UDFCD Heavy Rainfall Guidance Tool – Upgrades for 2016 Operational Season

TECHNICAL MEMO

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Submitted by:

Dewberry
990 S. Broadway, Suite 400
Denver, CO 80209

Submitted to:
Urban Drainage and Flood Control District
2480 W 26th Ave, #156B
Denver, CO 80211

Contents

Submitted to:

Contributors

Dmitry Smirnov, PhD
Project Meteorologist
dsmirnov@dewberry.com
303.951.0644

Stuart Geiger, CFM
Project Manager
sgeiger@dewberry.com
303.951.0620

Jason Giovanettone, PhD, PE
Project Engineer
jgiovannettone@dewberry.com
703.849.0636

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OVERVIEW

In early 2015, Dewberry designed a Heavy Rainfall Guidance Tool (hereafter, Tool) for the Urban Drainage and Flood Control District (UDFCD; hereafter, District). The main features of the Tool are to provide a high resolution distribution of the heavy rainfall threat, in both time and space, across the District. Additionally, the Tool's probabilistic approach provides a measure of confidence that end-users can employ to help with decision making. The Tool's 2015 performance was validated in the 2015 Final Report (Dewberry, 2015) and showed encouraging results during its inaugural season, especially given the lack of any post-processing. The Report noted several potential avenues to improve Tool performance. UDFCD authorized this research & development in April 2016 and this Technical Memo summarizes the results of that effort.

Suggested Refinements and Outcomes of this Memo

For reference, the goals of this project, which are excerpted from the 2015 HRG Final Report (Dewberry, 2015) are italicized below, along with the outcome.

Overall Outcome: A method of post-processing Tool output led to substantially more accurate and reliable forecasts of the probability of exceeding 1 inch per hour of rainfall. In addition, a consistent District-wide threat level was developed in order to characterize the overall threat by unifying the forecasts across all Forecast Zones.

1. ***Assess model-by-model performance.*** *Up to this point, it has been assumed that each of the 13 models contributing to the Tool is equally skillful. This is not necessarily the case, since model performance can vary strongly from model to model, often times even for apparently similar models. We propose investigating the data collected during the 2015 season to separate models by their performance, and as necessary, weight them to use skillful models more heavily than less skillful ones.*

   Benefit: *We expect this to yield better reliability (see Location section), and potentially to reduce False Alarm Rates, especially if there are models that have a high bias on rainfall amounts.*

   - **Outcome:** Correction of model climatology was implemented. Ensemble statistics (mean, max) served as key predictor of 1 inch per hour exceedance probability. However, model weighting was ruled out due to insufficient basis.

2. ***Historically-based bias correction.*** *A weather model has its own physical world, which often times does not exactly replicate the true physical world we live in. As such, many past studies have shown marked increases in model performance from bias correcting with actual observed data. In Colorado, many operational forecast agencies use* ***precipitable water (PW)*** *to evaluate the heavy rainfall threat. Higher PWs can result in higher rainfall rates. Using statistical relationships based on the 2015 data collected as part of the Tool, we can develop objective bias-correction techniques of how to modify Tool rainfall intensities based on knowledge of the PW measurement. Note that there are several PW measuring sites in eastern Colorado that could be used for this analysis.*

   Benefit*: We expect that this may lead to a potentially substantial reduction in False Alarm rates, especially for marginal threat situations.*

- **Outcome:** Observed and forecasted variables were tested for independent predictive skill. Ultimately, forecasted mid-afternoon wind speed was found to be a significant predictor and implemented in post-processing.

DATA COLLECTION

Observations

The main focus of this effort is improvement in the Maximum Quantitative Precipitation Forecast (**QPF-max**), which is an essential part of the Tool. Of particular interest are instances where 1 hour rainfall amounts are expected to exceed 1 inch. A key limitation of this effort is that such rainfall intensities are rare in Colorado. For example, during 2015, over the 918 observed (using both gage and radar data) zone-day 1-hour rainfall maximums (6 Forecast Zones x 153-day operational season = 918 observed zone-day rainfall maximums), only 71 (5.8%) experienced an hourly rainfall amount greater than or equal to 1 inch.

As model bias correction is strongly dependent on having a sufficient amount of validation data (Scheuerer 2014), two additional "buffer" zones were added to increase the number of observed events as shown in Figure 1. These were strategically located over relatively well-sampled areas, with the North Buffer zone being centered on Fort Collins and the South Buffer zone included Colorado Springs. The main benefit of including these zones is the potential to capture more heavy rainfall events outside the District that had similar meteorological properties to storms observed within the District and could have been observed there.

The resulting benefit of these two "buffer" zones on supplementing very heavy rainfall statistics is dramatic. Table 1 shows the top ten hourly rain amounts with and without the inclusion of the buffer zones. When including the two buffer zones, 5 of the top 10 occurred within these zones, including the top 3 events. This was due to the exceptionally rainy months of May and June 2015 observed over the Palmer Ridge, and in general over northeastern Colorado. The full seasonal evolution of 1-hour maximum rain amounts is shown in Figure 2.

Table 1: *Top 10 hourly rain amounts from 2015, with and without the inclusion of the two buffer zones shown in Figure 1. *Denotes events that were observed in both samples.*

With buffer	2.68	2.51	2.41	2.40*	2.31*	2.21	2.16*	1.82*	1.82	1.76*
Without	2.40*	2.31*	2.16*	1.82*	1.76*	1.72	1.68	1.64	1.61	1.6

Table 2 identifies the sources of observed and estimated rainfall data, hereafter collectively referred to as Quantitative Precipitation Estimates (QPE), that were collected for use in the ensuing model validation and bias correction. The first two datasets are gridded products that were converted to a common 0.04 degree grid spanning the forecast domain. Although NWS River Forecast Center QPE was obtained, it was found to perform significantly worse compared to NOAA Stage IV QPE (using 24-hour ALERT and CoCoRaHS rainfall data as ground truth) and was not used in this analysis.

The last three datasets shown in Table 2 are from rain gages, of which the District's ALERT data represented the highest spatial coverage with 195 actives sites across the region. It should be noted that the ALERT gages showed small amounts of precipitation from the delayed melting of hail in the rain bucket on days when no precipitation occurred. As a result, the CoCoRaHS dataset was used to provide quality control of the ALERT data.

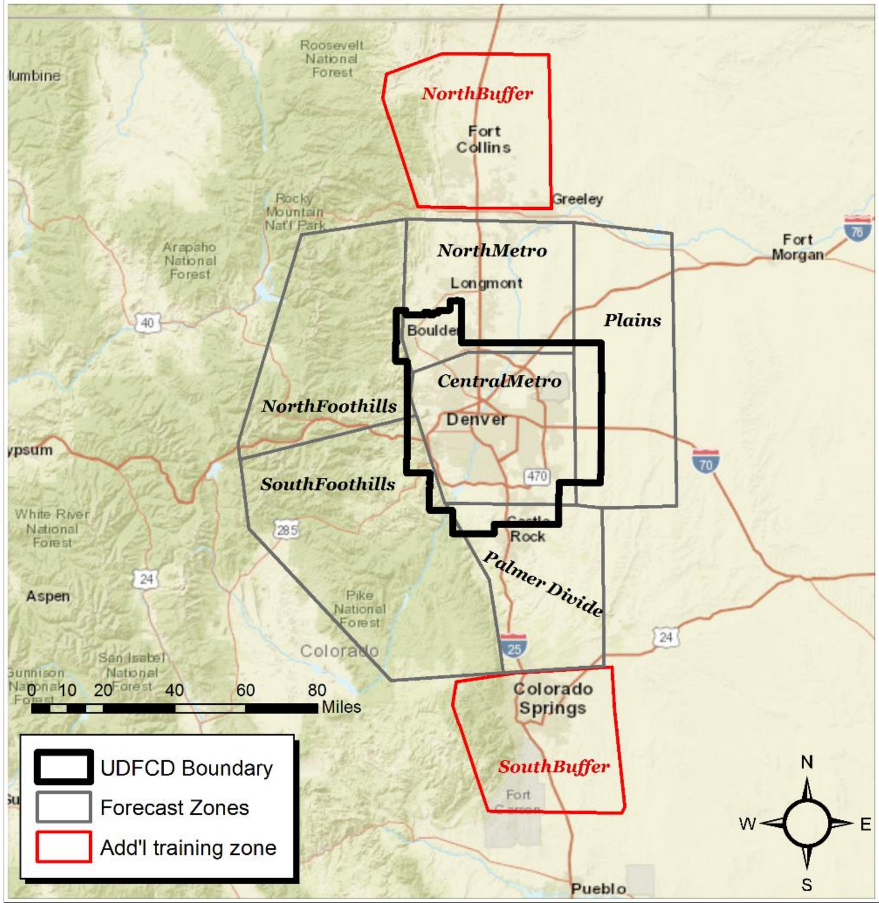

Figure 1: *Location of the six Forecast Zones and two additional training zones (red) in respect to the District boundary.*

Table 2: *Sources of observed and estimated rainfall*.

Name / Source	Type	Frequency	Period Obtained
River Forecast Center	Gridded	Daily	2015 only
NOAA Stage IV	Gridded	Hourly	Since 2002
UDFCD ALERT	Gage	Bucket tip	Since 2000
CoCoRaHS	Gage	Daily	Since 2000
NOAA Integrated Surface Daily	Gage	Hourly	Since 2000

As in the 2015 Final Report (Dewberry 2015), daily maximum *hourly* rain amounts were found for each of the six Forecast Zones and two buffer zones shown in Figure 1 using the ALERT data and the Stage IV data. The higher of the two estimates for each day was used to account for (i) storms that reached peak intensity between ALERT gages (where Stage IV should have higher values) and (ii) instances where Stage IV underestimated rain rates since this product does not always use ALERT data during its gage-correction step. Figure 2 shows the resulting daily evolution of the maximum hourly rain amounts across the District as well as the buffer zones. The beginning of the 2015 warm season was very rainy across the entire Front Range of Colorado (both within the District's Forecast Zones as well as the buffer zones) with numerous days experiencing rainfall amounts exceeding 1 inch. The 2015 warm season was also unusual in that most of the heavy rainfall days occurred prior to

July 1st, whereas climatology would suggest that July and August are the prime months for heavy rainfall (discussed later; see Table 6).

