STATISTICAL AND HYDROLOGICAL EVALUATIONS OF RAIN GAUGE- AND RADAR-DERIVED PRECIPITATION FOR THE FLORIDA PENINSULA

By

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ABSTRACT

The Multisensor Precipitation Estimator (MPE) software blends the strengths of rain gauge- and radar-derived precipitation estimates to produce a more accurate precipitation product than either data source alone. MPE produces hourly rainfall estimates on a 4 x 4 km grid. The MPE procedure provides several intermediate radar and gauge products along with the final blended estimate. This paper evaluates these components and the final product within the Florida peninsula using two approaches.

The first approach uses an independent set of rain gauges to statistically evaluate each of the MPE components during 1996-1999. The statistics describe the strengths and limitations of each product as related to season and precipitation type. Results show that the final MPE product generally outperforms products that use either gauge or radar data alone. Gauge data alone generally do not adequately describe rainfall spatially or temporally, especially during convective type rainfall. Conversely, radar data alone describe precipitation patterns very well, but many contributing factors lead to its severe underestimation (~50%) of stratiform type precipitation. Compared to the independent set of gauges, the final MPE product generally exhibits highest correlations (~0.73), smallest root mean square differences (~0.13 in.), and smallest biases (-0.002 in. or -2.8%). Florida’s large precipitation variability over small distances prevents even better agreements between the gauge and 4 x 4 km values.
The second part of this study is a hydrometeorological case study of an extreme tropical rainfall event during September 2001 (Tropical Storm Gabrielle). The quantity and spatial distribution of rainfall for this event are evaluated using both a sparse and a dense gauge network as input to the MPE algorithm. Streamflow is simulated based on mean areal precipitation derived from the various MPE products over both a large and a small headwater of the upper St. Johns River in Florida. The streamflow simulations are compared to observed stage data. The results clearly reveal the advantage of having a dense gauge network. Streamflow simulations derived from the final MPE product are found to be superior to those derived from the other radar-influenced precipitation products because the radar by itself severely underestimates actual rainfall. Nonetheless, the final MPE product still underestimates the observed peak stage in each case – probably due to residual radar Precipitation Processing System (PPS) truncation errors, especially in areas where the radar does not detect rain. Although the gauge-only products are found to yield fair results for this rather uniform rain event, the convective type precipitation that often occurs in Florida probably would yield inferior gauge-only products.
CHAPTER 1
INTRODUCTION

Flooding is a major weather-related killer and one of the most damaging forces in nature. Each year in the United States, millions of dollars worth of property are washed away or destroyed; there are over one hundred casualties; and about three quarters of all Federal Disaster declarations are related to heavy rainfall (NSSL 2002). While casualties over the past 100 years have not changed due to better forecasting, the dollar amount of destruction due to floods has increased due to expanding construction. Improved flash flood forecasting and river stage forecasting could limit the destruction that floods cause each year.

Drought also can have societal implications. Florida needs plentiful rainfall to maintain the nation’s largest freshwater aquifer because most of the state’s drinking water comes from that aquifer. Florida’s average annual rainfall is approximately 54 in., which converts to about 150 billion gallons of water per day. Approximately 110 billion gallons of water are lost each day to plant consumption and evaporation, and more than 100 million gallons are used by Floridians per day (Florida Water Services 2001). The aquifer must be maintained with rainwater to keep freshwater plentiful and keep salination (salt water intrusion) from occurring. With Florida’s population expected to double by 2030, and water use expected to increase even more rapidly, water
management issues will become the key to a successful water balance.

Whether related to drought or flooding, it is very important to know where, when, and how much precipitation occurs within a region. The need for accurate high-resolution rainfall data is becoming more important each day due to the emergence of better hydrological modeling. Hydrologists cannot accurately model streamflow, runoff, groundwater, etc. with inaccurate rainfall information. The chances of a given rainfall event producing a flash flood are dramatically affected by such factors as precipitation amount, the size of the drainage basin, the topography of the basin, the amount of urbanization within the basin, etc. (Vieux and Bedient 1998; Stellman et al. 2001).

Accurate precipitation measuring devices are necessary for determining rainfall, and precipitation information can be collected from several primary sources. The rain gauge is the oldest instrument for determining rainfall, and it remains the most reliable sensor even now, hundreds of years since its invention. The rain gauge has gone through many changes over the years. The latest models are heated, automated tipping bucket mechanisms, which have a gauge rim diameter of approximately 8 in. and a resolution of 0.01 in.

Although the tipping bucket produces reliable information most of the time, they are problematic. First, evaporative losses and wind turbulence around a gauge can contribute to an undercatch of precipitation (Groisman and Legates 1994). Second, mechanical malfunctions can cause erroneous articulation problems such as double tipping or other tipping errors intrinsic to the device. Poor placement of a gauge, such as near a building or where there is vegetation growth, also can cause problems. Nesting species, animal deposits, and leaves can clog the funnel and obstruct rain falling into the
gauge. Although devices that reduce the chances of gauge clogging have been constructed, they are not widely used due to the added expense.

A final fundamental concern with gauges pertains to their sole use in analyzing rainfall. That is, unless rain is falling uniformly over the region of interest, gauges cannot correctly depict the rainfall at any distance away from their own locations. Thiessen polygons often are used to describe area-wide rainfall based on rain gauges (Viessman and Lewis 1996), but this closest neighbor approach does not correctly assess the spatial variability of the rainfall. Even high-density rain gauge networks may fail to correctly capture the intense convective cells that often develop on a hot Florida afternoon (Wilson and Brandes 1979; Smith et al. 1996a; Baeck and Smith 1998). The spatial resolution problem of gauges is exacerbated by their random siting. Gauge densities are not uniform, and consequently the dependability of a gauge-only product over a region varies as a function of gauge density. Although clustering three or four gauges within a few hundred meters of each other can serve as a quality control check, the use of many gauges can be inefficient and costly (Steiner et al. 1999).

To resolve the temporal and spatial problems associated with gauges, remote sensing has been applied to precipitation studies. The operational Weather Surveillance Radar 1998 Doppler (WSR-88D) Precipitation Processing Subsystem (PPS) provides reflectivities with a high spatial (as small as 1 km range and 1 degree azimuth) and temporal resolution (every 5-6 minutes). PPS provides rainfall estimates in three dimensions with an aerial coverage extending 230 km from the radar site.

Relationships between radar reflectivity and precipitation are commonly used to estimate the rate of precipitation. The power received by the radar ($P_r$) from a target at
range \( (r) \) is a function of the radar’s characteristics (e.g., beam wavelength, antenna gain, and transmitted power) given by \( C \), and can be written as

\[
P_r = \frac{CkZ}{r^2},
\]

where \( k \) is an attenuation constant, \( Z = \sum D_i^6 \) is the radar reflectivity factor, and \( D_i \) is the diameter of individual raindrops in a unit volume of air. The reflectivity factor can be deduced from \( P_r \), and measured values of \( P_r \) typically are within one decibel of the actual volumetric mean signal intensity (Austin 1987). To obtain the rain rate \( (R) \), the reflectivity factor \( (Z) \) is used in a Z-R relationship of the form

\[
R = aZ^b,
\]

where \( Z \) and \( R \) are functions of drop size distribution (units of \( \text{mm}^6\text{m}^{-3} \) and \( \text{mm hr}^{-1} \), respectively), and \( a \) and \( b \) are two parameters dependent on precipitation type. Results are very sensitive to the raindrop size distribution, which can vary significantly both temporally and spatially (Wilson and Brandes 1979; Austin 1987; Smith and Krajewski 1991; Steiner et al. 1999). Choosing the correct drop size distribution is of central importance in determining rainfall estimates from a Z-R relation. Different distributions of drop size can yield the same \( Z \) and can cause rainfall rates to differ by as much as a factor of three or four (Doviak 1983; Brandes 1975). Default, Convective, Stratiform, and Tropical Z-R relationships have been derived based on regional studies (Fulton et al. 1998; Brandes et al. 1999). Unfortunately, however, there is no universal relationship among the variables.

Several factors complicate radar measurements even before the difficulties just described regarding hydrometeors. First, obstructions or undesired scatterers (e.g., topography, radio wave transmitting towers, dense bird clusters, or aluminum coated
chaff) can interfere with or reflect the radar beam. Second, because of atmospheric refraction and the curvature of the Earth, the height of the radar beam increases as a function of increasing distance from the radar (Austin 1987; Steiner et al. 1999). Third, the width and depth of the radar beam also increase as a function of increasing distance. As a result of these problems, there may be only partial detection or nondetection of low-top stratiform precipitation or improper filling of the radar beam at far ranges (Anagnostou and Krajewski 1998). Finally, the reflectivity that is detected by the radar is not necessarily the same reflectivity that occurs at the surface because of evaporative, condensational or wind effects close to the Earth’s surface.

Certain hydrometeors also can cause quantitative errors in radar rainfall estimates derived from reflectivity. In addition to the effects of evaporation, condensation, and horizontal and vertical wind near the surface, bright banding results from reflectivity enhancement in the melting layer, and hailstones can produce erroneously high rainfall amounts (Doviak and Zrnic 1993; Smith 1986; Anagnostou and Krajewski 1998; Klazura et al. 1999). In addition, atmospheric attenuation or a wetted radome can cause unreliable rainfall estimates. The National Weather Service has implemented algorithms for clutter suppression, attenuation, hail contamination, and range degredation to reduce these errors in the PPS (Fulton et al. 1998).

Forty-six adaptable parameters have been introduced into the PPS to handle radar-to-radar differences in local meteorological conditions, radar siting, topography, and temporal changes in rain type and seasonal effects (Fulton et al. 1998; Anagnostou and Krajewski 1998). Hence, the PPS must be reliably calibrated by finding optimal parameters for each radar site. Contributing to the Z-R discrepancies, a deficiency in the
design of the PPS has been discovered recently. Precipitation amounts may be universally underestimated due to slight truncations during the computation of rainfall totals. Studies have found that this truncation problem is worse for stratiform and long duration events than for brief, convective events, with hourly estimated errors as great as 7.50 mm (Hydrology Laboratory 2000; Hydrology Laboratory 2002).

