 5. (a) Level-II radar mosaic of CONUS radar with no quality control, (b) WDT quality controlled Level-II radar mosaic.

Reflectivity data from WDT are remapped from their native spherical coordinates to a Cartesian coordinate system and ingested by SPASRT. Level II base reflectivity information is provided at a temporal resolution of 5 minutes, a spatial scale of 1x1 km resolution (about 0.33 square miles) and reported at a precision of 0.50 dBZ (dBZ or decibel, is the unit of radar reflectivity).

SPASRT conducts further QC on the radar mosaic by utilizing a beam blockage mask and minimum/maximum allowable radar values. The clean radar mosaic across the watershed is the basis for accurate precipitation estimates over the course of the last hour. Radar reflectivity forecasts are being evaluated as a means of providing short-term (1-6 hours) precipitation forecasts, but are not currently implemented.

Z-R Relationship

SPASRT derives high quality precipitation estimates using the WDT Level–II radar data together with quality-controlled rain gauge data to calibrate the radar-precipitation relationship. Understanding and optimizing the relationships between NEXRAD reflectivity and rain gauge data are essential to confirm the accuracy and reliability of the radar-derived rainfall. In general, most current radar-derived rainfall techniques rely on a relationship between radar reflectivity and rainfall rate. This non-linear relationship is described by the Z-R equation:

\[ Z = A R^b \]

where Z is the radar reflectivity (measured in units of dBZ), R is the rainfall rate (millimeters per hour), A is the “multiplicative coefficient” and b is the “power coefficient”. Both A and b
are directly related to the rain drop size distribution (DSD) and rain drop number distribution (DND) within a cloud (Martner and Dubovskiy, 2005). The National Weather Service (NWS) utilizes several different Z-R algorithms, depending on the rainfall characteristics, to estimate rainfall through the use of their network of NEXRAD radars located across the United States (Figures 2 and 6) (Baeck and Smith, 1998 and Hunter, 1999). A default Z-R relationship of \( Z = 300R^{1.4} \) is the primary algorithm used throughout the continental U.S. It is widely known that radar-based estimates of precipitation that use this approach suffer from deficiencies that may lead to over or under-estimation of rainfall (Clarke, 2009). The variability in the results of Z vs. R is a direct result of differing DSD, DND and air mass characteristics across the United States (Dickens, 2003). The DSD and DND are determined by complex interactions of microphysical processes within a cloud. The DSD and DND fluctuate regionally, seasonally, daily, hourly, and even within the same cloud. For these reasons, SPASRT calculates an optimized Z-R relationship each hour based on observed rain rates and radar reflectivity.

<table>
<thead>
<tr>
<th>RELATIONSHIP</th>
<th>Optimum for:</th>
<th>Also recommended for:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marshall-Palmer ( (z=200R^{1.4}) )</td>
<td>General stratiform precipitation</td>
<td></td>
</tr>
<tr>
<td>East-Cool Stratiform ( (z=130R^{2.6}) )</td>
<td>Winter stratiform precipitation - east of continental divide</td>
<td>Orographic rain - East</td>
</tr>
<tr>
<td>West-Cool Stratiform ( (z=75R^{2.6}) )</td>
<td>Winter stratiform precipitation - west of continental divide</td>
<td>Orographic rain - West</td>
</tr>
<tr>
<td>WSR-88D Convective ( (z=300R^{1.4}) )</td>
<td>Summer deep convection</td>
<td>Other non-tropical convection</td>
</tr>
<tr>
<td>Rosenfeld Tropical ( (z=250R^{1.4}) )</td>
<td>Tropical convective systems</td>
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Figure 6. Commonly used Z-R algorithms by the U.S. National Weather Service.

Instead of adopting a standard Z-R, SPASRT utilizes an iterative procedure for optimizing the Z-R relationship each hour of an event. The process begins by determining if sufficient observed hourly rainfall data are available to compute a reliable Z-R. If insufficient observed rainfall data are available, then the Z-R relationship will either adopt the previous hours Z-R relationship (if available) or apply a user-defined default Z-R algorithm. If sufficient rainfall data are available, they are related to the hourly sum of NEXRAD reflectivity at each rain gauge location. A best-fit power function using the data points is computed. The resulting multiplicative coefficient (A), power coefficient (b) and maximum predicted rainfall are subjected to several tests to determine if the Z-R relationship and its resulting precipitation rates are within a certain tolerance based on observed data and the default Z-R result. From our experience, the actual, optimized Z-R relationship is often significantly different from the NWS developed Z-R relationships as shown in Figure 7.
Figure 7. Comparison of the SPASRT optimized hourly Z-R relationships (black lines) vs. a default 75R2.0 Z-R relationship (red line) for a period of 99 hours for a storm over southern California.

Once a mathematically optimized hourly Z-R relationship is determined, it is applied to the total hourly Z grid to compute an initial rainfall rate at each grid cell. Spatial differences in the Z-R relationship may exist across the domain due to differences in DSD and DND. To account for these differences, SPASRT computes residuals, the difference between the initial precipitation analysis (from the Z-R equation) and the actual observed precipitation (observed – initial analysis), for each gauging station. These point residuals, also referred to as bias, are interpolated to a grid using an inverse distance squared weighting technique. A pre-final hourly precipitation grid is created by adding the residual grid to the initial analysis; this allows the precipitation at the grid cells for which gauges are “on” to be true and faithful to the gauge measurement.