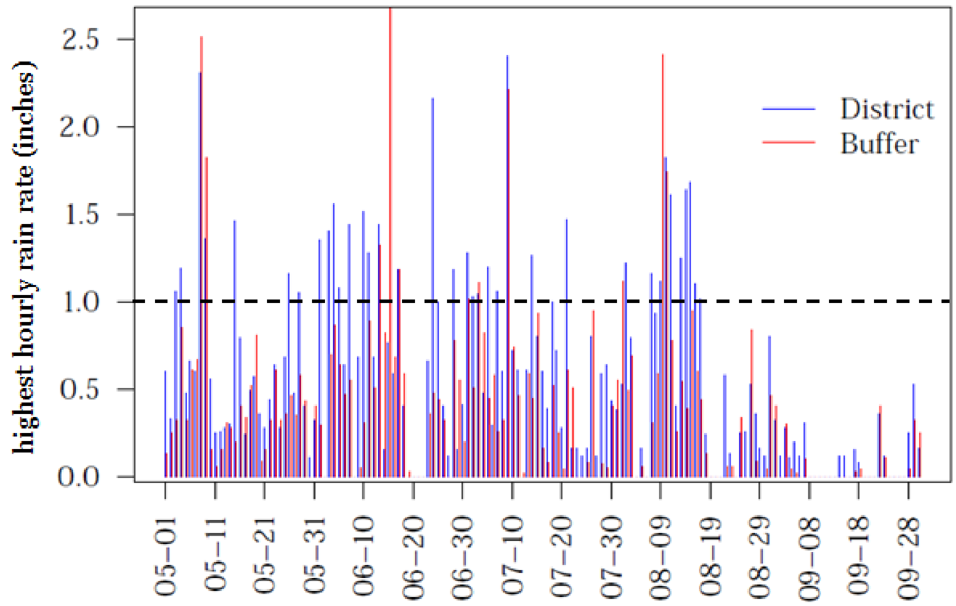

Figure 2: *The daily maximum hourly rain amount for the 2015 season within the District (blue) and in the buffer zones (red). The 1.00 inch per hour threshold (dashed line) was of particular significance for the Tool.*

In addition to rainfall data, Table 3 shows other atmospheric parameters that were collected to determine their potential use in providing additional predictive skill during the Tool's post-processing. For example, it is known that high values of Integrated Precipitable Water (IPW), a measure of total atmospheric moisture content, can have an impact on rainfall rates (e.g. Kuo et al., 1993; Hammill et al., 2004). Additionally, it was hypothesized that wind speed could potentially modulate heavy rainfall rates: for example, stronger mid-level winds could result in faster storm motions (lower storm residence times) that limits rainfall intensities at a given locale.

Table 3: *Sources of other observed atmospheric parameters*.

Name / Source	Frequency	Time Coverage	Notes
NOAA GPS Integrated Precipitable Water (IPW)	15-min	Since 2000	Used the Skaggs Research Center site (Boulder, CO)
Denver radiosonde	2x daily (6AM, 6PM MDT)	Since 2000	Included temperature, wind speed/direction and humidity

Forecasts

The Tool uses Quantitative Precipitation Forecasts (QPF) from a variety of operational and research modeling centers. Table 4 provides a summary of each modeling center and the models that it contributes. Up to thirteen models were available during 2015 for the morning update (posted 8AM MDT), and an additional four models were available by the afternoon update (posted 12PM MDT). *Even though all analyses presented in this Memo are for the morning update, for operational purposes, the findings will be applicable to all models*. [During real-time operations, not all models were available for each day, but at least four models were available 152 out of 153 days (99.3%) and at least 10 models were available on 139 days (90.8%).] Table 4 also categorizes each ensemble into a model "family" that was used for aggregating statistics of similarly structured models. In other words, ensembles arising from the same model family are expected to be statistically independent from each other on the basis that their outcome is dependent only on the initial atmospheric conditions and not the model physics and dynamics. To assign model families, we take a conservative approach, yielding six model families, based on the "dynamical core" of the Weather and Research Forecasting (WRF) model used, as well as separating by modeling center. Given additional research, it may be possible to consolidate this further (yielding expanded statistics for each "family"), but this is not attempted at this time.

The main input obtained from the ensembles in Table 4 is hourly QPF data across the UDFCD area. This results in a 4-dimensional raster (ensemble, time, latitude and longitude) from which processed statistics are determined and output to the Tool's web-based visualization. There are two key statistics that warrant further description. The first statistic is referred to as **QPF-max**, or the maximum QPF across a certain dimension or dimensions of the entire dataset. For example, one key Tool output is the hourly QPF-max *across all ensembles for all 24 hours* of a given day: this is what is shown in the Tool's "Maximum 1-hour rainfall" map. The other key statistic or Tool output is the probability of exceeding 1 inch per hour of precipitation *at any time during the 24-hour period for each Forecast Zone*; hereafter, this is referred to as **POP1** (**P**robability **O**f **P**recipitation exceeding **1** inch in one hour).

Table 4: *Sources of QPF data.*

Modeling center	Ensembles (Model/Family)	Total ensembles
National Severe Storms Laboratory (NSSL)[#]	1. arw / A 2. arw-ctl / A 3. arw-p1 / A 4. arw-n1 / A 5. arw-p2 / A 6. nmb-ctl / B 7. nmb-n1 / B 8. nmb-p1 / B 9. nmb-p2 / B	9
National Centers for Environmental Prediction (NCEP)[+]	10. hires-arw / C 11. hires-nmm / D 12. namnest-00Z / E 13. namnest-06Z / E	4
National Center for Atmospheric Research (NCAR)[#]	10 members (#14-23) Family: F	10*
[#]Research / operational center *[+]Operational center* **Not used in 2015 operations, only for testing*	**Total Ensembles**	**13 (ops)** **23 (ops + testing)**

In addition to precipitation, it is reasonable to expect that *forecasted* atmospheric variables may provide predictive skill for heavy rainfall forecasts. In order to investigate this, we obtained several atmospheric variables from archived 15-hour forecast data from the 06Z (12AM MDT) operational NCEP GFS model; this corresponds to the 3PM MDT forecast, which coincides with peak activity in heavy rainfall activity across the District (Dewberry, 2015). The following variables were obtained: 300mb, 500mb and 700mb meridional and zonal winds, which were used to determine wind speed and direction, and precipitable water.

ANALYSIS

Verification Metrics

The use of several verification metrics is required given the complex nature of verifying rainfall forecasts, especially when probabilities are involved (Centre for Australian Weather and Climate Research, 2014). Table 5 shows the verification metrics that are used to compare the overall reliability of the Tool before and after the refinements discussed in this report. Each metric provides valuable information, and overall conclusions are made by considering all metrics together (see Flood Control District of Maricopa County's 2015 Report for an application in an operational setting).

Table 5: *Description of the verification metrics used for comparing forecast performance*.

Metric	Description	Notes
Equitable Threat Score (ETS)	Assess forecast performance on an event by event basis using hits, misses and false alarms.	Non-probabilistic; ranges from -1/3 to 1 with skill shown by higher values
Brier Skill Score (BSS)	The probabilistic mean square error, compared to using simple climatology (Murphy, 1973).	Probabilistic; ranges from 1 (no skill) to 0 (no error)
Reliability Diagram (RD)	Compares how well the forecasted probability matches the observed frequency of occurrence (Brocker and Smith, 2007). A good companion with ROC.	Probabilistic; perfect relationship is a line with a slope of 1
Relative Operating Characteristics (ROC) diagram	Compares the false alarm rate ("false positive") with the probability of detection ("true positive") as a function of increasing higher probabilities. A good companion to RD.	Probabilistic; perfect relationship is a straight line with the true positive increasing while the false positive is 0; no skill is a line with a slope of 1

Approach

With the probabilistic focus of the Tool, a natural choice for post-processing is through the use of a logistic regression:

$$(1) \qquad Y = \left[1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}\right]^{-1}.$$

In this equation, Y is the probability of exceedance of a certain rainfall intensity threshold based on continuous or discrete predictors X_1, X_2 … X_n and their corresponding coefficients β_1, β_2 … β_n and intercept β_0. Specifically, the Tool currently has four thresholds:

- 1.0 inch in 1 hour,
- 2.5 inches in 3 hours,
- 3.5 inches in 6 hours and
- 4.5 inches in 24 hours.

This Memo focuses on the first threshold, namely exceeding 1.0 inch in 1 hour (POP1), which is arguably the most important threshold for the District since it captures the essence of most flash flood threats. It is expected that most findings herein will either directly or indirectly apply to the other three thresholds; however, a detailed consideration of these thresholds is bypassed in order to do gain a better understanding of the hourly rainfall characteristics.

In order to demonstrate how equation (1) can be applied, Figure 3 shows the dependence of maximum hourly rain rates on the morning (8AM MDT) Integrated Precipitable Water (IPW) at the Boulder GPS-IPW site. This figure uses ALERT data from the 2000-2015 period, resulting in a large sample size of 2,295 days. Note that ALERT data is separated in a binary fashion: a 1 is assigned if 1.00 inch per hour was exceeded on a given day, a 0 is assigned if it was not. The regression results are shown in the table below, where β_0 represents the intercept and β_1 represents the constant associated with the IPW (X_1).