The newest advance in remote sensing of rainfall estimates is satellites. With the help of the Tropical Rainfall Measuring Mission (TRMM), satellite-derived precipitation estimates have improved greatly over the years. However, TRMM data are too coarse, among many other limitations, to be more effective than radar for most precipitation studies (Nesbitt et al. 2000). However, satellite data can be a very useful source for supplying at least some type of temporal and spatial rainfall data over oceanic or mountainous regions where radar data are unavailable or limited due to blockages.

Many studies have compared the spatial and temporal capabilities of radar- vs. gauge-derived rainfall. Ratios of gauge-derived to radar-derived rainfall accumulations (G/R) have been computed to test the accuracy of the radar. Studies have found that radar-derived values underestimated gauge rainfall by approximately 40% in Oklahoma (Fo et al. 1998). The G/R ratio is greatly affected by the precipitation type (i.e., stratiform or convective). Convective events generally produce good agreement between gauge and radar pairs; however, radar-derived estimates typically underestimate gauges by about 50% in stratiform type rainfall (Baeck and Smith 1998; Klazura et al. 1999).

Gauges can be used to correct radar-derived rainfall over a portion (or complete) radar umbrella. A multiplicative bias generally is applied to radar-derived estimates to “correct” the radar-derived rainfall. The main purpose for creating a multiplicative bias
is to remove many of the area-wide problems associated with radar estimation. Studies have shown that applying a radar-wide (or local) bias helps to reduce quantitative error produced by the radar (Smith and Krajewski 1991). However, several complicating factors still must be addressed. First, an 8-in. diameter point measurement typically is being compared to a 4 x 4 km radar area. A single point measurement does not represent an area that is millions of times greater than itself. However, a larger sample of gauge-radar pairs can produce a reliable bias adjustment factor over a domain. Second, mean field biases are not constant from hour to hour, from storm to storm, or even over the course of a single storm. Therefore, hourly biases are computed, and localized biases (rather than radar-wide biases) can provide better results for larger density gauge networks. Localized biases help resolve range dependent biases that occur within each radar umbrella. Mean field and localized bias adjustment have been the subject of many studies, and their use in National Weather Service (NWS) operational products has produced improved hydrologic forecasting (Smith and Krajewski 1991; Seo et al. 1999; Steiner et al. 1999).

Four widely used products are produced by the WSR-88D Radar Product Generator (RPG) (Fulton et al. 1998), and each is mapped onto the 4 x 4 km Hydrologic Rainfall Analysis Project (HRAP) grid. Stage I is the 4 x 4 km resolution, hourly Digital Precipitation Array (denoted DPA). The RPG calculates DPA data by converting PPS-derived radar reflectivities into hourly rain rates, which then are converted to hourly rainfall accumulations by averaging the rates for each grid cell. Stage II merges gauge data with Stage I radar-derived precipitation accumulations within each radar domain. Stage III applies quality control techniques to both the gauge and radar data and is
designed to mosaic Stage II estimates for an entire River Forecast Center (RFC) region. Finally, Stage IV is simply a nationally mosaicked version of Stage III.

With the help of multiple data sources, many problems that are associated with rainfall sensors can be reduced. One method of multisensor analysis includes removal of radar-wide or localized biases produced by raw radar. A scheme called P1 (Young et al. 2000) is a local biasing of precipitation analyses that is designed to use the radar’s spatial information as a way of interpolating gauge estimates over the gridded analysis. P1 is similar to another local bias adjustment (LMOSAIC) developed by the Hydrologic Research Lab (HRL) and described in more detail later. Young et al. (2000) compared Stage III with the P1 method and determined the strengths and weaknesses of each product. A primary limitation of the P1 process with Florida convection concerns the widespread variability of precipitation (Woodley 1975; Seed and Austin 1990). Relying on the detection of rain at the gauge site to produce a local bias ratio, P1 could produce significant problems during convection. Therefore, Stage III data have been shown to produce better results for convective scenarios and is more appropriate for Florida.

The HRL recently developed a new precipitation estimation scheme known as River Forecast Center Wide Multisensor Precipitation Estimator (RFC-wide MPE), denoted MPE (Breidenbach and Bradberry 2001). The MPE final product (MMOSAIC) is much like Stage III data and is designed to merge the two independent precipitation estimates to produce a product that relies more on those gauges closest to the HRAP grid point, but relies more on radar-wide bias-removed radar estimates farther away from the closest gauge. RFC-wide MPE combines the quantitative strengths of rain gauges and
the spatial strengths of radar-derived precipitation to produce a more dependable precipitation product. The methodology behind MPE is described later in Chapter 2.

This research compares and contrasts the different types of rainfall products produced by MPE. The study consists of two components. First, a statistical analysis is performed using three 8-in. tipping bucket rain gauges (independent of all product calculations) that serve as a validation that is compared against the corresponding 4 x 4 km HRAP grid pixel from gauge-derived, radar-derived, and multisensor products produced by the MPE algorithm. The second component is a hydrometeorological case study that employs streamflow simulations driven by six estimates of mean areal precipitation derived from six rainfall products. Simulated streamflow is compared with observations, and dense and sparse gauge networks are utilized by each of the products to reveal the value of having more gauges. The comparison will describe the accuracy, temporal, and spatial characteristics of radar-only and gauge-only products. Our goal is to demonstrate the meteorological and hydrological strengths and weaknesses of multisensor products.
CHAPTER 2
DATA AND METHODOLOGY

2.1 Precipitation Data Sources

Hourly gauge and radar data for the years 1996-1999 and September 2001 are the chief input for this research. Generally, gauges accurately describe precipitation at their location, while radar measurements describe the rainfall spatially. In this study the strengths of the two input sources are utilized to form a multi-sensor precipitation product using the Multisensor Precipitation Estimator (MPE).

2.1.1 Rain Gauge Data

Two different gauge densities were used to perform the MPE calculations. Comparing results from the dense gauge network with those from the sparse network shows the value of having the additional gauges. Locations of all gauges used in the MPE calculations are shown in Fig. 1.

Three Florida Water Management Districts (WMDs) supplied hourly tipping bucket rain gauge data for 1996-1999 and September 2001 (Fig. 1a). The St. Johns River Water Management District (SJRWMD), The Southwest Florida Water Management District (SWFWMD), and the South Florida Water Management District (SFWMD) contributed 181, 166, and 275 gauges, respectively. With a total of 622 gauges covering
the Florida peninsula, the gauge network is very dense (approximately one gauge every 15 km). However, there are sections in the state with relatively few gauges, especially in the southwest corner.

The gauge data exhibited varying degrees of quality. Each WMD had performed quality control procedures (QC) on their respective gauge data to remove erroneous values. Approximately 90% of the gauge data were considered good. Approximately 5% of the data were determined to be erroneous because of gauge malfunctions in tipping or reporting, while the final 5% of the gauge data consisted of accumulated precipitation totals over some number of hours. Accumulated totals were caused either by double
tipping of the sensor or signal failure from the gauge to the central data collection site. Although we developed a method to distribute the accumulated gauge values over the missing period by utilizing radar-derived values, this method did not show sufficiently positive results (when performed on a good data set) to use with confidence. Therefore, accumulated values were considered to be erroneous for those hours and were omitted from the MPE calculations. The WMD gauge data alone were used in the MPE calculations in Chapter 3.

The Office of Hydrology (OH) supplied gauge data for 1996-1999. However, during this period about 95% of the OH gauges had a resolution of 0.1 in. (not 0.01 in.) and were not used. Three of the 0.01 in. resolution gauges (Daytona Beach, Orlando, and West Palm Beach) were used as independent data for the verification, and these three gauges are denoted in Fig. 1a by asterisks. Since each station recorded over 1500 hours with 0.01 in. or greater precipitation over the four-year period, this constituted a sufficiently large data set for verification.

Figure 1b shows the sparse OH gauge network (asterisks) used to compare against the WMD dense gauge network (filled circles) over the St. Johns River basin (outlined in the figure) for September 2001 (Chapter 4). The sparse gauge network, consisting of 130 gauges over the Florida peninsula, was provided by the Southeast River Forecast Center (SERFC). During September 2001, most of the sparse network gauges supplied data at 0.01 in. resolution. This data set currently is used in operational forecasting at SERFC.


2.1.2 Radar Data

SERFC provided radar-derived precipitation data for the 28 radars within their area of responsibility for September 2001 and 1996-1999, excluding December 1999 (missing radar data). The Digital Precipitation Array (DPA), known as the Hourly Digital Precipitation (HDP) array before 2000, contains Stage I radar information. Having a resolution of approximately 4 km, each DPA radar product uses the 131 x 131 local Hourly Rainfall Analysis Project (HRAP) grid to map one-hour accumulations in polar stereographic coordinates. Each radar’s local HRAP grid domain can be inserted into the national HRAP grid domain for use in larger scale studies. The typical radius of a single radar’s coverage domain is 230 km. Beyond 230 km the radar beam is too voluminous and elevated to reliably approximate surface rainfall due to reflectivity degradation caused by improper beam filling and the beam overshooting rain echo tops.

DPA precipitation estimates were produced from multiple elevation scans. The PPS utilizes a hybrid scan algorithm (based upon beam geometry and a digital elevation model) to minimize the impact of terrain induced beam blockages (O’Bannon 1997). The lowest elevation angle that clears the ground by at least 500 feet at a particular location is used in the DPA product. When higher beam heights must be used to avoid blockages, range degradation can occur at closer distances to the radar.

2.1.3 Climatological Data Sources

In addition to the hourly gauge and radar input data, MPE requires several climatological data references. These include seasonal radar masks and precipitation and elevation combined products.
Unlike Stage III products, the MPE algorithm utilizes radar masks derived from radar climatologies. Radar-derived precipitation and precipitation frequencies were computed from four years of DPA products for each of the 28 radars in the SERFC region. These climatologies revealed areas of radar range degradation and beam obstructions that were not properly treated in the hybrid scan that was applied to the DPA product. The resulting radar mask can be defined as the region of reliable radar observations within each radar domain. The climatologies and masks were prepared seasonally. During the winter season, echo tops typically are lower than during the warm season. Overshooting of low, stratified precipitation is much more likely to occur during the winter season. However, Florida’s low terrain and persistent convection produced few major differences among the masks.

The Parameter-elevation Regressions on Independent Slopes Model (PRISM) procedure adjusts precipitation data based on a digital elevation model (Breidenbach 2001). The goal is to improve MPE estimates in higher terrain areas where blockages are abundant. PRISM climatologies had very little (if any) effect on Florida precipitation because of the state’s relatively flat terrain.

