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GOES-R Advanced Baseline Imager (ABI) Algorithm Theoretical Basis Document For Probability of Rainfall

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LIST OF ACRONYMS

ABI – Advanced Baseline Imager
AIT – Algorithm Integration Team
ATBD – Algorithm Theoretical Basis Document
BADC – British Atmospheric Data Centre
CDF – Cumulative Distribution Function
CLASS – Comprehensive Large Array-data Stewardship System
EDR – Environmental Data Record
F&PS – Functional and Performance Specification
GAS – GOES-R Archive System
GOES – Geostationary Operational Environmental Satellite
GPM – Global Precipitation Measurement
GPO – GOES-R Program Office
IR – Infrared
LEO – Low-Earth Orbit
LZA – Local solar Zenith Angle
MRD – Mission Requirements Document
NASA – National Aeronautics and Space Administration
NESDIS – National Environmental Satellite, Data, and Information Service
NOAA – National Oceanic and Atmospheric Administration
OSDPD – Office of Satellite Data Processing and Distribution
PR – Precipitation Radar
SCaMPR – Self-Calibrating Multivariate Precipitation Retrieval
SEVIRI – Spinning Enhanced Visible Infrared Imager
STAR – Center for Satellite Applications and Research

ABSTRACT

This Probability of Rainfall Algorithm Theoretical Basis Document (ATBD) contains a high-level description (including the physical basis) of an algorithm for predicting pixel-scale probability of rainfall exceeding 1 mm during the next 3 h based on intermediate output from the Rainfall Potential nowcasting algorithm, which in turn is driven by rainfall rates derived from images taken by the Advanced Baseline Imager (ABI) flown on the Geostationary Operational Environmental Satellite-Series R (GOES-R) series of National Oceanic and Atmospheric Administration (NOAA) geostationary meteorological satellites. A brief overview of the GOES-R observing system is followed by a more specific description of the Probability of Rainfall algorithm, validation efforts, and planned improvements.

1 INTRODUCTION

1.1 Purpose of This Document

The Probability of Rainfall Algorithm theoretical basis document (ATBD) provides a high-level description of and the physical basis for the estimation of probability of more than 1 mm of rainfall for the next 3 hours using the output from two other algorithms that use images taken by the Advanced Baseline Imager (ABI) flown on the GOES-R series of NOAA geostationary meteorological satellites. The probability of rainfall is produced as an EDR and is based on inputs from the GOES-R Rainfall Potential and Rainfall Rate Algorithms.

1.2 Who Should Use This Document

The intended users of this document are those interested in understanding the physical basis of the algorithms and how to use the output of this algorithm in a manner that is consistent with its underlying assumptions. This document also provides information useful to anyone maintaining or modifying the original algorithm.

1.3 Inside Each Section

This document is broken down into the following main sections.

- **System Overview**: Provides relevant details of the ABI and provides a brief description of the products generated by the algorithm.

- **Algorithm Description**: Provides all the detailed description of the algorithm including its physical basis, its input and its output.

- **Test Data Sets and Output**: Provides a description of the test data set used to characterize the performance of the algorithm and quality of the data products. It also describes the results from algorithm processing using simulated input data.

- **Practical Considerations**: Provides an overview of the issues involving numerical computation, programming and procedures, quality assessment and diagnostics and exception handling.

- **Assumptions and Limitations**: Provides an overview of the current limitations of the approach and gives the plan for overcoming these limitations with further algorithm development.

1.4 Related Documents

This document currently does not relate to any other document outside of the specifications of the GOES-R Ground Segment Functional and Performance Specification (F&PS) and Missions Requirements Document (MRD) and to the ATBD's for the Rainfall Rate and Rainfall Potential Algorithms.

1.5 Revision History

Version (0.1) of this document was created by Dr. Robert J. Kuligowski of NOAA/NESDIS [National Environmental Satellite, Data, and Information Service]/STAR [Center for Satellite Applications and Research] and its intent was to serve as a draft submission to the GOES-R Program Office (GPO) for initial comments.

Version (1.0) of this document was created by Dr. Robert J. Kuligowski of NOAA/NESDIS and its intent was to accompany the delivery of the 80% algorithm to the GOES-R AWG Algorithm Integration Team (AIT).

2 OBSERVING SYSTEM OVERVIEW

This section will describe the products generated by the ABI Probability of Rainfall Algorithm and the requirements it places on the sensor.