Coefficient	Value	Std. Error	Confidence
β_0	-7.95	0.45	>99%
β_1	6.15	0.46	>99%

In order to demonstrate the usefulness of these results, the probability of exceeding 1 inch per hour *anywhere* in the District is estimated assuming a morning Boulder IPW of 1.0 and 1.2 inches. Using 1.0 inch in equation (1) produces Y (POP1) = 0.14 or a 14% chance of exceeding 1 inch in 1 hour; an IPW of 1.2 implies a 36% chance of exceedance. The regression coefficient [β_1 in equation (1)] of 6.15, which is significant at the 99% confidence level, signals a strong relationship, implying that for every 1 inch increase in the IPW value, there is a greater than 6-fold increase in the chance of observing a rainfall intensity of 1 inch per hour across the District. Even though the estimated regression is predictive in nature (note that we are using the morning IPW information whereas heavy rainfall is almost always observed later in the day), it still needs to be demonstrated that this information can provide *independent* predictive skill compared to the QPF data already being used in the Tool. Stated differently, since the Tool uses QPF from models that presumably ingest this IPW information, it may be the case that the QPF alone already incorporates the full predictive value of the IPW.

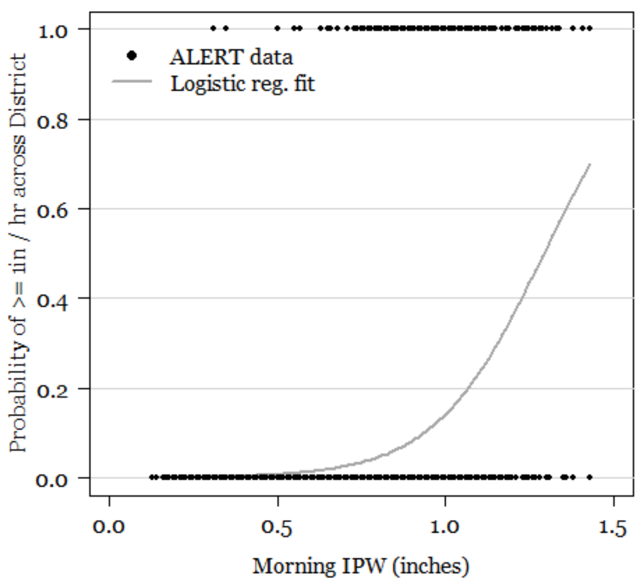

Figure 3: *Predictive skill between morning IPW at Boulder and 1 inch per hour rainfall rates across the District.*

Factors Impacting Heavy Rainfall Across the District

The District spans a complex terrain which plays a key factor in its hydrometeorological characteristics. Two of the most notable of these characteristics are *seasonality* and *spatial variation*. Regarding *seasonality*, Table 6 shows that heavy rainfall probabilities across the District (using ALERT data over the 2000-2015 period) show marked variability between months with values rapidly increasing from May through July and then decreasing into August and September. Although we considered incorporating seasonality into the analysis, there were two main reasons why this was not done: (i) any sub-dividing of 2015 statistics (recall that unfortunately we only have QPF for 2015) would result in such a small dataset that sufficiently rigorous results would be difficult to validate, and (ii) historically-speaking, 2015 was quite unusual in that many of the 1.00 inch+ hourly rainfall amounts occurred during May and June (see Figure 2). However, we believe that any subsequent Tool refinement take into account seasonality given that additional data will be available then.

Table 6: *Impact of seasonality on heavy rainfall occurrence using 2000-2015 ALERT data.*

	Daily probability of exceeding (in/hr):		
Month	**0.50**	**0.75**	**1.00**
May	10%	5%	3%
June	16	7	4
July	31	20	14
August	27	13	7
September	8	4	4

Regarding *spatial variation*, Figure 4 shows the 100-year 1-hour rainfall intensity from NOAA Atlas 14 across the District. The variability is significant, with topography serving as the main controlling factor. High elevation regions in Forecast Zones A & B have values as low as 1.50 inches per hour in the highest elevations, while the lower elevation regions (C-F) reveal values ranging from just under 2.00 inches per hour to as high as 2.80 as one moves east. To account for this variability, certain portions of our analysis separated the high elevation zones (A, B) from the low elevation zones (C-F).

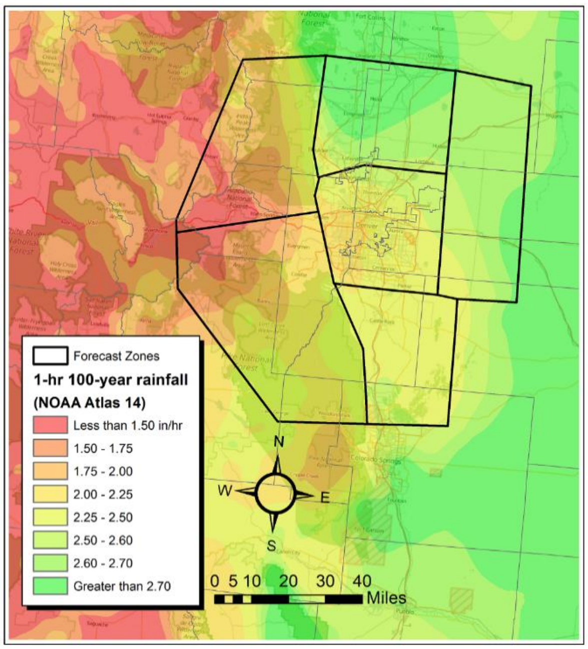

Figure 4: Estimates of 1-hour 100-year rainfall across the District using NOAA Atlas 14 Volume 8.2.

Model Performance

During the development of the Tool, each of the 13 ensemble members was given equal weight when generating the final output. In order to explore the validity of this assumption, Table 7 shows basic model performance statistics for each model, as well as the model ensemble mean and maximum. This was calculated by finding QPF-max for each model for each zone and the observed max rainfall, and then concatenating all zones into a single large time series. Alternatively, a similar table was produced for District-wide statistics but is not shown here because results were similar. The metrics in Table 7 are (in order of the columns):

Bias: The mean difference between observed and forecasted values.
Mean Absolute Error [MAE]: The mean absolute difference between observed and forecasted values.

Pearson correlation [Cor (p)]: Typical measure of correlation.

Spearman correlation [Cor (s)]: A different measure of correlation that is based on rank and not values.

Hit rate: Fraction of days the model correctly forecasted (or did not forecast) QPF-max exceeding 1.00 inch per hour.

False alarm rate [FA]: Fraction of days the QPF-max exceeding 1.00 inch per hour but that did not occur.

Miss rate: Fraction of days 1.00 per hour QPE was observed but was not forecasted.

Equitable Threat Score [ETS]: Uses 1.00 inch per hour as threshold. See Table 5 for description.

Table 7: *Verification table for raw QPF data over the entire Forecast Zone region. Ensemble mean and max statistics are shown twice: the first values include only the 13 ensembles used during the 2015 operational season; the second values include all 23 ensembles. Red and green shading denotes models with notable (exceeding 0.1 inch) underestimate or overestimate biases, respectively.*

Ens #	Bias	MAE	Cor (p)	Cor (s)	Hit	FA	Miss	ETS
1	-0.04	0.28	0.61	0.73	0.8	0.04	0.15	0.17
2	0.03	0.31	0.61	0.68	0.83	0.06	0.12	0.28
3	-0.10	0.29	0.60	0.68	0.81	0.03	0.16	0.15
4	-0.10	0.29	0.59	0.74	0.78	0.02	0.20	0.09
5	-0.07	0.29	0.62	0.75	0.8	0.04	0.16	0.15
6	-0.05	0.29	0.61	0.71	0.82	0.06	0.12	0.26
7	-0.03	0.29	0.64	0.73	0.81	0.06	0.13	0.25
8	-0.04	0.29	0.61	0.70	0.82	0.04	0.14	0.24
9	-0.04	0.3	0.59	0.72	0.81	0.04	0.15	0.18
10	-0.18	0.32	0.58	0.72	0.77	0.03	0.21	0.09
11	0.02	0.31	0.61	0.72	0.82	0.05	0.13	0.25
12	0.35	0.47	0.71	0.8	0.78	0.18	0.03	0.39
13	0.4	0.54	0.62	0.78	0.77	0.19	0.04	0.34
Ens mean	0.02	0.26	0.7	0.81	0.83	0.05	0.12	0.29
Ens max	0.66	0.72	0.67	0.76	0.69	0.29	0.02	0.26
14	-0.22	0.33	0.54	0.67	0.78	0.01	0.20	0.09
15	-0.26	0.34	0.57	0.67	0.78	0.01	0.22	0.07
16	-0.24	0.33	0.55	0.66	0.80	0.01	0.20	0.11
17	-0.23	0.34	0.53	0.67	0.76	0.02	0.22	0.04
18	-0.21	0.34	0.53	0.65	0.78	0.01	0.21	0.07
19	-0.19	0.30	0.64	0.73	0.82	0.01	0.18	0.18
20	-0.20	0.35	0.49	0.60	0.78	0.02	0.20	0.09
21	-0.22	0.32	0.59	0.70	0.79	0.02	0.19	0.12
22	-0.18	0.32	0.58	0.69	0.79	0.02	0.19	0.11
23	-0.21	0.32	0.59	0.68	0.80	0.01	0.19	0.12
Ens mean	-0.09	0.25	0.72	0.80	0.82	0.01	0.17	0.19
Ens max	0.68	0.74	0.67	0.76	0.68	0.30	0.02	0.25

Table 7 shows that despite some experience during 2015 that seemed to suggest certain models perform better than others, there was no objective evidence to support this claim. For example, Models 12 and 13 had the highest bias, but had high correlation and particularly high ETS, thus leaving no basis to remove them or lower their weighting. Furthermore, all of the NCAR ensembles (14-23) had significant underestimate biases but also had the lowest false alarm rates, though their ETS was the lowest. One important caveat from Table 7 was that it does not show any information about model climatology.