2.2 Multisensor Precipitation Estimation (MPE) Algorithm

RFC-wide MPE optimizes the synthesis of radar- and gauge-derived precipitation to produce more accurate precipitation information (Breidenbach and Bradberry 2001; NCRFC 2002). MPE was configured for use in the AWIPS (Advanced Weather Interacting Processing System) environment at the RFCs and NWS offices across the country. The code was supplied by the Hydrology Laboratory, and for research purposes
at Florida State University (FSU), it was converted from an INFORMIX driven environment to one primarily using flat files. The hourly output produced by MPE was mosaicked onto a Southeast-centered 305 x 382 HRAP grid in the XMRG format. Although the grid mosaic used in this study consisted of the domains of all available radars within the SERFC region, our focus was the Florida peninsula. The MPE algorithm consists of a number of individual components that are described in the following sections.

2.2.1 Thiessen Polygon Mosaic (PMOSAIC)

The first product of the MPE algorithm is a gauge-only precipitation estimate. This output, called PMOSAIC, is based on one of the oldest schemes used to estimate surface rainfall over an area – Thiessen Polygons. Precipitation at each 4 x 4 km grid cell is exclusively determined by the closest available gauge ($G_c$)

$$POLYGON_{ij} = G_c.$$ (3)

Each gauge value defines a polygon whose area depends on the gauge density around the gauge of interest. Although the spatial variability of rainfall with this method is limited, RFCs continue to use Thiessen polygons for streamflow modeling.

2.2.2 Gauge-only Mosaic (GMOSAIC)

Another MPE product that uses gauges alone to produce a precipitation analysis is denoted GMOSAIC. This algorithm produces an optimal estimate of rainfall using a gauge weighting technique that is determined by the gauge’s proximity to each 4 x 4 km grid cell relative to other close gauges. The Optimal Estimation (OE) method (Seo
1998a; Seo 1998b) uses a version of kriging to estimate rainfall amounts directly from the gauges, and its use serves as a tool for removing some of the estimation errors (observed in PMOSAIC) that are caused by spatially varying precipitation. The GMOSAIC approach can be described as

\[ GMOSAIC_i = G_1W_1 + G_2W_2 + G_3W_3 + G_4W_4, \]  

(4)

where each \( W_x \) is the weight for each \( G_x \), and the sum of all weights equals one. OE methods were used in this study because their results have been proven to be more accurate, less biased and more realistic than the more popular reciprocal distance squared method (Seo 1998a). The four nearest gauges within a given radius provide the weighting for a specific cell. When two or more gauges occupy the same grid cell, the gauges in that cell are averaged and interpolated to other cells based on their distance from other nearby cells. Although (4) considers the four nearest gauges, that number is an adaptable parameter.

### 2.2.3 Radar-only Mosaic (RMOSAIC)

The radar only mosaic from MPE consists of the Stage I DPA data for that hour. Each DPA is mapped onto the national HRAP grid, utilizing the radar masks produced prior to running the MPE code. In determining which radar to use for any given grid cell in the mosaic, the evaluated radars must meet the following three conditions: (1) The radar data are available for the given hour. (2) The specified pixel is not a misbin, i.e., not outside the specified radar's mask. (3) The height of the radar beam at the cell location cannot exceed the height of any other radar beam that satisfies the first two conditions.
A mosaicked index radar mask is produced hourly to show which radar’s DPA is used for each cell based on the criteria for producing radar mosaics. Basically, the best radar (no beam blockage, lowest height, and available radar data) is used for each grid cell. If no radar meets the three conditions, then no radar is assigned to the index mask mosaic. The corresponding height mask is simply the height of the specific DPA’s radar beam (corresponding to the index radar mask) for each grid cell. These heights show the elevation for which calculations are made for each cell.

2.2.4 Bias Adjusted Radar Mosaic (BMOSAIC)

Radar-wide biases are calculated for each radar. This hourly computation is done by taking the sum of the gauge values (within each radar mask) divided by the total of the corresponding paired radar values at each gauge cell. Seo et al. (1999) represent the mean field bias ($\text{Bias}_a(k)$) for each hour $k$ and each radar $a$ as

$$
\text{Bias}_a(k) = \frac{\sum_{j=k-l}^{k} \sum_{i=1}^{n(j)} g(j,u_i)}{\sum_{j=k-l}^{k} \sum_{i=1}^{n(j)} r(j,u_i)},
$$

where $g(j,u_i)$ and $r(j,u_i)$ contain the $i$th positive gauge/radar pair at hour $j$, and $n(j)$ represents the number of gauge radar pairs at each hour $j$. Gauge radar pairs are selected only from areas of good coverage within the radar’s domain, and both gauge and radar values must be greater than 0.00 in. In MPE’s adaptable parameters, $l$ is set to fifteen gauge/radar pairs needed to compute a radar-wide bias. If fifteen gauge radar pairs are not found at the current hour, the bias is estimated on different time scales (ranging from hourly to daily to seasonally) by using recursive estimation via exponential smoothing.
The selection of the best bias for each radar umbrella is determined by comparing how recent the bias computation is against the reliability (or sample size) of the gauge-radar pairs. Studies that further describe the process of determining a bias using recursive estimation via exponential smoothing include Smith and Krajewski (1991) and Seo et al. (1999).

The multiplicative bias factor is applied to the entire radar umbrella. Thus, the radar is used for spatially distributing the rainfall, while the gauges are used to calibrate the radar as a whole using relationship

\[ BMOSAIC_{ij} = \text{Bias}_a(k) \times RMOSAIC_{ij}, \]  

where \(BMOSAIC_{ij}\) is each cell of the BMOSAIC product.

### 2.2.5 Local Bias Adjusted Radar Mosaic (LMOSAIC)

The mean field bias adjustment described above corrects for inappropriate radar-wide Z-R relationships and errors in radar calibration. However, the spatial and temporal variability of the Z-R relationship (i.e., varying precipitation types and the presence of hail) can yield local deficiencies. To deal with these locally varying conditions, the LMOSAIC component of MPE performs local bias calculations over the entire RMOSAIC field. Similar to BMOSAIC, LMOSAIC determines a bias based on recursive estimation via exponential smoothing. However, a bias is calculated every 4\(^{th}\) grid cell based on at least 5 gauge/radar pairs (an adaptable parameter) within a 100 km radius from the cell of interest (another adaptable parameter). Local biases for the remaining grid cells are objectively interpolated from those cells having bias calculations, and a local bias field (LOCBIAS) is generated. The locally unbiased radar field then is
computed using the same theory as (6), but substituting $LMOSAIC_{ij}$ for $BMOSAIC_{ij}$ and $LOCBIAS_{ij}$ for $Bias_{a(k)}$.

$LMOSAIC$ initially was thought to be too computationally expensive to run on FSU Sun Workstations (Breidenbach 2001). However, further collaboration and interest in comparisons with $LMOSAIC$ later led to its implementation into the MPE algorithm at FSU. Thus, $LMOSAIC$ is used with the September 2001 data, but it was considered too painstaking (with only little benefit) to rerun all results for the complete 1996-1999 period. Data from August and September 1998 were processed to develop suitable adaptable parameters for the September 2001 study with $LMOSAIC$.

2.2.6 Multisensor Mosaic (MMOSAIC)

The multisensor mosaic field (MMOSAIC) is the final product of the MPE algorithm. MMOSAIC combines gauge data with the bias corrected radar field (either $BMOSAIC$ or $LMOSAIC$) to optimize the use of each sensor and to reduce the error produced by the other products. The OE scheme (described in the GMOSAIC product) again is used to determine the rainfall assigned to each cell of the MMOSAIC product. The four nearest gauges (an adaptable parameter) within a given radius of each cell are used

$$MMOSAIC_{ij} = G_1W_1 + G_2W_2 + G_3W_3 + G_4W_4 + BMOSAIC_{ij}W_5,$$  \hspace{1cm} (7)

where $W_x$ is the weight for each gauge $(G_x)$ determined by its proximity from each grid cell. The closer (farther) a gauge is to an evaluated cell, the greater (smaller) its weight. The bias corrected radar weight $(W_5)$ increases as a function of distance from the nearest gage. The sum of all the weights together equals one. Any grid cell containing a gauge
is assigned that gauge value, and gauge values are averaged when two or more gauges fall within the same grid cell.

A stratiform versus convective test was investigated and implemented into MPE to set the adaptable parameters associated with the weighting of MMOSAIC. A single set of adaptable parameters would not be optimal. Based on in-depth sensitivity testing, we discovered that the optimum adaptable parameters were mostly bi-modal in nature. While convective type events generally are localized and produce relatively intense rainfall, stratiform type rain events typically exhibit more uniform precipitation. Although the distribution and intensity of precipitation over the Florida peninsula varies from hour to hour and during a single hour, two sets of adaptable parameters were selected for the entire peninsula. The type of precipitation was determined each hour by calculating the standard deviation of radar-derived rainfall (from RMOSAIC) for cells indicating rain over the entire Florida Peninsula. The stratiform/convective standard deviation threshold was determined subjectively by viewing precipitation patterns over the Florida Peninsula. A standard deviation of 0.11 in. provided a good separation between the two types of precipitation. Any standard deviation above (below) 0.11 in. was deemed to be convective (stratiform) precipitation.

Three adaptable parameters were set based on the simple standard deviation test: (1) gauge radius of influence, (2) lag-0 indicator cross-correlation, and (3) lag-0 conditional cross-correlation. The gauge radius of influence determines the distance over which each gauge influences its surroundings. We set the radius of influence to be 30 km for convective events and 40 km for stratiform events. These values were selected so that at least one gauge’s influence covered each cell in the peninsula based on the dense
gauge network. In addition, we wanted to keep the range as small as possible to limit unrepresentative gauge data at the cell of evaluation. The lag-0 indicator cross-correlation and lag-0 conditional cross-correlation parameters assist in assigning gauge and radar weights to determine the detection and amount of precipitation, respectively. Values of the correlation parameters range from zero to one, with zero yielding the GMOSAIC product, and one producing the BMOSAIC product. Thus, greater correlation values yield a greater influence of BMOSAIC. More weight theoretically should be given to BMOSAIC (gauges) during convective (stratiform) events because rainfall typically is heavy (light) and spotty (uniform). Therefore, after numerous sensitivity tests, both adaptable parameters were set at 0.925 for convective and 0.65 for stratiform types of precipitation.