2.1 Products Generated

The Probability of Rainfall Algorithm produces a field of probability of more than 1.0 mm of rainfall in the next 3 hours associated with the most recently available GOES imagery. In terms of the F&PS, it is responsible directly for the Probability of Rainfall product within the Hydrology product sub-type. The Probability of Rainfall Algorithm design calls for a quantitative rainfall probability in percent at the pixel scale of the GOES Imager.

Requirement Description	Requirement Value
Name	Probability of Rainfall
User	GOES-R
Geographic Coverage	Full Disk
Temporal Coverage Qualifiers	Day and night
Product Extent Qualifier	Quantitative out to at least 70 degrees LZA or 60 degrees latitude—whichever is less—and qualitative beyond
Cloud Cover Conditions Qualifier	N/A
Product Statistics Qualifier	Over rainfall cases and mesoscale-sized surrounding regions
Vertical Resolution	N/A
Horizontal Resolution	2.0 km
Mapping Accuracy	1.0 km
Measurement Range	0 – 100%
Measurement Accuracy	25%
Product Refresh Rate / Coverage Time (Mode 3)	15 min
Refreshment Rate / Coverage Time (Mode 4)	5 min
Vendor Allocated Ground Latency	266 sec
Product Measurement Precision	40%

Table 1. F&PS Requirements for the Probability of Rainfall algorithm.

2.2 Instrument Characteristics

The Probability of Rainfall will be produced for each pixel observed by the ABI with a latitude of less than 60 degrees and a local zenith angle (LZA) relative to the satellite sub-point of 70 degrees. The Probability of Rainfall algorithm does not make direct use of any ABI data, but only uses the forecasts of rainfall rate out to 3 h at 15-min intervals that are produced as gridded quality information data by the Rainfall Potential algorithm. Please refer to the Rainfall Rate ATBD for additional details on the ABI data used in the Rainfall Rate retrievals that are used as input to the Rainfall Potential algorithm.

3 ALGORITHM DESCRIPTION

This section will provide a complete description of the algorithm at the current level of maturity (which will improve with each revision).

3.1 Algorithm Overview

The Probability of Rainfall Algorithm derives probability of more than 1.0 mm of rainfall during the next 0-3 hours on a pixel level in ABI imagery. These probabilities are derived from the outputs of the Rainfall Rate and Rainfall Potential Algorithms that are run through a statistical post-processor that was earlier calibrated on a static data set. Additional details on these two algorithms can be found in their respective ATBD's.

3.2 Processing Outline

The processing outline of the Probability of Rainfall Algorithm is summarized in the figure below. The Probability of Rainfall Algorithm can run on individual pixels of data or larger groups of pixels as desired.