In order to fairly compare the models head-to-head, there is a need to bring all models onto a consistent climatology. This was done by employing a quantile-quantile mapping approach (Scheuerer, 2014) where the QPF-max climatology for each zone using each model family was determined. Values for each zone were then concatenated, ranked and compared to observations. Note that this does not seek to explore "how well each model performs from day to day" but instead "how well the model world compares to the real world over the course of the entire season". Two additional steps were required to accomplish this. First, to be consistent with the known climatology (Figure 4), Forecast zones were separated into two-groups: the high-elevation zones (A, B) and the low-elevation zones (C-F). Second, instead of producing a quantile map for each model separately, models were grouped into their respective families. The result for the low-elevation zones is shown in Figure 5 as a "Q-Q plot", which compares the ranked model climatology of QPF-max to their respective observations [a similar result was seen for the high-elevation zones though with lower values]. There are several clear findings: models belonging to the E family are much too wet, while most of the other models are either on par with observations or slightly too dry. The exception are families C and F, which are notably drier than observations.

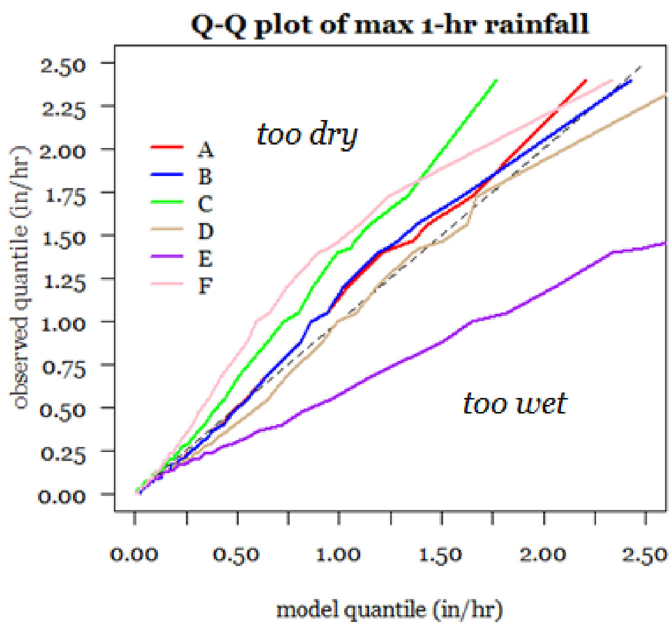

Figure 5: Quantile-Quantile (Q-Q) plot for the low-elevation zones (C-F) comparing model hourly rainfall intensity with observations as a function of model family (see Table 4).

After correcting model climatology using quantile mapping (where each QPF-max is "mapped" to its bias-corrected observational position using Figure 5), Table 8 shows that model performance is now more uniform across all models. Furthermore, quantile mapping has actually increased overall skill. Note that 18 of 23 models have a higher 1 inch in 1 hour ETS; in addition, 19 of 23 have a higher 0.75 inch in 1 hour ETS (not shown). These results confirm that after applying corrections using quantile mapping, *no objective basis was found to support the weighting of models.* Finally, Table 8 reveals that the model ensemble mean performs as well or better than any individual model. This key concept was leveraged during the ensuing post-processing method development.

Table 8: *Same as* **Table 7** *except after quantile mapping (see text for description).*

Ens #	Bias	RMSE	Cor (p)	Cor (s)	Hit	FA	Miss	ETS
1	0.02	0.3	0.60	0.73	0.82	0.07	0.11	0.25
2	0.11	0.35	0.60	0.68	0.80	0.12	0.08	0.28
3	-0.06	0.3	0.59	0.68	0.80	0.04	0.16	0.13
4	-0.05	0.3	0.58	0.74	0.79	0.07	0.14	0.21
5	-0.02	0.3	0.61	0.74	0.81	0.05	0.14	0.21
6	0.02	0.32	0.60	0.71	0.80	0.09	0.11	0.25
7	0.04	0.33	0.62	0.73	0.82	0.08	0.10	0.26
8	0.01	0.31	0.61	0.70	0.82	0.07	0.11	0.28
9	0.02	0.33	0.57	0.72	0.80	0.06	0.14	0.17
10	-0.02	0.32	0.57	0.71	0.77	0.08	0.15	0.17
11	0	0.32	0.60	0.72	0.82	0.04	0.14	0.26
12	-0.01	0.28	0.69	0.80	0.84	0.05	0.11	0.40
13	0.02	0.32	0.60	0.78	0.81	0.09	0.10	0.29
Ens mean	0	0.26	0.69	0.80	0.82	0.06	0.12	0.28
Ens max	0.43	0.52	0.66	0.73	0.73	0.24	0.03	0.30
14	-0.05	0.32	0.56	0.66	0.80	0.05	0.15	0.19
15	-0.11	0.32	0.57	0.67	0.81	0.03	0.16	0.18
16	-0.08	0.32	0.55	0.66	0.78	0.06	0.16	0.19
17	-0.06	0.32	0.53	0.67	0.79	0.05	0.16	0.18
18	-0.02	0.34	0.55	0.65	0.80	0.07	0.13	0.22
19	0	0.33	0.64	0.73	0.82	0.05	0.13	0.28
20	-0.02	0.37	0.49	0.60	0.78	0.08	0.14	0.21
21	-0.04	0.31	0.59	0.7	0.81	0.06	0.13	0.24
22	0.01	0.33	0.59	0.69	0.80	0.07	0.13	0.23
23	-0.03	0.31	0.59	0.68	0.82	0.06	0.12	0.28
Ens mean	-0.02	0.25	0.71	0.80	0.84	0.02	0.14	0.29
Ens max	0.55	0.61	0.68	0.73	0.68	0.31	0.01	0.25

Developing a post-processing method

The exploratory data analysis steps described previously were geared towards providing insight into the ultimate question: *compared to simply using raw QPF data as was done during 2015, can Tool output be post-processed to produce more reliable and accurate forecasts of POP1*? This question was investigated by testing a logistic regression equation given a variety of potential predictors. Equation development was guided by the following findings:

1. Are there optimal predictor(s) based solely the Tool's QPF ensemble?

One notable limitation of using raw ensemble forecast probabilities is that due to a finite number of models, the full distribution may be underrepresented. Figure 6 shows an example of this for May 6th, 2015, for the entire forecast domain. Note that the highest hourly rain rates from the ensemble are between 1.4 and 1.5 inches. However, higher rain rates may have been forecasted if additional ensembles were included. Because running additional ensemble simulations, especially at such high resolution, is computationally taxing, several well-documented alternate methods have been proposed to address this limitation. Two such methods were considered here: the “ensemble model-output statistics” approach (Scheuerer 2014; also Scheuerer and Hamill 2015) and a logistic regression approach (Hamill et al. 2004). The latter approach was chosen here due to its mathematical simplicity, lesser need for a longer training dataset as well as favorable performance compared to other methods as described by Wilks and Hamill (2007) and Scheuerer (2014).

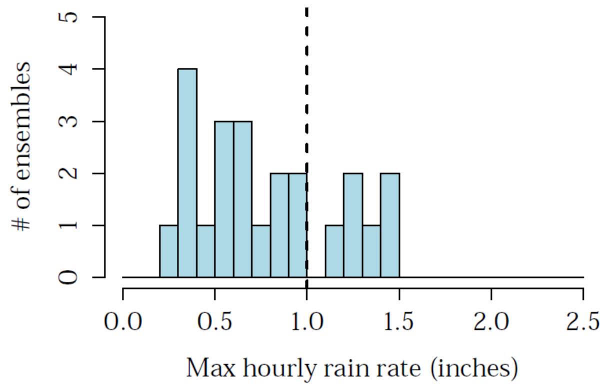

Figure 6: *Example of max hourly rain rates from the QPF ensemble for May 6, 2015 across all Forecast Zones.*

We seek to find optimal predictors of the hourly QPF-max given the ensemble statistics. Using Hamill et al. (2004) as guidance, the **ensemble mean of the daily 1-hour QPF-max** was chosen as a predictor. This was used for each Forecast Zone as well as all Forecast Zones together. The rationale for using this variable can be seen from Tables 7 and 8, which reveals that the ensemble mean shows a higher ETS than most of the ensemble members individually. Note that due to strong correlation between Forecast Zones, the overall POP1 estimate across all zones is not simply the sum of the POP1’s in each Forecast Zone. For example, if a heavy rainfall producing storm develops in the eastern part of Zone B, there is a significant chance that it spreads to Zones C and/or F with 1 inch per hour rainfall exceeded in multiple zones.

In addition to the ensemble mean value, we also found that using the **maximum 1-hour QPF-max across all Forecast Zones** was also a strong predictor of the max 1-hour rain rate *for each zone*. The explanation for this is that although each ensemble cannot exactly place the position of heavy rain-producing storms, using pooled “neighborhood” information increases the probabilistic prediction skill for any particular zone. This approach is similar to that described by Scheuerer (2014).

2. Addition of NCAR ensemble

Although the NCAR ensemble was initially brought in for comparison purposes, it is on the frontier of research and features some of the most sophisticated data assimilation methods used in any operational modeling to date (Schwartz et al., 2015). The NCAR ensemble also nearly doubles the original ensemble size, which enhances the quantification of uncertainty and should ultimately translate to more reliable forecasts. However, the value it contributes is not known as it has not been rigorously validated against the other ensembles. In addition the operational status of the NCAR ensemble is uncertain, with some indication that it may be discontinued as early July 2016.

We compared the impact of adding the NCAR ensemble in a hindcast setting using 2015 data. Initial results suggested that it added some skill in terms of the ETS (see Table 8), ROC and RD metrics (not shown). Thus, the decision made here was to include the NCAR ensemble for the 2016 operational season; however, contingency plans are in place in case this source goes offline.