2.3 National Weather Service River Forecast System (NWSRFS)

We operated the NWSRFS interactive forecast program (IFP) to obtain streamflow simulations for two headwater sub-basins within the St. Johns River basin of central Florida during September 2001 (Fig. 1b). NWSRFS is a collection of hydrologic models that processes the required parameters and data to simulate river flows and stages (Hydrology Laboratory 2002b). The calibration, Operational Forecast System (OFS), and Extended Streamflow Prediction (ESP) are the three processes within NWSRFS, but only calibration and OFS have applications to this research. Based on historical gauge data, calibration determines the proper parameters to input into OFS and ESP forecasting. OFS maintains model parameters and produces short-term river forecasts for the St. Johns River basin. Output from OFS consists of six-hourly simulated streamflow and 6-
hourly mean areal precipitation. These two output products were calculated from each of
the six different precipitation products (described above) as input to OFS. Simulated
streamflow results from the September 2001 heavy rain event then were compared with
observed streamflow (validation) for the two basins. Shown in Fig. 1b, the Geneva
watershed (GENF1 ~2035 mi²), the larger of the two basins, reached flood stage during
the September 2001 event. However, the smaller watershed, Wekiva River (WEKF1
~210 mi²), did not reach flood stage although heavy rainfall occurred over the basin.

2.3.1 Mean Areal Precipitation (MAPX)

NWSRFS OFS simulations are driven by the precipitation within each basin. The
six precipitation products produced by the MPE algorithm were input separately into
OFS. The MPE data go through pre-processing calculations to derive 1-hourly Mean
Areal Precipitation (MAPX) in each basin. The arithmetic mean of all 4 x 4 km grid
points located within the basin is used to calculate MAPX. Within the OFS execution, 6-
hourly MAPXs are derived by summing 1-hour MAPXs, and 6-hourly precipitation data
were used to guide streamflow simulations into the future.

2.3.2 Calibration of NWSRFS

Calibration of the St. Johns River basin was performed by SERFC. Based on the
knowledge, experience, and many months of effort by SERFC hydrologic forecasters,
their calibration was considered the best that could be done for the relatively flat, slow-
response river basin. Furthermore, since IFP is used as a comparative technique, with
different rainfall inputs that included operationally available data, we wanted to match
the design of the SERFC operational NWSRFS during September 2001.

Two key calibration procedures are essential to the simulated streamflow data. First, the Sacramento Soil Moisture Accounting Model (SACSMA) is used to influence stream runoff calculations using sixteen parameters that account for basin characteristics such as terrain, vegetation cover, percolation rates, and other soil properties (NWSRFS users manual). Studies have investigated SACSMA’s sensitivity to different spatial and temporal scales of precipitation data (Finnerty et. al. 1995). Errors between observed and simulated streamflows have been shown to be very large with some SACSMA parameters.

The unit hydrograph is the second OFS input that requires occasional calibration. Unit hydrographs are derived from historical gauge precipitation and streamflow data, and calibration is performed by relating the two data sources over time. Unit hydrographs for the two basins of this study were derived by SERFC (Fig. 2). The amount of direct stream runoff (with units cfs) resulting from an average of one inch of rainfall over the basin over a specified time defines the unit hydrographs. Obviously, the larger GENF1 basin has a slower response time and greater flow rate than the smaller WEKF1 basin. The unit hydrographs and SACSMA parameters, along with MAPX data, are input to the OFS to determine simulated streamflow for the two diverse basins.
Figure 2. Unit hydrographs for the Geneva (GENF1) and Wekiva River (WEKF1) sub-basins.
CHAPTER 3
STATISTICAL RESULTS

MPE-derived rainfall estimates using the WMD gauge network (Fig. 1a) were compared with independent gauge observations during a 47-month period (January 1996 – November 1999) to evaluate the strengths and weaknesses of each product. Gauges comprising the independent “ground truth” data set were located at Orlando, St. Augustine, and West Palm Beach. These gauges were not used in the MPE calculations. The hourly gauge data were paired with the value of the encompassing 4 x 4 km HRAP grid cell, and these hourly pairs also were summed to daily and monthly totals. Additional evaluations were performed based on season and precipitation type. The first subsection compares the three gauges against MMOSAIC, while the second subsection compares MMOSAIC with other gauge- and/or radar- derived products.

The ability of a radar to estimate precipitation at a location depends greatly on its geometry relative to that location. The Orlando and Daytona Beach gauge sites are located approximately 75 and 125 km, respectively, from the Melbourne radar, while the West Palm Beach site is located 125 km from its closest radar (Miami). Corresponding beam elevations at these gauge locations are below 2 km; therefore, radar sampling issues (i.e., beam spreading and overshooting of precipitation) should be less pronounced than in the study by Wilson et al. (1979).
Several statistical tools were used in the evaluation. Scatter diagrams illustrate the agreement between the MPE products and independent gauges. Four statistical measures (correlation \(r\), bias \(BIAS\), mean absolute difference \(MAD\), and root mean square difference \(RMSD\)) quantify the evaluation. These measures are defined as follows:

\[
\begin{align*}
    r &= \frac{n(\Sigma x_i G_i) - (\Sigma x_i)(\Sigma G_i)}{\sqrt{n(\Sigma x_i)^2 - (\Sigma x_i)^2} \sqrt{n(\Sigma G_i)^2 - (\Sigma G_i)^2}}, \\
    BIAS &= \frac{\sum(x_i - G_i)}{n}, \\
    MAD &= \frac{\sum|x_i - G_i|}{n}, \quad \text{and} \\
    RMSD &= \sqrt{\frac{\sum(x_i - G_i)^2}{n}},
\end{align*}
\]

where \(x_i\) is the MPE value at the gauge \((G_i)\) location and \(n\) is the number of \(G_i-x_i\) pairs. Bias percentages were calculated by dividing \(BIAS\) by the hourly (or daily or monthly) gauge average and then multiplying by 100. Either a gauge or at least one of the five MPE products (BMOSAIC, GMOSAIC, etc.) must have exhibited rainfall to be characterized as a pair.

### 3.1 Gauge-MMOSAIC Precipitation Comparison

Evaluating hourly MPE products is a rigorous test of their performance. However, the scatter diagram of hourly MMOSAIC precipitation (Fig. 3a) shows that values agree quite well with the independent gauge observations. There is an overall
Figure 3. Scatterplots of a) hourly, b) daily, and c) monthly MMOSAIC vs. gauge amounts for three independent gauges between 1996 and 1999.
-0.002 in. (-2.8%) bias between the gauges and the final MPE product. This relatively small bias is evident in the generally even distribution of gauge-MMOSAIC pairs above and below the 1 to 1 line. However, there is a considerable negative bias for gauge values greater than ~ 1 in. The other statistical measures also show good agreement between the independent gauges and MPE product, e.g., $r = 0.73$, RMSD = 0.13 in., and MAD = 0.05 in.

The negative bias associated with greater rainfall totals is not as obvious when daily and monthly totals are compared (Figs. 3b and 3c, respectively). The underestimation of the larger totals described earlier now is reduced considerably. The MMOSAIC daily and monthly totals exhibit a BIAS of −0.008 in. and −0.118 in., respectively. The greater BIAS is attributed to larger rainfall totals when integrating the
hourly totals over longer periods. Daily and monthly percent biases (-2.8%) are the same as the hourly data because overall differences between MMOSAIC and the gauges are the same at any time scale. The daily and monthly correlations of 0.86 and 0.92, respectively, are greater than the 0.73 observed for the hourly data. Like the BIAS calculations, the RMSD and MAD values increase due to the increasing rainfall totals over these longer periods.

Some of the difference between the MMOSAIC and gauge accumulations is not due to error in the MPE-estimated product, but due to natural spatial (and temporal) variations of precipitation within the 4 x 4 km MPE grid cells. There is a distinct sampling problem when comparing a gauge whose area is much less than 1% of the 4 x 4 km MPE area. Young et al. (2000) presented correlograms of gauge-to-gauge rainfall to define precipitation variability within an Oklahoma gauge network, and we have performed similar calculations for Florida rainfall (Fig. 4). Six years of “ground truth” high-density gauge data (1996-2001) were utilized. These gauges comprise the densest area of the SFWMD mesonetwork, with 79 gauges between 26-27°N and 80-81°W.

Figure 4a is a gauge-to-gauge correlogram of hourly precipitation. As expected, the agreement between gauges decreases rapidly with increasing gauge-to-gauge distances, with r < 0.20 beyond 30 km. Even at a distance of 10 km, the average correlation is only ~ 0.45. Corresponding correlograms from the Oklahoma network (Young et al. 2000) exhibited average correlations of 0.45 at a gauge-to-gauge distance of 30-40 km. Thus, the spatial variability of precipitation is greater in Florida than in Oklahoma.
Figure 4. Correlograms of a) hourly and b) daily precipitation totals for 1996-2001 gauge data. The solid line represents the least squares fit line.
The average correlation between two gauges at a 4 km distance (Fig. 4a) is approximately 0.68, revealing the large variability in rainfall that is possible within even our 4 x 4 km computational areas. The RMSD of gauge pairs (not shown) at 4 km distance averages 0.22 in., with MAD averaging 0.11 in. However, with only 32 gauges separated by a maximum distance of 4 km, these values are only approximations. Nevertheless, the large spatial and temporal variability within small areas is realistic given the large precipitation gradients that occur within Florida, especially during the summer.

Figure 4b shows correlograms of daily precipitation. Since temporal differences tend to average out over longer time periods, the daily correlations are larger than the hourly values at all gauge-to-gauge distances. This explains why better results also were evident in the daily scatter diagrams (Fig. 3b). Still, it is important to note that even daily gauge totals can differ significantly at separations within 4 km. Average correlations at 4 km are ~ 0.80 vs. 0.68 for the hourly data. Values of RMSD and MAD increase to 0.42 and 0.25, respectively, mainly because daily totals typically are greater than hourly totals. Much of the gauge-to-gauge difference that is removed by using daily or monthly data is believed to be due to temporal sampling. These differences can occur in the hourly data when one gauge receives rain during the following or previous hour compared to a neighboring gauge – perhaps due to propagating precipitation features. The remainder of the difference that is retained in daily and monthly statistics is attributed to spatially varying rain accumulations.