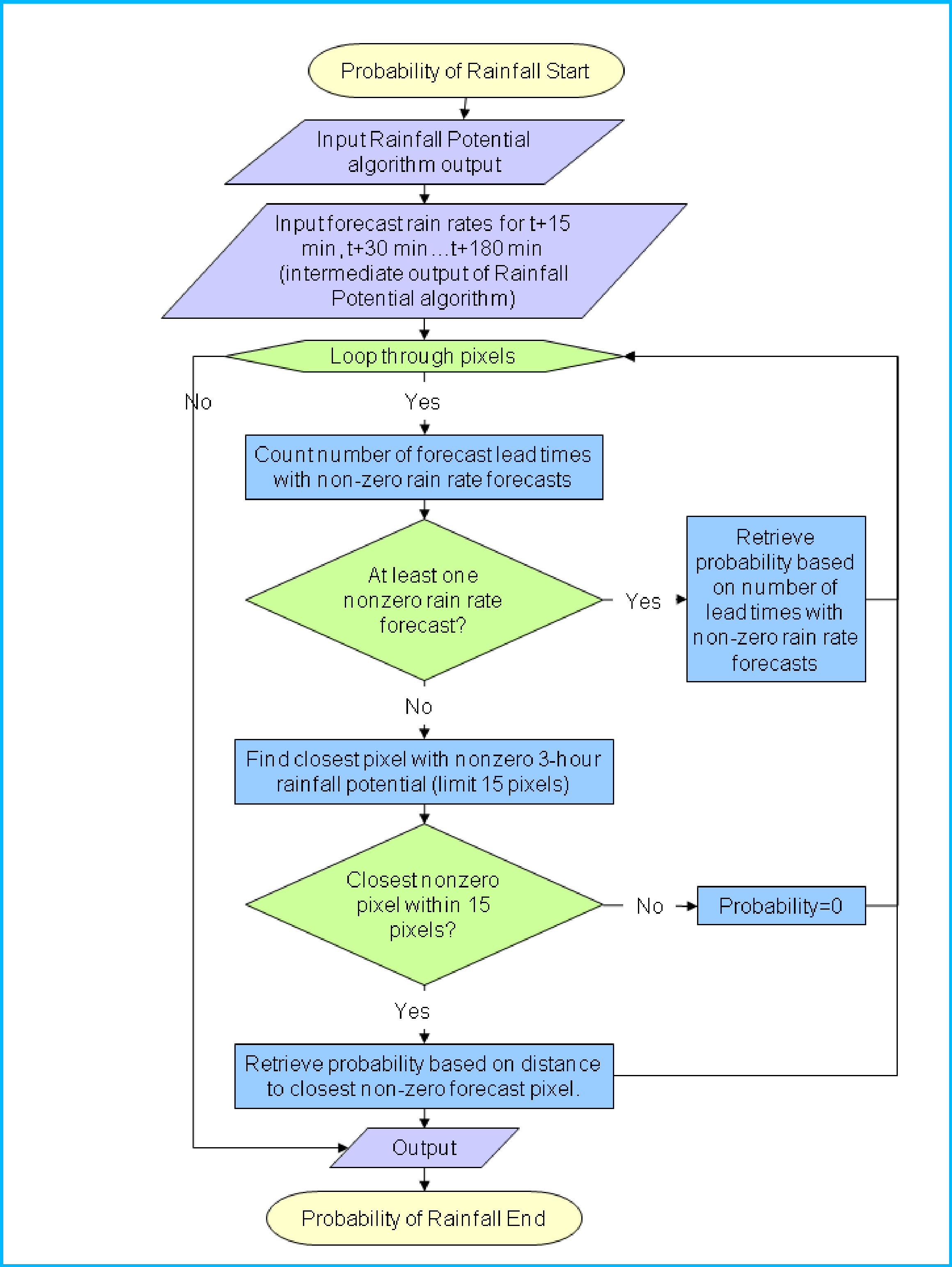

Figure 1. High-level flowchart of the Probability of Rainfall Algorithm, illustrating the main processing sections.

3.3 Algorithm Input

This section describes the input needed to compute the probability of rainfall. While the probability of rainfall is derived for each pixel, the rainfall rates that serve as input to the algorithm may contain information from the surrounding pixels (5x5), and the rainfall potential values are derived from data from a much larger area surrounding the pixel. Therefore, the probability of rainfall can be derived on a pixel-by-pixel basis, but the fields that serve as input into the probability of rainfall cannot.

3.3.1 Primary Sensor Data

The Rainfall Potential algorithm does not directly use any sensor input but relies solely on ABI Rainfall Potential Algorithm output, which in turn relies on output from the Rainfall Rate algorithm; please refer to the Rainfall Rate Algorithm ATBD for details on the sensory input to that algorithm.

3.3.2 Ancillary Data

The Probability of Rainfall Algorithm uses the intermediate rainfall rate nowcasts at 15-min intervals out to 3 h lead time from the Algorithm Quality outputs from the Rainfall Potential Algorithm (dynamic ancillary data).

3.4 Theoretical Description

The probability of at least 1.0 mm of rainfall at a pixel during the subsequent 3 hours is a function of two factors: the rainfall being predicted for that pixel during that time period, and the degree of confidence in that forecast. Consequently, the approach that is most desirable and that ensures maximum consistency with the corresponding rainfall rate and rainfall potential products is to post-process these two products in a manner that accounts for any uncertainty and bias they may exhibit.

3.4.1 Physics of the Problem

While the most straightforward approach would be to assign a probability of 100% to pixels where the Rainfall Potential Algorithm output exceeded 1 mm in 3 hours and a probability of 0% otherwise, such a product contains no information on the confidence level of the forecast. Confidence can be determined by comparing the forecasts against ground truth and deriving a statistically-based measure of confidence that also accounts for any biases in the system. This approach is rooted in the work of Klein (1971) and Glahn and Lowry (1972) in which a statistical analysis of a historical database of observations (and forecasts, in the latter case) were used to derive forecast parameters not directly available from a numerical weather model and to account for bias and confidence issues in the model.

The following subsections describe the application of this approach to deriving probability of rainfall fields from the rainfall rate and rainfall potential products. The first subsection describes the analysis for deriving the statistical relationships between the current and predicted rainfall and the rainfall probability, and the second subsection describes its application in the real-time algorithm processing to produce the Probability of Rainfall product.