3. Addition of observed or forecasted atmospheric variables

The value of adding various observed and forecasted predictor variables (aside from QPF) to the POP1 predictive equation was also assessed (Table 9). All forecasted data were derived from the 06Z simulation of NCEP Global Forecast System (GFS) at 0.5 degree resolution. This data is available by 5AM MDT, ensuring its availability for the Tool's morning update. Each variable was chosen based on physically-based rationale that it may affect heavy rainfall. For example, higher IPW values should promote higher *potential* rainfall rates (interestingly, forecasted IPW was used by Scheuerer, 2014). Meanwhile, higher wind speeds could promote lower rainfall rates, especially if they are representative of storm steering winds: the faster a given storm moves, the less rainfall in any given location. It was also important to consider wind speed anomalies, as opposed to actual raw values. The reason for this is that because of the coincidence that winds weaken from May to July (for example, at 500mb [roughly 13,000 feet A.G.L.] average values decrease from 32 to 22 mph), while heavy rain frequencies increase (see Table 6), this leads to the right conclusion that stronger wind speeds favor lower rainfall but for the wrong reason. However, using anomalies circumvents this issue by removing the seasonal cycle.

Table 9: *Additional (non-QPF) POP1 predictors*

	Significance	
Predictor	**By itself**	**W/ QPF**
8AM *observed* IPW at Boulder	Yes	No
8AM *observed* IPW anomaly at Boulder	Yes	No
8AM *observed* 500mb wind speed anomaly at Denver	Yes	No
3PM *forecasted* IPW	Yes	No
3PM *forecasted* Convective Available Potential Energy	Yes	No
3PM *forecasted* 300mb wind speed anomaly	Yes	No
3PM *forecasted* 500mb wind speed anomaly	Yes	Yes
3PM *forecasted* 700mb wind speed anomaly	Yes	No
3PM *forecasted* 700mb wind direction	No	No

In order to gain a better understanding concerning the value of the above potential predictor variables, POP1 logistic regressions were developed using only the variable, as well as including the variable after inclusion of the two QPF-based predictors described in point (1). Ultimately, we seek only variables that can add skill independent of that already provided by the QPF-max statistics. We use the 90% confidence level as the threshold for statistical significance. Interestingly, Table 9 shows that of the nine considered predictors, all but one showed statistically significant skill by themselves. However, once QPF-max information is brought in, only one significant predictor remains: the mid-afternoon 500mb wind speed anomaly forecast. Across the District, 500mb equates to about 13,000 above ground level (away from the foothills), which is a good first-guess proxy of the storm steering speed. This variable is incorporated into the final Forecast Zone-specific POP1 equation (2).

i) Equation for Forecast Zone-specific probability of exceeding 1 inch per hour

The final equation for determining post-processed zone-specific POP1 is shown below.

(2)
$$Y = \left[1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3)}\right]^{-1}$$

The table below shows that three predictor variable were retained in the analysis: ensemble mean QPF-max (after quantile mapping) for a given zone, the maximum quantile-mapped QPF-max for the entire District, and the forecasted 3PM GFS 500mb wind speed anomaly for a grid point roughly over the Denver metro. Each predictor variable had significance exceeding 95%. Surprisingly, the zone specific ensemble mean QPFmax (X_1) carried roughly the same weight as the maximum QPF-max over the entire District. This reiterates how, despite not being able to exactly place a heavy rainfall storm, knowledge of neighborhood activity increases the confidence in a specific zone.

Predictor	Description	Coef.	Value	Std. Error	Confidence
---	Intercept	β_0	-5.560	0.480	99%
X_1	Ensemble mean, bias-corrected QPF-max across zone (inches)	β_1	1.260	0.540	95%
X_2	Forecasted 3PM GFS 500mb wind speed anomaly over District (m/s)	β_2	-0.096	0.033	98%
X_3	Maximum bias-corrected QPF-max over entire District (inches)	β_3	1.530	0.290	99%

Although the predictor variables shown above are statistically significant, it is essential to validate the equation's utility with a variety of metrics. Figure 7 shows the Relative Operating Characteristics (ROC) curve and the Reliability Diagram (RD) comparing the performance of equation (2) with the raw QPF data that was used during 2015. In both situations, the post-processing has substantially improved performance. For example, the ROC curve shows that the black line is consistently higher than the red line, which translates into more hits and fewer false alarms compared to raw QPF data. Note that a perfect relationship would be represented by no movement of the line in the x-direction. Meanwhile, the RD curve shows that the raw data significantly over-predicted events, as discussed in the 2015 Final Report. The post-processing yields a more reliable prediction system. Note that these results are replicated, and are even more drastic, using the slightly looser 0.9 inch and 0.8 inch thresholds, as shown in Appendix B; the reason for including lower thresholds was to increase the sample size of heavy rain "events".

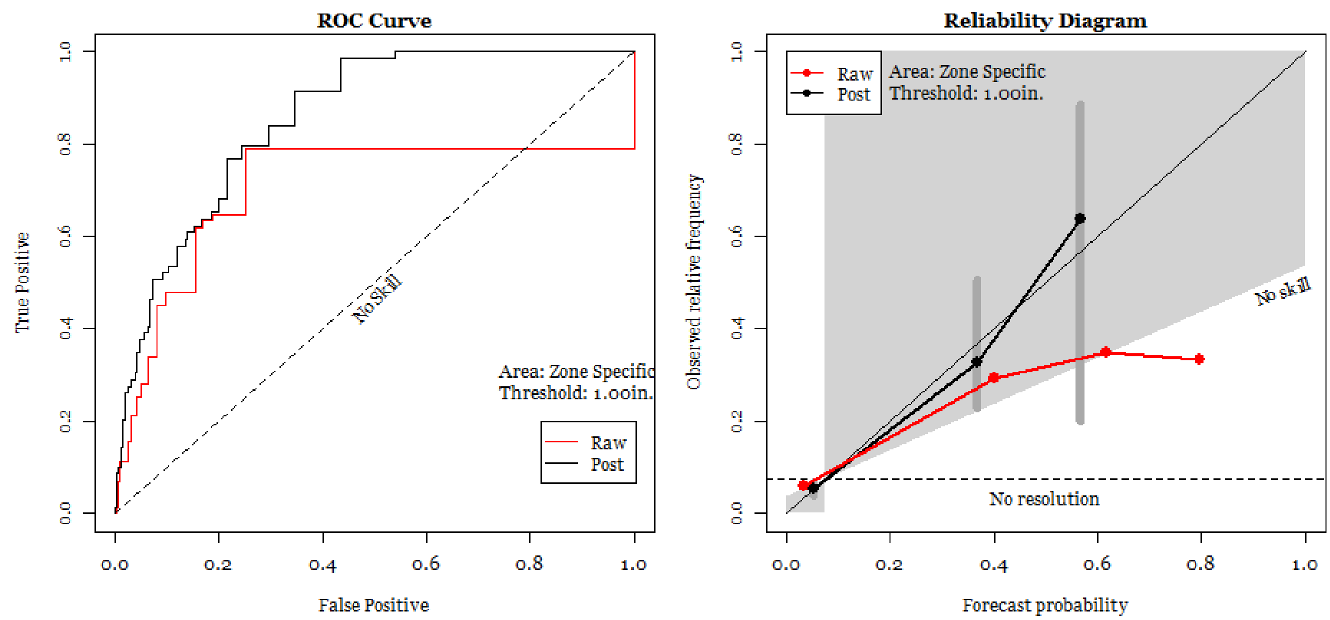

Figure 7: *ROC and RD plots for the zone-specific POP1 equation (black), compared to using raw model QPF (red).*

Table 10 shows the summary of additional and more condensed metrics. The Brier Skill Score (BSS) is a probabilistic measure of how much skill is contained in the prediction system. Values range from 0 to 1, with higher values being more skillful. However, any value above 0 indicates skill beyond using climatology. The post-processed data shows a higher BSS, which is an encouraging sign that it is performing better than raw data. Appendix B shows that BSS values increase as the threshold is lowered from 1.0 inch per hour to 0.9 and 0.8, indicating there is more skill in identifying *zone-specific* heavy rainfall threats for weaker events. Appendix B also shows that the conclusions seen in Table 10 apply to the slightly lower thresholds as well.

Table 10: *Zone-specific Brier Skill Score (BSS) and Equitable Threat Scores for increasing probabilities comparing the raw and post-processed performance. Green boxes are used to more easily visualize the higher-skill product.*

		Equitable Threat Score with probability of exceeding 1.00in/hr:					
Zone Specific	**BSS**	**5%**	**10%**	**20%**	**30%**	**40%**	**50%**
Raw	0.08	0.13	0.15	0.18	0.14	0.13	0.07
Post-processed	0.13	0.11	0.14	0.21	0.17	0.14	0.09

Meanwhile, the Equitable Threat Score (ETS) measures system performance using a contingency table (i.e. "yes/no" and not probabilistic) type approach by valuing "hits" and subtracting for "false alarms" and "misses". This metric ranges from 0 to 1, with 1 being perfect and anything above 0 indicating skill beyond climatology. Interestingly, results are mixed with the raw data performing better for lower probability events, while the post-processing improves the higher probability events. The ETS results should be interpreted with caution as they are sensitive (more so than the BSS) to the number of samples.

ii) Equation for District-wide (all zones) probability of exceeding 1 inch per hour.

As originally designed, the Tool only provided zone-specific probabilities (and threat levels) making it somewhat difficult to determine the overall threat across the District. A limitation of this approach is illustrated with an example. Envision a scenario where only 1 Forecast Zone had elevated chances of heavy rainfall (let's say with a greater than 20% probability), but all 5 of the remaining zones were right on the edge. In such a case, the Tool would show a Low threat for the single Forecast Zone, but no threats elsewhere. *In reality, due to the imperfect nature of storm placement, the chances of seeing something somewhere across the District, regardless of where, are likely much higher than what is being conveyed. To alleviate this limitation, here we introduce a post-processing method for determining POP1 for the entire District, which will be added to the Tool's web output for the 2016 season.* Equation 3 shows the final District-wide predictive equation, and the table below quantifies the coefficient value and confidence.