To determine whether the MMOSAIC vs. gauge evaluations vary with season, the hourly data were divided into cold season and warm season categories (shown in Figs. 5a
Figure 5. Scatter plots of a) cold season and b) warm season MMOSAIC vs. gauge hourly data.
and 5b, respectively). The cold season consists of all hourly data between October and March, while the warm season encompasses the remainder of the year. In comparing the diagrams, the scatter is visibly smaller for the cold season rain events than for warm season events. Indeed, correlations decrease from 0.78 for cold events to 0.71 for warm events. This contrast remains when comparing correlations for daily and monthly totals (not shown). Since lighter precipitation and weaker precipitation gradients generally occur during winter, there is less spatial variability within the 4 x 4 km radar bins.

Although spatial variability typically causes a relatively small correlation during the summer months, biases are greater during the winter season (Fig. 5). MMOSAIC produces a 0.007 in. (9%) underestimation of winter precipitation compared to 0.001 in. (2%) overestimation during the warm season. This underestimation during the cold season likely occurs because some rainfall is poorly detected. In addition, the optimum bias at a given location can vary over the radar domain. These issues are described further in the following section when components of the MPE algorithm are evaluated.

It is informative to determine whether results of the MPE algorithm depend on the type of precipitation that occurs. Therefore, each hour was categorized as having either predominantly stratiform or convective precipitation. This was done by calculating each hour the standard deviation of radar-derived precipitation estimates over the entire Florida Peninsula. Hours with standard deviations greater than 0.11 in. were deemed to have predominantly convective type precipitation, and all other hours were characterized as stratiform. The value 0.11 in. was determined subjectively by viewing spatial patterns of precipitation. This same threshold was used to determine adaptable parameters such as gauge radius of influence and correlation scales for MMOSAIC (Section 2). One should
note that this methodology does not adequately account for hours having a mix of convective and stratiform precipitation. It only considers the aggregate type. Nonetheless, results of the procedure are informative.

Figures 6a and 6b show scatter diagrams of hourly stratiform and convective type rainfall, respectively. One should note the small number of observations exceeding 1 in. in the stratiform type category. Although approximately 60 gauge observations (~1.11%) record greater than 1 in. during the convective hours, only two gauges (~0.06%) record this amount during stratiform events. Large precipitation totals typically cause an hour to be characterized as convective due to the large differences between maximum and minimum amounts. Similarly, the hourly stratiform and convective averages (0.04 in. stratiform, 0.09 in. convective) differ greatly because lighter rain typically is associated with stratiform events.

The statistics show mixed results between the convective and stratiform hours (Fig. 6). The correlation is greater in the convective category (0.74 vs. 0.68), and the bias of -0.001 in. (1% underestimation) is lower (vs. –0.004 in. corresponding to 10% underestimation). Conversely, values of RMSD and MAD reveal better agreement for stratiform precipitation because smaller hourly errors and less spatial variability are associated with the smaller rain amounts. Similar results are seen in daily and monthly accumulations (not shown). Very light stratiform precipitation is not captured well by the radar due to possible overshooting of very shallow cloud tops and truncation errors in the PPS algorithm. A mix of convective and stratiform type precipitation minimized these effects in the cold season results (Fig. 5a). Nevertheless, most stratiform type precipitation occurs during the cold season.
Figure 6. Scatter plots of hourly a) stratiform and b) convective type precipitation.
3.2 Product Intercomparisons

The MPE algorithm produces precipitation estimates by combining gauge data with radar estimates. The five stages of the final MPE product (Section 2) now will be examined. Since rainfall estimates at hourly time intervals are most useful in hydrologic modeling, the section focuses on hourly totals instead of daily or monthly values.

Figure 7 is a scatterplot of GMOSAIC (gauge-only) estimates compared to the three independent gauges used as verification. Compared to MMOSAIC (Fig. 3a), GMOSAIC clearly has greater scatter, with correlations of 0.73 for MMOSAIC vs. 0.42 for GMOSAIC. Furthermore, GMOSAIC contains approximately 50% more zero values than MMOSAIC when the independent gauges observe precipitation greater than zero. It also is important to note the 0.003 in. (5%) overestimate of precipitation by GMOSAIC. The overestimate can be attributed to GMOSAIC giving a value greater than zero, when the gauge reports zero, about 40% more than when the opposite occurs. These relatively poor statistics demonstrate the inability of gauge-only products to correctly assess the distribution and timing of precipitation. The GMOSAIC product clearly is inferior to the final MMOSAIC product.

The scatter plot of Thiessen Polygon estimates (PMOSAIC) vs. gauge accumulations (Fig. 8) is similar to that of GMOSAIC, except the scatter is even greater (r = 0.37 vs. 0.42). Although gauges are very dense near each of the three independent gauges being evaluated (Fig. 1a), they still do not describe accurately the spatial and temporal variability of precipitation on the hourly time scale. Timing problems due to nearby gauges influencing the evaluated grid cell could be reduced by integrating over longer time scales. However, the MMOSAIC product always outperforms the two
Figure 7. Scatter plot of GMOSAIC vs. gauge hourly precipitation data.

Figure 8. Scatter plot of PMOSAIC vs. gauge hourly precipitation data.
gauge-only derived products (GMOSAIC and PMOSAIC) even at longer time scales (not shown) since spatial distribution problems always remain with gauge-only products.

Since the gauge-only products do not depict adequately the spatial distribution of rainfall, radar data are the primary source of precipitation patterns in the MMOSAIC product. Scatter diagrams of hourly RMOSAIC (radar only) rainfall are shown in Fig. 9. Correlations, RMS differences, and mean absolute differences are much improved over the gauge-only products (Figs. 7 and 8). Although the scatter ($r = 0.70$) is comparable to that of MMOSAIC ($r = 0.73$, Fig. 3a), RMOSAIC shows a 0.008 in. (12%) underestimation of precipitation compared to only $-0.002$ (-2.8%) for MMOSAIC – perhaps related to an inappropriate Z-R relationship or truncation errors in the PPS. Wilson et al. (1979) found that a radar underestimated gauge amounts by 63% in Oklahoma. Although their comparison contained many more gauges throughout the radar’s entire domain, radar underestimates are just as prominent in Florida as Oklahoma.

BMOSAIC uses gauge information to remove the mean field bias contained in the RMOSAIC product. Although the goal is to have no remaining bias in BMOSAIC, this does not occur (Fig. 10). Instead, BMOSAIC retains an ~7% underestimate. The Oklahoma study produced bias-applied underestimates of 24% (Wilson et al. 1979). Upon closer inspection, approximately 25% of all gauge-RMOSAIC pairs consist of the radar value being zero when the gauge reports (typically light) rain. Therefore, with the multiplicative radar-wide adjustment in MPE calculations shown in (6), BMOSAIC always remains zero when RMOSAIC estimates zero. However, MMOSAIC incorporates nearby gauge information with the bias-corrected radar spatial information to (hopefully) remove any remaining bias (using the added gauge detail) and to preserve
Figure 9. Scatter plot of RMOSAIC vs. gauge hourly precipitation data.

Figure 10. Scatter plot of BMOSAIC vs. gauge hourly precipitation data.
the spatial texture of the radar-derived precipitation field. One should recall that MMOSAIC calculations (Fig. 3a) reduced the overall bias underestimate to less than 3%.

As the final component of this section, it is informative to examine statistics describing the five MPE products as a function of season and precipitation type. Table 1 provides seasonal statistics, while Table 2 shows statistics regarding precipitation type for all five MPE products. The cold season and stratiform type radar-derived estimates are severely underestimated. For example, the raw radar product (RMOSAIC) underestimates stratiform type rainfall by almost 50%, impairing the correlation calculations due to the many null estimates of light precipitation. With the bias corrected radar product (BMOSAIC), the underestimate improves to 20%, and improves to 10% for MMOSAIC (when the gauge data are combined with the bias corrected radar information). These radar underestimates are more severe for stratiform precipitation than during the cold season because the cold season does contain some convection that is easier for the radar to detect.

The gauge-only products perform especially poorly during the warm season and with convective type precipitation (Tables 1 and 2). Although, the cold season and stratiform type comparisons yield better gauge-only results, the radar-derived and merged products continue to be far superior to the gauge-only procedures even during their best times. Despite the glaring problems associated with gauges, especially during convective type rainfall, hydrologists continue to use mean areal precipitation derived from gauge-only procedures in their lumped models because of their point precision and the long historical record that gauges provide. However, as radar data become more abundant, models can be calibrated with the radar-derived products.
Table 1. Seasonal Hourly Statistics

<table>
<thead>
<tr>
<th>SEASON</th>
<th>METHOD</th>
<th>Correlation</th>
<th>RMSD</th>
<th>MAD</th>
<th>BIAS</th>
<th>Bias %</th>
</tr>
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<tbody>
<tr>
<td>COLD</td>
<td>MMOSAIC</td>
<td>0.78</td>
<td>0.12</td>
<td>0.05</td>
<td>-0.007</td>
<td>-9.27%</td>
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<tr>
<td>COLD</td>
<td>RMOSAIC</td>
<td>0.72</td>
<td>0.12</td>
<td>0.05</td>
<td>-0.025</td>
<td>-34.56%</td>
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<tr>
<td>COLD</td>
<td>BMOSAIC</td>
<td>0.76</td>
<td>0.12</td>
<td>0.05</td>
<td>-0.010</td>
<td>-13.81%</td>
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<tr>
<td>COLD</td>
<td>GMOSAIC</td>
<td>0.56</td>
<td>0.15</td>
<td>0.06</td>
<td>-0.001</td>
<td>-1.59%</td>
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<tr>
<td>COLD</td>
<td>PMOSAIC</td>
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<td>0.17</td>
<td>0.07</td>
<td>-0.002</td>
<td>-2.63%</td>
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<tr>
<td>WARM</td>
<td>MMOSAIC</td>
<td>0.71</td>
<td>0.14</td>
<td>0.05</td>
<td>0.001</td>
<td>2.07%</td>
</tr>
<tr>
<td>WARM</td>
<td>RMOSAIC</td>
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<td>0.05</td>
<td>0.003</td>
<td>4.90%</td>
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<tr>
<td>WARM</td>
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<td>0.05</td>
<td>-0.001</td>
<td>-1.61%</td>
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<td>0.23</td>
<td>0.09</td>
<td>0.008</td>
<td>12.46%</td>
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Table 2. Precipitation Type Hourly Statistics