3.4.1.1 Deriving the Retrieval Relationships

The data set used to calibrate this algorithm consists of matched data sets of the observed probability of rainfall for a given pixel over a 3-hour period (set to 100% if at least 1.0 mm rainfall was observed and 0% if it was not), and the corresponding predicted rainfall rates at 15-minute intervals out to 3 hours that are provided as an intermediate product from the Rainfall Rate Algorithm. These relationships were derived using data from 1-5 January, April, July, and October 2005, and evaluated using an independent data set from the 6^{th} through the 9^{th} of the month.

For pixels with a 3-h Rainfall Potential value of at least 1 mm, the frequency of observed rainfall of at least 1 mm in 3 h was computed as a function of the number of 15-min intervals with predicted rain rates of at least 1 mm/h. In other words, the percentage of pixels with observed rainfall of at least 1 mm in 3 h was computed for that subset of pixels with predicted instantaneous rainfall rates of at least 1 mm/h for 1 of the 12 lead times, 2 of the 12 lead times, etc. The resulting function was smoothed slightly to produce a final set of equations for deriving probability of rainfall from the number of 15-min intervals with predicted rain rates of at least 1 mm/h. For pixels with a 3-h Rainfall Potential value below 1 mm, the predictor is the distance to the nearest pixel with a 3-h Rainfall Potential value of at least 1 mm. The frequency of observed rainfall exceeding 1 mm in 3 h was then computed for each distance bin, and the resulting function was smoothed with a linear approximation. This represents a static retrieval of the coefficients, to be performed once and then used in the probability of rainfall retrieval unless an improved set of coefficients is derived in the future.

3.4.1.2 Probability of Rainfall Retrieval

The resulting equations are then applied to the current real-time output of the Rainfall Rate Algorithm and the intermediate output rainfall rates from the Probability of Rainfall Algorithm. Any physically unrealistic values (less than 0% or greater than 100%) are truncated accordingly and flagged.

3.5 Mathematical Description

For each ABI pixel, the first step is to compute the total number N of lead times (up to 12, at 15-min intervals out to 3 h) in which the Rainfall Potential algorithm predicted a rain rate exceeding 1.0 mm/h as indicated in its Algorithm Quality files. If $N>0$, then the probability of rainfall is computed according to the equations given in Table 1.

Number N of lead times with rain rate >1.0 mm/h	Probability of Rainfall (PoP)
1-4	0.76 + 0.02*N
5	0.85
6	0.87
7-12	0.82 + 0.01*N

Table 2. Relationship between number N of lead times with predicted rain rate > 1.0 mm/h and retrieved probability of rainfall.

If none of the lead times at the pixel of interest had predicted rainfall rates exceeding 0.1 mm/h (i.e., if N=0), then the distance D in pixels to the nearest pixel with a Rainfall Potential value exceeding 0.10 is determined, up to a maximum distance of 15 pixels. If nonzero Rainfall Potential is found within that 15-pixel radius, then the probability of rainfall is expressed as

and the value of PoP is given as zero otherwise.

3.6 Algorithm Output

The final output of this algorithm is the Probability of Rainfall product—a field of rainfall probabilities (expressed as a decimal) at the same resolution as the ABI IR data—2 km at nadir. This product will also be accompanied by a grid of corresponding quality flags, with values of 0 for good data and non-zero for data that are of questionable quality due to deficiencies in the input data, as described in Table 3:

Byte	Bit	Flag	Source	Value
0	0	Probability of Rainfall output	PR	1=bad data; 0=OK
	1	Satellite zenith angle block-out zone	SDR	1=zenith angle>70° or lat>60°; 0=OK
	2	Missing input Rainfall Potential value at 15-min lead time	RP-QI	1=bad data; 0=OK
	3	Missing input Rainfall Potential value at 30-min lead time	RP-QI	1=bad data; 0=OK
	4	Missing input Rainfall Potential value at 45-min lead time	RP-QI	1=bad data; 0=OK
	5	Missing input Rainfall Potential value at 60-min lead time	RP-QI	1=bad data; 0=OK
	6	Missing input Rainfall Potential value at 75-min lead time	RP-QI	1=bad data; 0=OK
	7	Missing input Rainfall Potential value at 90-min lead time	RP-QI	1=bad data; 0=OK
1	8	Missing input Rainfall Potential value at 105-min lead time	RP-QI	1=bad data; 0=OK

	9	Missing input Rainfall Potential value at 120-min lead time	RP-QI	1=bad data; 0=OK
	10	Missing input Rainfall Potential value at 135-min lead time	RP-QI	1=bad data; 0=OK
	11	Missing input Rainfall Potential value at 150-min lead time	RP-QI	1=bad data; 0=OK
	12	Missing input Rainfall Potential value at 165-min lead time	RP-QI	1=bad data; 0=OK
	13	Missing input Rainfall Potential value at 180-min lead time	RP-QI	1=bad data; 0=OK
	14-15	Not used		

Table 3. Quality flags for the Probability of Rainfall product.