(3)
$$Y = \left[1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2)}\right]^{-1}$$

Predictor	Description	Coef.	Value	Std. Error	Confidence
---	Intercept	β_0	-4.290	0.667	99%
X_1	Ensemble mean of QPFmax over entire District	β_1	2.346	1.201	90%
X_2	Maximum QPFmax over entire District	B_2	1.192	0.657	90%

Unlike for the zone-specific equation, the wind speed predictor is not statistically significant at the 90% confidence level and is not included, while both QPF-max predictors are still present. [There is currently no explanation for why this is the case, but one hypothesis is that District-wide equation contains only 153 data points compared to the 918 contained in the zone-specific equation. Thus, there may not be enough data to statistically extract the wind signal even if one exists.] Coefficient confidence is slightly lower but still significant enough to include. Figure 8 shows the ROC and RD curves. The ROC results are not as clear as for the zone-specific plot (compare to Figure 7), however the RD continues to show more reliability after post-processing. Similar results are seen for the lower thresholds, as outlined in Appendix B.

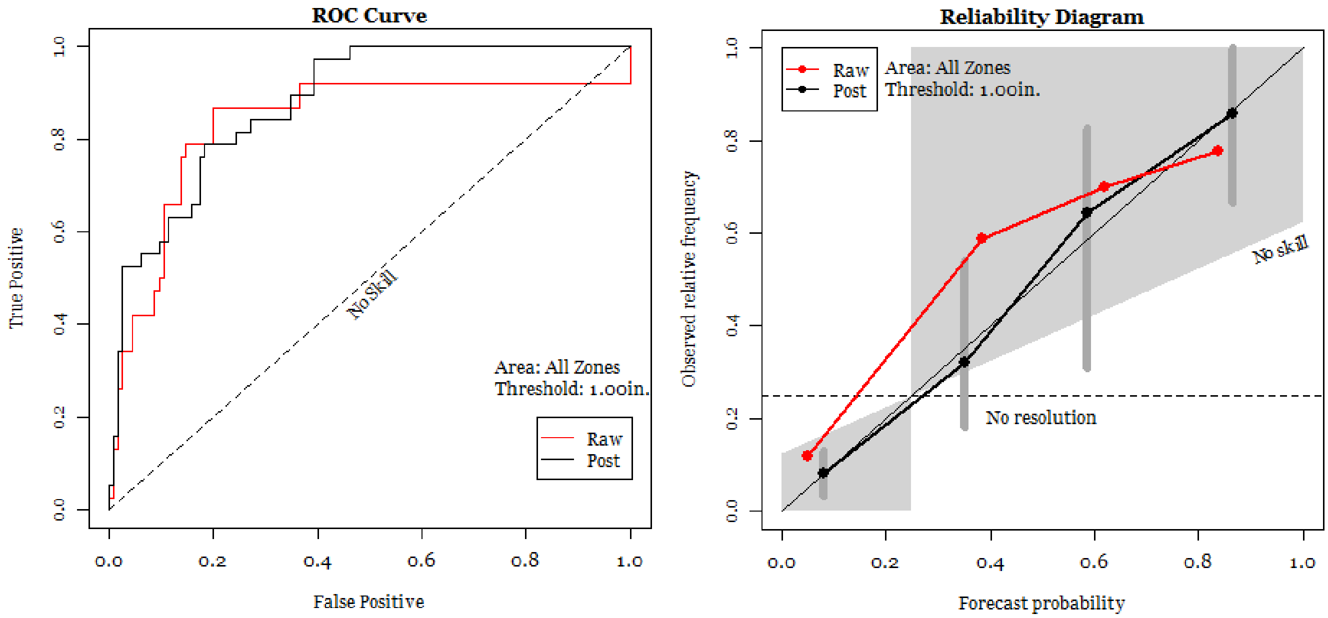

Figure 8: *ROC and RD plots for the District-wide (all zones) POP1 equation (black), compared to using raw model QPF (red).*

Finally, Table 11 presents the BSS and ETS metrics. The BSS continues to be higher after post-processing, indicating the utility of the equation. However, ETS results are mixed with the raw data performing notably better for lower probabilities, while the post-processed data performs notably better for middle and high probabilities. Overall, however, the post-processed data is more consistent. Appendix B shows that similar conclusions are found for the lower thresholds as well.

A full 2015 hindcast of zone-specific and District-wide post-processed equation output can be found in Appendix C.

Table 11: *District-wide (all zones) Brier Skill Score (BSS) and Equitable Threat Scores for increasing probabilities comparing the raw and post-processed performance.*

		Equitable Threat Score with probability of exceeding 1.00in/hr:					
All Zones	**BSS**	**5%**	**10%**	**20%**	**40%**	**60%**	**80%**
Raw	0.32	0.26	0.39	0.42	0.24	0.20	0.09
Post-processed	0.35	0.15	0.23	0.32	0.31	0.31	0.15

CONCLUSIONS

- Statistical post processing of raw model QPF results in substantially more reliable estimates of the probability of exceeding 1.00 inch per hour rainfall. This is measured by the RD and ROC curves (see Figure 7, 8).
- The final post-processing methodology is based on a multi-step procedure starting with a correction of model climatology using quantile mapping, followed by replacing raw model probabilities with those based on a logistic regression.
- The zone-specific logistic regression uses bias corrected model statistics including the ensemble mean zone-specific QPF-max, the ensemble District-wide QPF-max and the forecasted afternoon wind speed anomaly over the District.
- A District-wide processing step has been introduced to unify the zone-specific results. This will address instances where threat probabilities are close to but just below threshold level across many zones, even though the probability of the threat District-wide is relatively high. Appendix C can be used to compare the difference between the zone-specific and District-wide probabilities.
- Because each model has a different climatology (Figure 4), bias correction substantially increases the consistency of Tool output during times when not all model data is available.

FUTURE RESEARCH & APPLICATION

- Seasonality was not considered during post-processing due to an already limited data size and the "front-heavy" 2015 warm-season that was highly unusual from a climatological perspective. It is likely that including a seasonal-dependence to the corrective steps will further enhance the post-processed guidance compared to using the raw model data. It is suggested that this be attempted at the conclusion of the 2016 season when two full years of data are available.
- Table 9 showed that other atmospheric variables may provide useful corrective skill to QPF. However, due to the lack of readily available archived forecast data, these predictors used here were deterministic, and limited to one grid point and one time-step. It is suggested that using higher-resolution and more comprehensive (e.g. ensemble mean) forecast data could provide substantial additional forecast skill, especially at the zone-specific level. Specifically, experience suggests that forecasted wind direction could provide useful skill in correcting both QPF amount, and possibly location.

ACTION ITEMS FOR 2016 OPERATIONS

- Implement zone-specific quantile mapping of hourly QPF-max based on model "family"-dependent mapping tables.
- Use quantile mapping tables to scale spatial QPF-max data for visualizing the "Max 1-hour QPF" that is currently shown on the Tool's web output.
- Incorporate NCAR ensemble, with contingency plans in case the product is no longer operational.
- Given good model performance in capturing the effect of the Continental Divide on weather patterns during 2015, boundaries for Forecast Zones A and B will be truncated at the Continental Divide; this will reduce false alarms for the District.
- Introduce a District-wide probability of exceedance (and threat level).
- Use equations (2) and (3) to determine probabilities of exceedance and threat levels instead of using raw model QPF as was done during 2015.

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APPENDIX A – COMPUTATIONAL INFORMATION

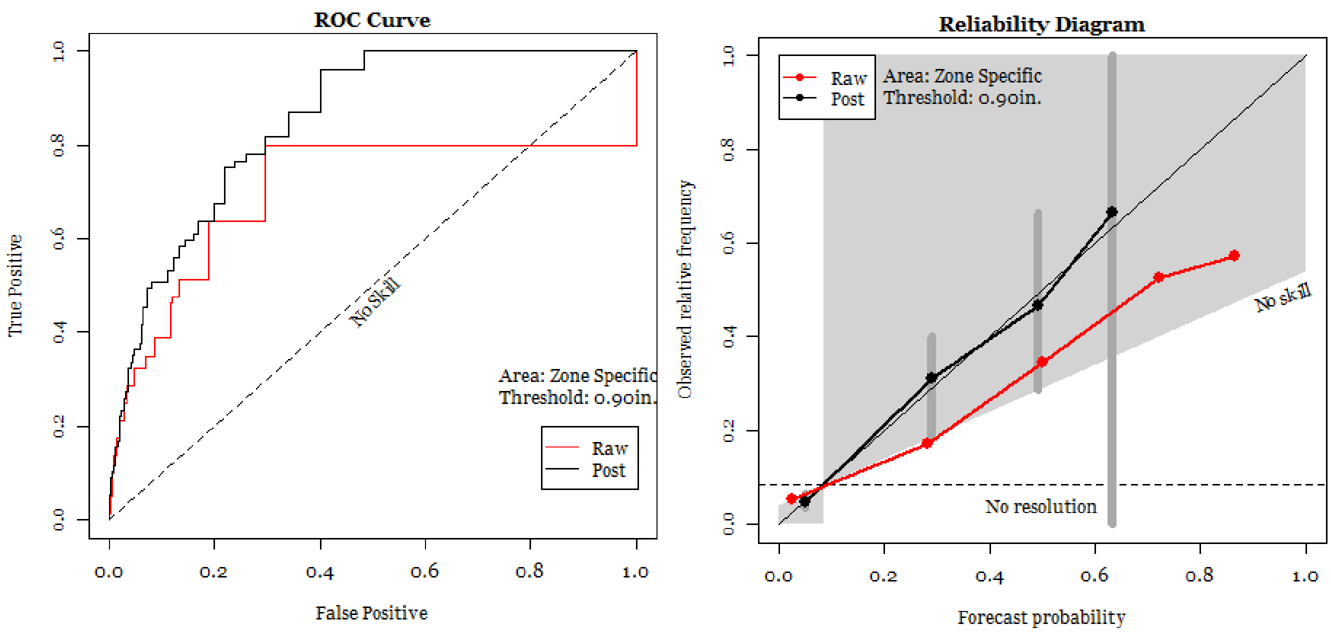
The analysis and visualization presented in this research was conducted using open-source computing software. The NCAR Command Language (NCL) was used for re-gridding NOAA Stage IV precipitation data onto a common 0.04^{o} grid. NetCDF operator (NCO) functions were used for post-processing hourly model data (concatenating, finding maximum/minimum, etc.). The statistical software *R* (version 3.2.2 "Fire Safety") was used for the majority of the analysis. In particular, the following *R* packages were found very useful: **SpecsVerification**, **ROCR**, **SpatialVx**, **zoo**, **lmomco**, **ncdf** and **verification**.