<table>
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<th>TYPE</th>
<th>METHOD</th>
<th>Correlation</th>
<th>RMSD</th>
<th>MAD</th>
<th>BIAS</th>
<th>Bias %</th>
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</thead>
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<tr>
<td>STRATIFORM</td>
<td>MMOSAIC</td>
<td>0.68</td>
<td>0.07</td>
<td>0.03</td>
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<td>RMOSAIC</td>
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<td>0.03</td>
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<td>-48.66%</td>
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<td>STRATIFORM</td>
<td>BMOSAIC</td>
<td>0.68</td>
<td>0.08</td>
<td>0.03</td>
<td>-0.007</td>
<td>-19.78%</td>
</tr>
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<td>STRATIFORM</td>
<td>GMOSAIC</td>
<td>0.45</td>
<td>0.08</td>
<td>0.04</td>
<td>0.000</td>
<td>0.84%</td>
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<td>PMOSAIC</td>
<td>0.39</td>
<td>0.10</td>
<td>0.04</td>
<td>0.002</td>
<td>6.65%</td>
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<td>CONVECTIVE</td>
<td>MMOSAIC</td>
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<td>0.16</td>
<td>0.06</td>
<td>-0.001</td>
<td>-0.89%</td>
</tr>
<tr>
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<td>RMOSAIC</td>
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<td>0.07</td>
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<td>-2.33%</td>
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<td>CONVECTIVE</td>
<td>GMOSAIC</td>
<td>0.40</td>
<td>0.22</td>
<td>0.10</td>
<td>0.005</td>
<td>6.07%</td>
</tr>
<tr>
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<td>PMOSAIC</td>
<td>0.35</td>
<td>0.25</td>
<td>0.10</td>
<td>0.005</td>
<td>5.82%</td>
</tr>
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</table>

In summary, gauge-only products do not describe accurately the spatial and temporal distribution of Florida’s rainfall even with the comparatively dense gauge network that is available in Florida. Conversely, RMOSAIC exhibits severe underestimates during the cold season and with stratiform type rainfall. The blended gauge-radar products (MMOSAIC and BMOSAIC) produce the best results. Although the two blended products are similar in many statistics, MMOSAIC tends to outperform BMOSAIC because of the residual effects of radar underestimates due to the radar not detecting rainfall at a point that is receiving rainfall. Thus, MMOSAIC is the optimum of
the five products due to the additional information missing in RMOSAIC and BMOSAIC.
CHAPTER 4

CASE STUDY OF THE ST. JOHNS RIVER BASIN DURING SEPTEMBER 2001

Tropical Storm Gabrielle made landfall along the west coast of central Florida around 1200 UTC 14 September 2001. Although September typically is considered a convective month, Gabrielle produced a mix of stratiform and convective precipitation over central Florida. Gabrielle’s circulation, coupled with a strong onshore flow, caused heavy rain along the northward flowing St. Johns River, with individual gauge totals reaching 10 in. The storm slowly traversed the peninsula, producing major flooding and $230 million of damage due to the heavy rains and winds (Lawrence et al. 2001). River flooding caused most of the damage. This is an example of when accurate streamflow modeling would be very important to the general public. And, as noted earlier, there is a need to better describe the precipitation amounts that are inserted into the hydrologic models. This chapter intercompares the six precipitation products from MPE, as well as their performance in a hydrologic model, for two headwaters of the upper St. John’s River. Two different gauge networks (a WMD dense network and an OH sparse network) were utilized in the product computations to show the dependence on gauge density.

Mean Areal Precipitation (MAP) and simulated streamflow (driven by MAP) were used to quantify the different products over the Geneva (~ 2035 mi²) and Wekiva
River (~210 mi²) headwaters of the St. John’s River (Fig. 1b). Values of MAP were computed at 1-hour intervals from the MPE precipitation data and then summed to 6-hour intervals between 10-27 September. MAP was computed for both basins and from both the sparse and dense rain gauge networks. Smith et al. (2000) found that final Stage III MAP was 20 percent smaller than gauge-derived MAP over northeast Oklahoma using a mesonetwork of rain gauges. Stellman et al. (2001) found that MAP computed from Stage III underestimated gauge-derived MAP by 40% for the Cullodin basin in Georgia using a sparse network of gauges.

4.1 East Central Florida Rainfall Comparisons

Total precipitation from 0000 UTC 12 September through 0000 UTC 16 September was derived from each of the six products. The WMD gauge network (Fig. 1b), also used in the MPE calculations in Chapter 3, has a spacing of approximately one gauge every 15 km, and four day accumulations from this gauge network are shown in Fig. 11. A sparse gauge network (Fig. 1b), denoted the OH gauge network, was used to produce the accumulations shown in Fig. 12. The sparse gauge network contained very few gauges near the St. Johns River district (~1 gauge per 100 km). The Geneva headwater (the larger watershed) and the Wekiva River headwater (the smaller watershed) are outlined in the two figures.

The Thiessen polygon (PMOSAIC) (Fig. 11a) and gauge optimal estimation (GMOSAIC) (Fig. 11b) precipitation products have similar 4-day accumulations. The greatest precipitation totals in the Geneva watershed (maximum ~8 in.) occur in the northern and eastern portions of the watershed, while the greatest totals in the Wekiva
Figure 31. Rainfall totals (in.) for 12-16 September 2001 using the dense (WMD) gauge network. The rainfall totals are derived from a) PMOSAIC, b) GMOSAIC, c) RMOSAIC, d) BMOSAIC, e) LMOSAIC, and f) MMOSAIC. Outline of the Geneva and Wekiva watersheds are shown.
Figure 12. Rainfall totals (in.) for 12-16 September 2001 using the sparse (OH) gauge network. The rainfall totals are derived from a) PMOSAIC, b) GMOSAIC, c) RMOSAIC, d) BMOSAIC, e) LMOSAIC, and f) MMOSAIC. Outline of the Geneva and Wekiva watersheds are shown.
watershed (maximum ~ 6 in.) occur in the northern part of the watershed. The total precipitation amounts are similar for both products because both are derived solely from gauges, although the interpolation schemes (discussed previously) are different for each. The jagged texture of PMOSAIC reveals discontinuities in the product. This is evident, for example, in the very southern portion of the Geneva watershed where 5 in. rainfall totals are adjacent to 2 in. totals. Although GMOSAIC is a much smoother analysis of the gauge data, neither of these gauge-derived products realistically depicts the spatial texture of the rainfall.

The radar only product (RMOSAIC) (Fig. 11c) exhibits a much-improved spatial variation of rainfall, but rain amounts are too small, not exceeding 4 in. in either watershed. In fact, the greatest RMOSAIC total in all of east central Florida is less than 5 in., although many gauges (especially north of the watersheds) report totals exceeding 6 in. Given the substantial gauge totals, the river flooding and the longevity of the event, one expects actual four-day totals to exceed these radar estimates.

The three blended products (BMOSAIC, LMOSAIC, and MMOSAIC) are shown in Figs. 11d-f. The MMOSAIC product (Fig. 11f) was calculated using BMOSAIC (not LMOSAIC), as done in the previous chapter. Precipitation in the extreme northern part of the Geneva basin and along the eastern Florida coastline increases from ~ 2-3 in. in RMOSAIC to ~ 4-6 in. in each of the blended products. The spatial texture derived from RMOSAIC generally is preserved in the blended products, and rainfall amounts in most locations are doubled compared to RMOSAIC. While blended precipitation totals are similar to those from gauges, the spatial variability of precipitation totals in the blended products is greater than (and seemingly more realistic than) the variability of precipitation
within the gauge-only products (Fig. 11a-b). Thus, blended products appear to improve precipitation estimates by combining the gauges’ accuracy in amount with the radars’ spatial structure.

When gauge only analyses are prepared from the sparser OH gauge network (Figs. 12a and 12b), the resulting texture is more uniform than from the dense gauge network as a result of the fewer gauges. RMOSAIC (Fig. 12c) is merged with the sparse gauges to produce the blended products in Fig. 12d-f. Although the spatial variability of the precipitation greatly improves with the added radar data, precipitation totals from the blended products are not much greater than the radar-only totals in many areas. With less gauge information, the corresponding bias calculations are less accurate than from the dense gauge network, producing less rainfall in these blended products than from the denser gauge network (Fig. 11d-f).

Four day MAP totals from each product (Table 3) were computed over the entire Upper St. Johns area and surrounding region (Figs. 11 and 12). The two gauge-only products produced the most rainfall, with total MAP accumulations reaching ~ 4.70 in. for the dense gauge network. RMOSAIC is ~ 55% less than the gauge-only products.

<table>
<thead>
<tr>
<th>Method</th>
<th>WMD network</th>
<th>OH network</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>PMOSAIC</td>
<td>4.68</td>
<td>5.40</td>
<td>-0.72</td>
</tr>
<tr>
<td>GMOSAIC</td>
<td>4.66</td>
<td>5.33</td>
<td>-0.67</td>
</tr>
<tr>
<td>RMOSAIC</td>
<td>2.16</td>
<td>2.16</td>
<td>0.00</td>
</tr>
<tr>
<td>BMOSAIC</td>
<td>3.24</td>
<td>2.94</td>
<td>0.30</td>
</tr>
<tr>
<td>LMOSAIC</td>
<td>4.31</td>
<td>1.90</td>
<td>2.41</td>
</tr>
<tr>
<td>MMOSAIC</td>
<td>3.68</td>
<td>3.16</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Table 3. Mean areal precipitation for East Central Florida (12-16 September 2001).
with a MAP of 2.16 in. Dense network BMOSAIC and MMOSAIC produce MAP totals of 3.24 in. and 3.68 in., respectively. MAPs from these blended products appear more realistic than MAP derived by RMOSAIC for this prolonged tropical rain event. Although LMOSAIC’s 4 day MAP total (4.31 in.) appears reasonable, some 4 x 4 km grid cells off the Florida coast (in the extreme northeastern portion of Fig. 11) exhibit unrealistic 1-hour precipitations that exceed 6 in. for some hours (not shown) because of improper local bias adjustments over the water. LMOSAIC’s MAP totals over land where gauges are abundant are more comparable to MMOSAIC.