Additionally, an independent precipitation grid is created by using only the gauge data and a climatologically-aided interpolation approach. The climatologically-aided approach uses the relationship between the observed precipitation and a grid of mean monthly precipitation to spatially distribute the precipitation. This interpolation approach has been shown to be reliable in complex terrain. (Hunter, 2005)
The pre-final precipitation grid is subject to some final QC checks to ensure the precipitation patterns are consistent with the terrain; these checks are particularly important in areas of complex terrain where even QCed radar data can be unreliable. Areas that are completely blocked from a radar signal are accounted for with the climatologically-aided gauge data (See Figure 8). Elsewhere, a blend of the climatologically-aided and radar-aided precipitation is used. (Parzybok and Tomlinson, 2004) The blended approach has proven to be an effective method for depicting precipitation patterns in complex terrain, yet retaining accurate radar-based precipitation in flat terrain where radar data is reliable. Figure 9 illustrates the evolution of a final precipitation grid from radar reflectivity in an area of complex terrain.

Figure 8. Depiction of (a) total 1-hour accumulated radar reflectivity across western Washington State and northwestern Oregon and (b) SPASRT precipitation. Note precipitation in areas with blocked radar data (west of the Olympic Mountains in red circle)
Performance measures computed and monitored each hour include the hourly Z-R coefficients, the observed hourly maximum precipitation, the maximum radar-estimated precipitation, the hourly bias, the hourly mean absolute error (MAE), root mean square error (RMSE), and the hourly coefficient of determination ($r^2$).

**OUTPUT**

SPASRT generates a variety of near real-time output which serves as input to hydrologic models or is the basis of other analyses. Depending on the NEXRAD temporal scale (5 minutes), the gridded hourly precipitation data can be disaggregated and delivered at a specified time interval to facilitate the requirements of the hydrologic model. Perhaps the most useful output of SPASRT is the gridded, high resolution rainfall grids; these grids are the basis for basin/sub-basin average rainfall statistics (Figure 10).
Hourly precipitation grids also serve as the basis for computing a storm’s Depth-Area-Duration (DAD) table. DADs are a powerful, yet often over-looked real-time application. DADs have been used for years in determining the probable maximum precipitation (PMP) at various area sizes and durations, but never in near real-time. A DAD analyses provides a three dimensional (time, space and magnitude) characterization of a storm’s precipitation. A DAD provides an objective means of comparing precipitation with past storm
events, and provide an effective tool for comparing rainfall accumulations to flooding thresholds (Parzybok et al., 2009). By calibrating the NEXRAD data to the rain gauge data, reliable rainfall amounts between gauges are computed, thereby increasing the accuracy of the DAD results. With an understanding of DADs, emergency management personnel and dam operators can establish criteria for imposing different actions based on the magnitude of the unfolding precipitation event.

Figure 11. An illustrative sequence (0800 Z – 1100 Z) of real-time 1-hour depth-area (DA) plots as compared to the DA of the storm of record.

Lastly, hourly precipitation grids also serve as the basis for computing the average recurrence interval (ARI) of the storm’s precipitation. Knowing the ARI, or probability of the precipitation occurring in any given year, is a unique, objective and powerful way of translating the precipitation into a meaningful descriptor. Figure 12 shows a sample case event.
Figure 12. Extremely heavy rainfall (a) and its average recurrence interval (b) for the 24-hour period ending at 21-Sep-2009 07:00 AM EDT across northern Georgia USA. Rainfall values in excess of 13 inches equated to a 500+ year event and resulted in severe flooding.

Expressing the rarity of precipitation in terms of an average recurrence interval (i.e. “return period”) provides an objective and useful perspective of the precipitation for decision-makers.

CONCLUSIONS

Grounded on years of scientific research with a demonstrated reliability in post-storm analyses, SPASRT has evolved into a meteorological/hydrological tool that provides accurate reservoir/lake inflow information in near real-time for reservoir management and optimization of hydropower generation. Likewise, SPASRT output has been increasingly used in storm water runoff model validation/calibration. Having reliable rainfall information over the watershed provides a significant improvement over using limited point rainfall measurements from individual rain gauges.

Incorporating NEXRAD data into storm rainfall analyses improves both the spatial and temporal resolution of the rainfall analyses. The approach taken by SPASRT relies on hourly, daily, and total event rain gauge observations to provide quantification of the rainfall amounts while relying on the NEXRAD data to provide the spatial distribution of rainfall between rain gauge sites. By determining the most appropriate coefficients for the Z-R equation on an hourly basis, the approach anchors the rainfall amounts to accepted rain gauge data while using the NEXRAD data to distribute rainfall among rain gauge sites for each hour of the storm. Hourly Z-R coefficient computations address changes in the cloud microphysics and storm characteristics as the storm evolves.

The increased accuracy of the precipitation analyses from SPASRT has eliminated the need for commonly made assumptions about the precipitation characteristics (e.g. uniform rainfall distribution), thereby greatly improving the precision and reliability of input precipitation into hydrologic runoff models. Using NEXRAD data, SPASRT extends rainfall information over open water regions (reservoirs, lakes and oceans) where precipitation information is usually
unavailable. Using high quality precipitation data together with hydrologic models provide valuable reservoir inflow information that can be used to optimize hydropower. Additionally, the unique capability of SPASRT to generate near real-time DADs and ARI maps provide valuable perspectives of precipitation for decision making. With an understanding of DADs and ARI maps, emergency management personnel and dam operators can establish criteria for imposing different actions based on the magnitude of the unfolding precipitation event.
REFERENCES