APPENDIX B – VERIFICATION FOR OTHER THRESHOLDS

The charts and tables below show Relative Operating Characteristics curves, Reliability Diagrams as well as Brier Skill Score and Equitable Threat Score metrics for the 0.9 inch per hour and 0.8 inch per hour thresholds. These lower thresholds were used to increase "event" sample size and ensure consistency of the 1 inch per hour results described in the main text. Below, data is grouped into Zone-specific and District-wide (all zones) categories, as in the main text.

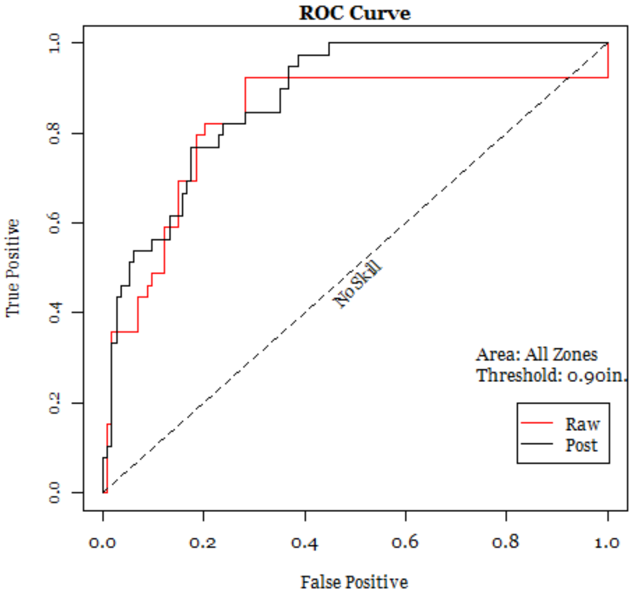
A. Greater than 0.9 inches per hour

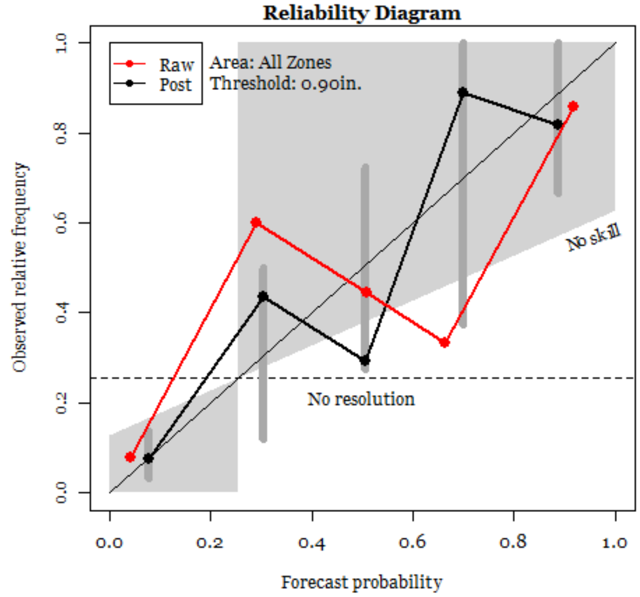
i) Zone Specific



Zone Specific	BSS	Equitable Threat Score with probability of exceeding 0.90in/hr: 5%	10%	20%	30%	40%	50%
Raw	0.09	0.12	0.14	0.15	0.16	0.18	0.15
Post-processed	0.14	0.10	0.14	0.22	0.19	0.14	0.08

ii) District-Wide (all zones)

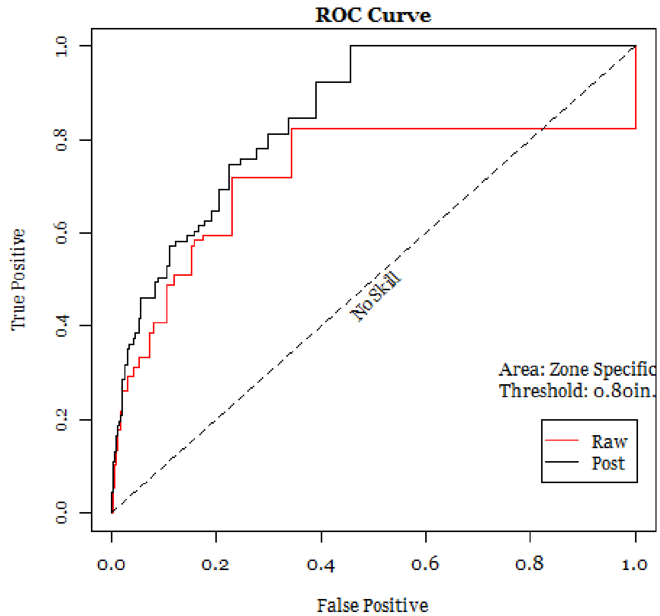


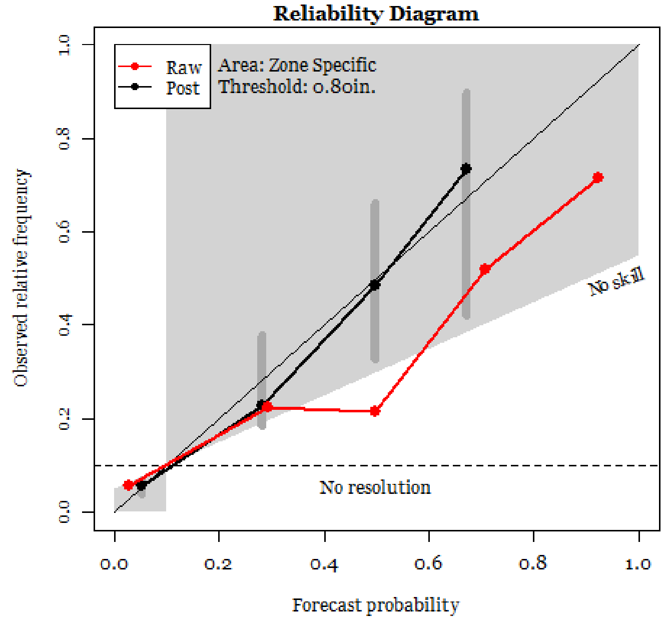


		Equitable Threat Score with probability of exceeding 0.90in/hr:					
All Zones	**BSS**	**5%**	**10%**	**20%**	**40%**	**60%**	**80%**
Raw	0.31	0.22	0.34	0.38	0.25	0.22	0.23
Post-processed	0.35	0.14	0.23	0.32	0.28	0.32	0.16

B. Greater than 0.8 inches per hour

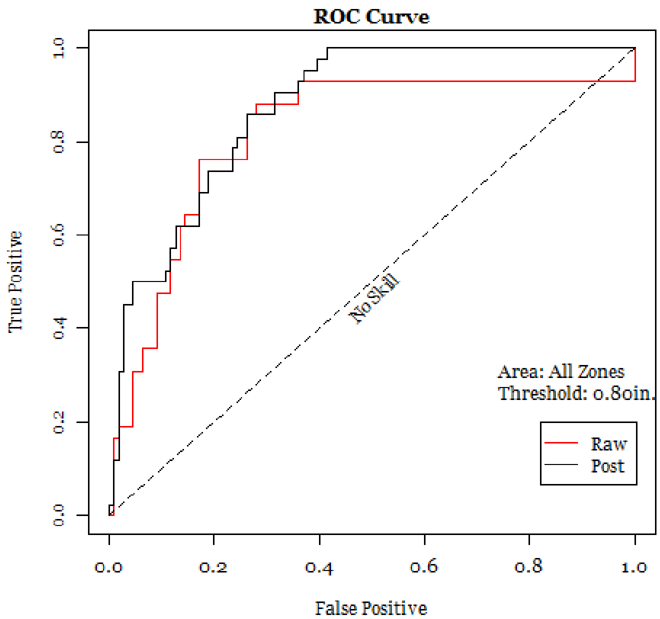
iii) Zone Specific

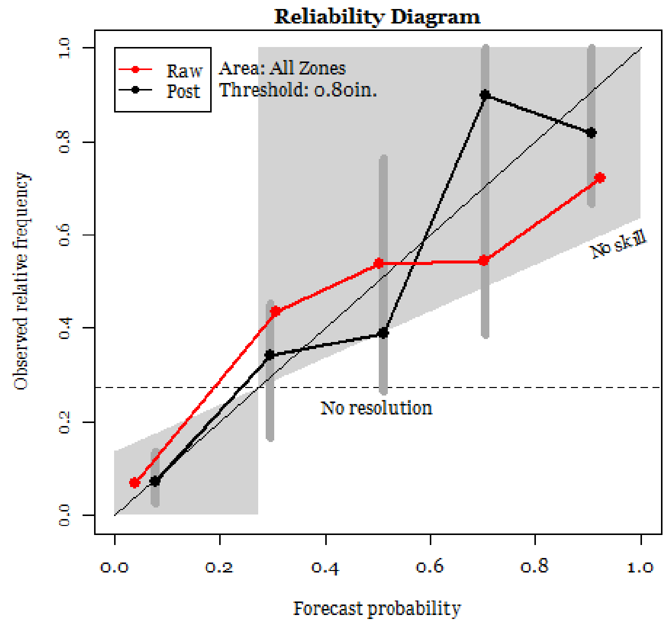




		Equitable Threat Score with probability of exceeding 0.80in/hr:					
Zone Specific	**BSS**	**5%**	**10%**	**20%**	**30%**	**40%**	**50%**
Raw	0.12	0.12	0.16	0.18	0.20	0.18	0.19
Post-processed	0.17	0.10	0.15	0.20	0.22	0.21	0.14

iv) District-wide (all zones)