There are clear differences in the results from the two gauge networks (Table 3). The two gauge-only products from the denser network produce a MAP that is ~ 0.70 in. smaller than the sparse gauge network. On the other hand, MMOSAIC MAP from the denser network is 0.52 in. greater than that from the sparse network, BMOSAIC MAP is 0.30 in. larger, and LMOSAIC is 2.41 in. larger. The small sparse network MAP produced by LMOSAIC probably occurs because there usually were fewer than five gauge-radar pairs in the sparse network to calculate the local bias. Thus, there was insufficient gauge information to create a reliable bias.

4.2 Large Headwater Basin – Geneva

Cumulative sums of MAP in the Geneva headwater were computed at 6-hour intervals between 1200 UTC 10 September and 1200 UTC 27 September 2001 from each precipitation product using the WMD gauges (Fig. 13a). The Geneva watershed contains 16 gauges (Fig. 1b), and these gauges are most concentrated in the southern part of the watershed. Another 5-10 gauges located outside of the watershed influence the MAP
Figure 13. Cumulative mean areal precipitation for the Geneva watershed during 10-27 September 2001 using (a) the dense gauge network and (b) the sparse gauge network.
calculations of this large basin. The two vertically dashed lines indicate the starting and ending times of the accumulations shown in Figs. 11 and 12. The plot shows that the heaviest precipitation occurs on 14 September. 17-day cumulative GMOSAIC and PMOSAIC MAP are almost identical, ~ 5.50 in. Conversely, RMOSAIC produces the smallest accumulation with 2.64 in. Cumulative amounts for the three blended products are between the gauge-only and radar-only products, with 4.02 in. for BMOSAIC, 4.63 in. for LMOSAIC, and 4.58 in. for MMOSAIC. The relatively small differences between the three blended products occur because the precipitation is relatively uniform, and the large number of gauges samples this spatial distribution well. The temporal increases in each product’s accumulated MAP typically are proportional to the other blended products during the 17-day period.

Only five sparse OH gauges (all located outside of the watershed) influence the entire 2035 mi² Geneva watershed (Fig. 1b), certainly an inadequate distribution to determine accurate MAP over the basin. As noted earlier, Geneva’s greatest precipitation totals from the dense network (shown in Figs. 11a and 11b) are located in the northern and extreme eastern portions of the watershed. Likewise, the OH gauges that influence the basin are located just north of the watershed and near the coast just east of the watershed. Therefore, the gauges do not sample the lighter precipitation that occurs in the southwest portion of the watershed. Hence, the OH gauge-only products overestimate MAP for the basin.

Cumulative sparse network MAP from BMOSAIC and MMOSAIC (Fig. 13b) are ~ 4 in. less than for gauge-only MAPs. There are two reasons for this difference. First, as noted above, the few gauges available to compute the gauge-only products
overestimate rainfall for the basin since there are no gauges where the lighter precipitation occurs. Second, there are too few gauge-radar pairs to determine the appropriate radar-wide bias for BMOSAIC and MMOSAIC. This limitation is most pronounced with LMOSAIC.

Stellman et al. (2000) showed that rainfall timing was an important issue between their different precipitation products, especially during convective type precipitation. They found that 1-hour radar-derived MAP had fewer temporal problems than 1-hour gauge-derived MAP. While gauge-only product timing issues are not the major problem for our dense network-derived 6-hour accumulations (Fig. 13a) as they were for Stellman et al. (2000), timing problems are evident in our sparse network-derived gauge-only products in the Geneva watershed (Fig. 13b). The timing of PMOSAIC and GMOSAIC precipitation clearly is different from the other products, especially near 14 September. MAP from the gauge-only methods does not rise proportionally with the radar-derived products because gauges outside the Geneva basin contribute to the basin’s MAPs.

Simulated streamflows in the Geneva watershed (Fig. 14) exhibit large differences due to the different MAP inputs (Fig. 13). Stage III data (Breidenbach et al. 1998) were input to NWSRFS before 10 September to compute the initial simulated stages that are shown. This was required since SERFC’s IFP software that we employed only could accommodate 17 days of MPE data. The simulations diverge after 10 September in response to the different MPE products. The NWSRFS simulations are based primarily on layered soil moistures at each time step.

Simulations from the dense network are shown in Fig. 14a. The observed peak stage of 8.6 ft is spread over about a one-week period due to the slow response of the
Figure 14. Streamflow simulations for the Geneva watershed during 10-27 September 2001 using (a) the dense gauge network and (b) the sparse network.
basin as a result of its flat topography and large size. Peak simulated stages range from only 6.9 ft for RMOSAIC to 9.3 ft for PMOSAIC and GMOSAIC. Peak stages from the two gauge-only products overestimate the observed peak, while all radar-influenced products underestimate the observed peak. Since the gauge density is ideal for small-scale bias calculations, LMOSAIC shows the best simulation, with only a 0.2 ft underestimate of the observed peak. MMOSAIC also produces a good simulation with only a 0.3 ft underestimate. One might expect even better results if LMOSAIC is substituted for BMOSAIC in the MMOSAIC calculations (from Eq. 7). A test simulation (not shown) using LMOSAIC to calculate MMOSAIC reveals a peak stage of 8.7 ft, only 0.1 ft above the observed peak stage. Thus, LMOSAIC provides better results than BMOSAIC in a dense gauge network. Finally, one should note that shapes of the various simulated hydrographs differ from the observed. These differences likely are due to the type of precipitation that occurred. Although this event was stratiform, the unit hydrograph forces a simulation that is similar to typical Florida convective events.

The radar-influenced streamflow simulations may underestimate the observed stage as a result of truncation errors in the PPS rainfall algorithm. These problems are not resolved entirely even after the bias correction is applied (BMOSAIC), especially where RMOSAIC does not detect precipitation. Since RMOSAIC is simply multiplied by a given factor dependent on gauge-radar pairs (from Eq. 6), BMOSAIC and LMOSAIC calculations always will exhibit no precipitation where the radar fails to detect precipitation. MMOSAIC is better in theory because it incorporates gauge information to modify precipitation in the vicinity of gauges receiving precipitation;
however, as Chapter 3 has shown, MMOSAIC may underestimate actual precipitation by up to 10%, especially in stratiform precipitation.

Simulations using the sparse network are shown in Fig. 14b. Peak stages range from 6.7 ft for LMOSAIC to almost 10.7 ft for PMOSAIC. The two gauge-only products overestimate the observed peak by ~ 2.0 ft; MMOSAIC and BMOSAIC underestimate the peak by ~ 0.5 ft; and LMOSAIC and RMOSAIC underestimate the peak by over 1.5 ft. None of the simulations accurately predicts the peak observed stage, and the overall rises and recessions of the simulated stages are different than observed.

It is clear that the dense WMD gauge network produces simulations that are much closer to the observed than those from the sparse OH network.

4.3 Small Headwater Basin – Wekiva River

Figure 15 shows cumulative sums of MAP in the Wekiva River headwater. Four WMD gauges are located inside or on the border of the Wekiva River headwater, and two more gauges from outside the basin also influence the MAP. Based on these dense WMD gauges (Fig. 15a), total 17-day accumulations range from 2.2 in. for RMOSAIC to slightly greater than 6 in. for both gauge-only products, with the heaviest precipitation occurring on 14 September. RMOSAIC is ~ 65% less than the gauge-only products. BMOSAIC, LMOSAIC, and MMOSAIC are ~ 35%, 20%, and 15% less, respectively. Although precipitation amounts from the various products are different, the timing of the heaviest precipitation throughout the 17-day period is similar among the products.

Greater MAP differences and precipitation timing problems again occur when only the sparse network of gauges is used (Fig. 15b). There are no OH gauges within the
Figure 15. Cumulative mean areal precipitation for the Wekiva watershed during 10-27 September 2001 using (a) the dense gauge network and (b) the sparse gauge network.
Wekiva watershed. Only three external gauges influence the MAP computations. One
gauge is located close to the basin’s southeastern border, while two other gauges are
located about 15 miles east and west of the watershed. At the end of the period,
MMOSAIC and BMOSAIC are ~ 45% and 55% less than the gauge-only products,
respectively. LMOSAIC (~ 1.9 in.) is ~ 75% less than the gauge-only products (~ 7.5
in.), while RMOSAIC is ~ 70% less than the gauge-only products. Precipitation timing is
similar among the radar-influenced products, but the gauge-only products show different
timings than the blended products. For example, greatest 6-hour precipitation amounts
for radar-influenced products occur between 1200 and 1800 UTC 14 September, while
gauge-only products produce the greatest 6-hour precipitation between 1800 UTC 14
September and 0000 UTC 15 September.

One should note the large increases in PMOSAIC and GMOSAIC on 22
September when OH gauges are used (Fig. 15b). An isolated thunderstorm produced
over 1 in. of rain at the gauge near the southeastern border of the basin. As a result of the
very few gauges near the Wekiva River watershed, the MAP calculations depend almost
entirely on this one gauge that produces a copious rain amount. The other products
derived from OH gauges, and all the products derived from WMD gauges, do not exhibit
the same spike because the radar and gauges within the dense gauge network better detect
the overall precipitation and correctly minimize the precipitation occurring from the
isolated, convective thunderstorm.

Simulations for the Wekiva River using the dense gauge network are shown in
Fig. 16a. The observed peak stage is 4.3 ft on 16 September. Peak simulated river stages
occur between 0000 and 1200 UTC 16 September, ranging from only 3.0 ft for the
Figure 16. Streamflow simulations for the Wekiva watershed during 10-27 September 2001 using (a) the dense gauge network and (b) the sparse network.
underestimated RMOSAIC product to 4.7 ft for the slightly overestimated PMOSAIC product. MMOSAIC (and GMOSAIC) perform nicely, with a simulated peak stage of 4.1 ft (4.5 ft), about 0.2 ft lower (higher) than observed. LMOSAIC performs almost as well as MMOSAIC, but BMOSAIC underestimates the stage by 0.7 ft (~ 15%), not quite as poorly as RMOSAIC’s 1.3 ft (~ 25%) underestimate. In a test calculation (not shown), MMOSAIC using LMOSAIC (instead of BMOSAIC) reveals only a 0.1 ft overestimate. Again, radar- influenced streamflow simulations may exhibit problems associated with slight truncation errors in the PPS, especially where the radar reports no precipitation.

Many of the forecast river stages differ less than 1 ft from observed. These relative agreements are attributed to the small basin area, which results in a smaller volume of precipitation, smaller variability of precipitation, and ultimately quicker river response of the watershed than with the larger Geneva watershed. The good agreements between the observed data and simulated data with respect to the timing and height of the peak suggest that the model is suitably calibrated for this watershed.