		Equitable Threat Score with probability of exceeding 0.80in/hr:					
All Zones	BSS	5%	10%	20%	40%	60%	80%
Raw	0.29	0.20	0.29	0.34	0.31	0.25	0.19
Post-processed	0.34	0.13	0.24	0.29	0.32	0.31	0.15

APPENDIX C – HINDCAST DISTRICT-WIDE AND ZONE-SPECIFIC EXCEEDANCE PROBABILITY FOR 2015

The table below shows the hindcast probability (%) of hourly rainfall amounts exceeding 1 inch (POP1) over the 2015 operational season using equation (2). Note that District-wide values are always less than or equal to the probability in each zone. Missing values are denoted by NA, and implies that one or more predictors was unavailable that day. This was apparently caused due to data lass during the GFS model data archiving process and is not expected to be an issue during real-time operations.

	Forecast Zone - Specific						
Date	A	B	C	D	E	F	District-wide
5/1/2015	10%	14%	15%	15%	12%	13%	46%
5/2/2015	2	2	2	2	2	2	5
5/3/2015	16	16	18	22	18	20	39
5/4/2015	30	36	49	30	27	33	77
5/5/2015	3	4	4	4	5	4	18
5/6/2015	7	6	8	10	8	8	33
5/7/2015	13	13	17	19	17	19	53
5/8/2015	5	5	6	7	6	6	30
5/9/2015	23	24	24	30	30	26	83
5/10/2015	1	1	0	1	0	0	2
5/11/2015	0	0	0	0	0	0	2
5/12/2015	2	2	2	2	2	2	8
5/13/2015	3	3	3	3	3	3	7
5/14/2015	1	2	1	1	1	1	5
5/15/2015	2	2	2	2	2	2	9
5/16/2015	12	12	15	13	12	13	32
5/17/2015	1	1	1	1	1	1	5
5/18/2015	6	6	7	7	6	6	18
5/19/2015	1	1	1	2	1	1	7
5/20/2015	2	2	2	2	1	2	8
5/21/2015	4	4	3	3	3	3	12
5/22/2015	4	4	4	6	5	6	27
5/23/2015	9	7	8	11	11	8	44
5/24/2015	16	15	18	21	17	18	48
5/25/2015	3	4	4	3	3	4	14
5/26/2015	3	3	4	4	3	3	13
5/27/2015	3	3	3	3	3	3	11
5/28/2015	8	8	9	11	10	9	21
5/29/2015	8	7	7	7	7	7	28
5/30/2015	3	3	3	3	3	3	9
5/31/2015	3	3	3	3	3	3	12
6/1/2015	3	3	4	4	3	3	12
6/2/2015	1	1	1	1	1	1	2
6/3/2015	27	25	27	40	34	34	61
6/4/2015	22	21	28	26	25	25	58
6/5/2015	20	19	22	38	31	32	94
6/6/2015	6	6	6	8	6	6	27
6/7/2015	16	17	18	18	16	18	62
6/8/2015	10	11	9	8	8	8	15
6/9/2015	4	3	4	3	3	3	14
6/10/2015	12	11	12	14	14	12	52
6/11/2015	60	67	69	73	64	69	97
6/12/2015	6	8	8	6	5	6	23

6/13/2015	36	36	29	27	26	28	55
6/14/2015	31	26	24	26	27	24	55
6/15/2015	37	45	46	50	41	39	89
6/16/2015	7	6	7	7	6	6	26
6/17/2015	13	14	15	24	17	19	61
6/18/2015	10	13	11	11	10	11	54
6/19/2015	1	1	1	1	1	1	2
6/20/2015	0	0	0	0	0	0	2
6/21/2015	1	1	1	1	1	1	2
6/22/2015	0	0	0	0	0	0	2
6/23/2015	8	9	13	9	8	8	37
6/24/2015	11	13	12	11	11	11	30
6/25/2015	6	6	6	8	7	6	30
6/26/2015	4	3	3	3	3	3	20
6/27/2015	1	1	1	1	1	1	4
6/28/2015	5	5	5	4	3	3	33
6/29/2015	2	2	1	1	1	1	8
6/30/2015	13	10	8	8	9	9	38
7/1/2015	26	32	27	22	25	24	83
7/2/2015	11	13	13	10	12	13	58
7/3/2015	24	30	32	26	26	34	77
7/4/2015	3	4	4	3	4	3	14
7/5/2015	5	5	4	4	4	4	28
7/6/2015	18	23	19	15	18	20	67
7/7/2015	19	16	10	10	15	12	58
7/8/2015	44	49	59	52	46	46	94
7/9/2015	27	37	36	35	23	27	91
7/10/2015	2	3	3	3	2	3	20
7/11/2015	1	1	1	1	1	1	5
7/12/2015	1	1	1	1	1	1	3
7/13/2015	6	6	5	5	5	4	29
7/14/2015	14	14	10	10	9	10	38
7/15/2015	2	3	2	2	2	2	18
7/16/2015	1	2	1	1	1	1	6
7/17/2015	1	1	1	1	1	1	3
7/18/2015	3	3	2	3	3	3	16
7/19/2015	12	13	15	12	11	12	49
7/20/2015	4	5	3	3	3	3	18
7/21/2015	19	20	33	35	23	26	89
7/22/2015	1	1	1	1	1	1	7
7/23/2015	1	1	1	1	1	1	2
7/24/2015	2	3	2	2	2	2	11
7/25/2015	0	1	0	0	0	0	4
7/26/2015	4	5	6	5	4	5	19
7/27/2015	1	1	1	1	1	1	6
7/28/2015	0	0	0	0	0	0	3
7/29/2015	2	3	2	2	2	2	26
7/30/2015	4	5	6	4	4	4	18
7/31/2015	8	12	11	8	7	8	41
8/1/2015	3	3	3	3	3	3	10
8/2/2015	6	8	6	6	5	6	19
8/3/2015	6	7	6	4	4	5	37
8/4/2015	0	0	0	0	0	0	2
8/5/2015	0	0	0	0	0	0	2
8/6/2015	0	0	0	0	0	0	1
8/7/2015	4	4	5	7	5	5	30
8/8/2015	3	3	4	4	3	3	23

8/9/2015	2	3	3	3	3	2	12
8/10/2015	24	39	46	28	21	32	89
8/11/2015	35	52	60	33	30	39	93
8/12/2015	8	9	7	6	7	6	43
8/13/2015	11	13	8	7	7	7	43
8/14/2015	26	37	22	15	14	18	72
8/15/2015	5	6	5	5	4	4	16
8/16/2015	26	30	30	41	28	29	79
8/17/2015	16	23	31	19	15	21	78
8/18/2015	1	1	1	1	1	1	9
8/19/2015	0	0	0	0	0	0	2
8/20/2015	1	1	1	1	1	1	2
8/21/2015	1	1	2	1	1	1	5
8/22/2015	1	1	1	1	1	1	3
8/23/2015	1	1	1	1	1	1	2
8/24/2015	1	1	1	1	1	1	2
8/25/2015	1	1	1	1	1	1	5
8/26/2015	3	3	3	2	2	3	11
8/27/2015	2	2	2	2	2	2	18
8/28/2015	1	1	1	1	1	1	5
8/29/2015	2	2	2	2	2	2	5
8/30/2015	2	2	2	2	2	2	10
8/31/2015	7	9	9	8	7	8	38
9/1/2015	3	3	3	2	2	2	15
9/2/2015	1	1	1	1	1	1	4
9/3/2015	4	4	3	3	3	3	20
9/4/2015	1	1	1	1	1	1	6
9/5/2015	NA	NA	NA	NA	NA	NA	6
9/6/2015	1	1	1	1	1	1	6
9/7/2015	NA	NA	NA	NA	NA	NA	6
9/8/2015	0	0	0	0	0	0	2
9/9/2015	0	0	0	0	0	0	1
9/10/2015	5	4	5	6	6	6	17
9/11/2015	3	3	4	4	4	4	10
9/12/2015	0	0	0	0	0	0	1
9/13/2015	1	1	1	1	1	1	1
9/14/2015	1	1	1	1	1	1	4
9/15/2015	1	1	1	1	1	1	4
9/16/2015	1	1	1	1	1	1	4
9/17/2015	0	0	0	0	0	0	3
9/18/2015	0	0	0	0	0	0	2
9/19/2015	0	0	0	0	0	0	2
9/20/2015	0	0	0	0	0	0	1
9/21/2015	0	0	0	0	0	0	1
9/22/2015	3	3	3	3	3	3	8
9/23/2015	8	7	6	6	6	6	19
9/24/2015	2	2	2	2	2	2	3
9/25/2015	1	1	1	1	1	1	1
9/26/2015	1	1	1	1	1	1	1
9/27/2015	1	1	1	1	1	1	2
9/28/2015	8	9	10	9	10	10	35
9/29/2015	14	19	22	18	16	16	55
9/30/2015	1	1	1	1	1	1	4