The gauge-only products outperform the radar-influenced products when using the sparse OH gauge network (Fig. 16b). The gauge-only products follow the observed stage very well before and after the peak on 16 September. All other products under-simulate the observed stage by ~ 35% for LMOSAIC, ~ 30% for RMOSAIC, ~ 18% for BMOSAIC, and ~ 12% for MMOSAIC. This better agreement with the sparse gauge-only products is surprising since no sparse network gauges were located within the Wekiva basin. The agreement may be accidental. It is clear that additional cases should be run to verify this finding. The blended product under-simulations probably are caused primarily by not having enough gauges to compute a reliable bias for the region.
Although the GMOSAIC and PMOSAIC sparse network simulations respond best during Gabrielle’s uniform rain event, one should note that their simulated stages rise erroneously due to the large MAP on 22 September. All other methods show recessions similar to the observed response beyond 17 September.

All simulated stages from both gauge networks (Fig. 16a,b) show similar recessions between 16-20 September. However, after 20 September, all simulations (except for sparse network PMOSAIC and GMOSAIC after 22 September) recede quicker than the observed stages, probably because the unit hydrograph being used was based on historical data. Specifically, the mix of stratiform and convective rain that fell between 12 and 16 September as a result of Gabrielle is not typical of Florida warm season rain events. These results suggest that the end point blended MPE product (MMOSAIC) requires additional gauges to produce high quality streamflow simulations over the relatively small Wekiva River basin.

It is important to note that only the sparse gauges were used to determine the unit hydrographs and SACSMA parameters used in IFP. These are the data used operationally by SERFC. A long period of precipitation data would be needed to calibrate using the other blended products or the dense gauge network. Calibration using other products (or more gauges) might eliminate some of the differences between the blended product simulations and observed streamflow in Figs. 14 and 16. However, one should not expect perfect simulations because each rain event is unique, and soil and subsurface water concentrations, infiltration rates, evaporation, etc. vary temporally and spatially. Depending on where the precipitation occurs, SACSMA parameters may not correctly assess these features because the model averages over the whole basin, not
considering spatial variations of precipitation and calibrated parameters. Additional tests must be conducted to determine the validity of the conclusions made here.
CHAPTER 5
SUMMARY AND CONCLUSIONS

This research has evaluated six different precipitation products that are produced by the Multisensor Precipitation Estimator (MPE) software. These products included Thiessen Polygons (PMOSAIC), a gauge-only optimal estimation scheme (GMOSAIC), a radar-only scheme (RMOSAIC), a radar-wide bias adjustment scheme (BMOSAIC), a local bias adjustment scheme (LMOSAIC), and the final multisensor product (MMOSAIC). Each method produced hourly precipitation estimates on a 4 x 4 km grid over the entire Florida Peninsula. Data from a dense gauge network supplied by the Florida Water Management Districts (WMD gauges) and a sparse gauge network supplied by the Southeast River Forecast Center were used in computing the gauge-derived products. The radar-derived products utilized output from the Weather Surveillance Radar 1988 Doppler (WSR-88D) called Hourly Digital Precipitation (HDP) data. The final MPE product blended the strength of the gauges (accuracy at a point) with the strength of the radar (detailed patterns of spatial rainfall).

Two procedures evaluated the performance of each precipitation product. First, the precipitation products were compared statistically against independent verifying gauges (not used in the product calculations) during 1996-1999. Second, a case study of September 2001 investigated the quantity and spatial distribution of rainfall as well as
simulated streamflow from each of the precipitation products within two sub-basins of the St. Johns River.

The MMOSAIC product blends nearby gauge data with a bias corrected radar-derived rainfall field. Our overall statistical results showed that MMOSAIC outperformed the other precipitation methods. Scatterplots of hourly precipitation showed that MMOSAIC generally exhibited highest correlations (~0.73), smallest RMSD (~0.13 in.), smallest MAD (0.05 in.), and smallest biases (-0.002 in. or –2.8%). Although the best MMOSAIC correlations occurred during the cold season, biases were smallest during the warm season and for convective type precipitation. However, the statistics reveal that MMOSAIC certainly is not perfect, and there is considerable potential for improvement. The small-scale variability of precipitation and the human subjectivity of choosing appropriate adaptable parameters are among the two primary complications.

One cannot expect perfect agreement between gauge data and MPE products at 4 x 4 km resolution since large precipitation variability can occur within a 4 x 4 km area. Correlograms of hourly gauge precipitation revealed the variability of paired gauge amounts over a range of distances. Average correlations were approximately 0.7 at a gauge-to-gauge distance of 4 km. Therefore, to produce potentially better precipitation product correlations, the resolution of the radar-derived products must be increased, e.g., to 2 x 2 km or smaller.

MPE contains numerous adaptable parameters for which values must be selected. Optimal parameter values can vary regionally, temporally, and throughout the course of a storm. Our parameter values were selected based on a stratiform vs. convective type precipitation test. Whether precipitation was convective or stratiform was determined by
calculating the standard deviation of non-zero precipitation over the Florida peninsula each hour. The greater the standard deviation of rainfall is, the more variable and isolated the rainfall. When precipitation is highly convective and isolated (which occurs often in Florida), the gauge influence distance should be small, and the weights of nearby gauges also should be small. Conversely, the influence of nearby gauges should be greater when precipitation is stratiform because the radar does not adequately detect shallow stratiform precipitation due to beam overshooting and precipitation processing truncation problems that exist with light rain amounts.

Our examination of the various MPE products revealed their particular strengths and deficiencies. Gauge-only products (GMOSAIC and PMOSAIC) did not agree with the verifying gauge values temporally, especially during convective type rainfall. Therefore, our correlations for the gauge-only products generally were less than 0.4 during convective rain events. Although the radar-only product (RMOSAIC) showed reasonable results during convective and warm season events, it produced severe underestimates during stratiform type and cold season events. The estimates were found to be highly sensitive to the convective or stratiform nature of precipitation. The cold season and stratiform precipitation type categories exhibited ~ 35% and ~ 50% underestimation of gauge data, respectively. Thus, radars tend to be less accurate during the cool season and for stratiform rain types. Conversely, the bias-corrected radar product (BMOSAIC) performed quite well during times with deep convection and substantial rain rates, but nearby gauges were needed to generate precipitation greater than zero in areas where the radar failed to detect precipitation. LMOSAIC was not included in statistical testing, but the results of LMOSAIC would be expected to be
similar to those of MMOSAIC. Local biasing should perform well for a dense gauge network.

The second part of this study utilized the NWSRFS (run operationally by SERFC) to produce simulated streamflow from the six precipitation products during September 2001. NWSRFS supports the MPE formatted precipitation products to calculate MAP and forecast streamflow. The Geneva (~2035 mi²) and Wekiva River (~210 mi²) headwaters of the St. Johns River in central Florida were investigated when Tropical Storm Gabrielle impacted the area with rainfall up to 10 in. The two basins were diverse in size and river response.

Two gauge networks described simulated streamflow sensitivities during September 2001. The WMD dense gauge network generally provided better-simulated stages and responses than the RFC sparse gauge network. However, the sparse gauge-only products for the Wekiva River simulation produced nearly perfectly simulated peaks that may be attributed to the uniform precipitation and calibration based on a small number of gauges. Or, it may have been an accidental result. Based on this single case, it is not known whether such good agreement occurs routinely. Nevertheless, erroneous stage rises occurred in the sparse gauge-only products because of a single thunderstorm cell that produced over 1 in. of rain at a gauge near the Wekiva River watershed. Clearly a dense gauge network is more useful in MPE than a sparse gauge network, but additional research must determine how many gauges are necessary to produce optimum results at minimal cost. Hence, optimum gauge separation distances must be addressed for all regions.
Results from the streamflow simulations showed that the various precipitation products performed quite differently. When the radar-only precipitation product (RMOSAIC) was input to NWSRFS, the performance was poor compared to the other MPE products. These simulations underestimated observed streamflow by at least 25% in both basins, with MAP estimates substantially smaller than from the other products. The performance of RMOSAIC might improve during purely convective type precipitation, but rain gauge adjustment will continue to be necessary to remove radar-wide and local biases for stratiform type rainfall even in the warm season. When gauge information was added, the simulated results improved greatly, and MMOSAIC (and LMOSAIC with a dense gauge network) performed best of the radar-influenced products.

General findings regarding the MMOSAIC and gauge-only derived streamflow products cannot be deduced from a single case. While current results suggest that adjusting radar with rain gauges can significantly enhance the accuracy of both MAP estimates and resulting streamflow simulations, additional tests on different events are necessary to confirm that multisensor products are better than gauge-only products.

As the MPE technique continues to be used in operations, several future studies could benefit operational forecasters and hydrologists:

1) Develop a function that relates the gauge-radar weight and gauge radius of influence adaptable parameters to the standard deviation (or other variability parameter) of precipitation in order to create optimal adaptable parameter settings for each hour.

2) Increase the resolution of MPE to smaller than 4 x 4 km.
3) Run NWSRFS with MPE products during many different precipitation events and different seasons to define the hydrological sensitivity of the final product.

4) Calculate statistics and perform streamflow simulations with MPE in regions of the country where the character of the precipitation is different from Florida.

5) Calibrate NWSRFS with MPE data when at least 8 years of data become available.

6) Evaluate simulated streamflow derived from MPE precipitation products using distributed hydrologic models.
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BIOGRAPHICAL SKETCH

Gregory Sanders Quina III was born on March 30, 1977, in Fairfax, Virginia. At age 2, Greg and his family moved south to Pensacola, FL. After graduating high school in 1995, he began his college career at the University of West Florida in Pensacola. From his middle school days through his first two years of college, Greg enjoyed playing the baritone/euphonium in both marching and concert bands.

Upon receiving his AA degree from the University of West Florida, he left Pensacola in 1997 to study meteorology at Florida State University (FSU). In December of 1999, he graduated with a Bachelor of Science degree in Meteorology, with minors in Mathematics and Physics. Greg worked for two years at the FSU weather station starting in 1998, and in 2000 he was employed as a research assistant by Dr. Henry Fuelberg and continued toward a graduate degree in the same field. While at FSU, Greg has worked on research related to multisensor precipitation. He made the best decision of his life when he married Tabetha Michelle Frank on January 4th, 2003.