The metadata file will contain the information listed below in Table 4:

Type	Variable
Float	Total area (*number of pixels in image with probability of rainfall ≥ 1%*)
Float	Total probability (*sum of all probability values in grid*)
Long	Total number of pixels where retrieval was attempted
Long	Number of QA flag values: *15*
Long	Number of retrievals with QA flag value 0 (*all bits set to 0*)
String	Definition of QA flag value 0: *Good Probability of Rainfall retrieval*
Long	Number of retrievals with QA flag bit 0 set to 1
String	Definition of QA flag with bit 0 set to 1: *Bad Probability of Rainfall retrieval*
Long	Number of retrievals with QA flag bit 1 set to 1
String	Definition of QA flag with bit 1 set to 1: *Satellite zenith angle block-out zone*
Long	Number of retrievals with QA flag bit 2 set to 1
String	Definition of QA flag with bit 2 set to 1: *Missing input Rainfall Potential value at 15-min lead time*
Long	Number of retrievals with QA flag bit 3 set to 1
String	Definition of QA flag with bit 3 set to 1: *Missing input Rainfall Potential value at 30-min lead time*
Long	Number of retrievals with QA flag bit 4 set to 1
String	Definition of QA flag with bit 4 set to 1: *Missing input Rainfall Potential value at 45-min lead time*
Long	Number of retrievals with QA flag bit 5 set to 1
String	Definition of QA flag with bit 6 set to 1: *Missing input Rainfall Potential value at 60-min lead time*
Long	Number of retrievals with QA flag bit 6 set to 1
String	Definition of QA flag with bit 7 set to 1: *Missing input Rainfall Potential value at 75-min lead time*
Long	Number of retrievals with QA flag bit 7 set to 1

String	Definition of QA flag with bit 8 set to 1: *Missing input Rainfall Potential value at 90-min lead time*
Long	Number of retrievals with QA flag bit 8 set to 1
String	Definition of QA flag with bit 9 set to 1: *Missing input Rainfall Potential value at 105-min lead time*
Long	Number of retrievals with QA flag bit 9 set to 1
String	Definition of QA flag with bit 10 set to 1: *Missing input Rainfall Potential value at 120-min lead time*
Long	Number of retrievals with QA flag bit 10 set to 1
String	Definition of QA flag with bit 11 set to 1: *Missing input Rainfall Potential value at 135-min lead time*
Long	Number of retrievals with QA flag bit 11 set to 1
String	Definition of QA flag with bit 12 set to 1: *Missing input Rainfall Potential value at 150-min lead time*
Long	Number of retrievals with QA flag bit 12 set to 1
String	Definition of QA flag with bit 13 set to 1: *Missing input Rainfall Potential value at 165-min lead time*
Long	Number of retrievals with QA flag bit 13 set to 1
String	Definition of QA flag with bit 14 set to 1: *Missing input Rainfall Potential value at 180-min lead time*
Long	Number of retrievals with QA flag bit 14 set to 1

Table 4. Metadata for the Probability of Rainfall product.

4 TEST DATA SETS AND OUTPUTS

4.1 Simulated/Proxy Input Data Sets

As stated previously, the Probability of Rainfall Potential algorithm does not directly use any satellite data; rather, it uses as input the nowcast instantaneous rainfall rates from the Quality Assurance fields of the Rainfall Potential algorithm, which in this case were derived from Rainfall Rate retrievals that used as input SEVIRI observations as a proxy for ABI data, and blended microwave rainfall estimates as a calibration data source. The reader is referred to the Rainfall Rate Algorithm Theoretical Basis Document and the Rainfall Potential Algorithm Theoretical Basis Document for additional details..

4.2 Algorithm Output Using Proxy Input Data Sets

The Probability of Rainfall algorithm was applied to test data from the 6th through the 9th of January, April, July, and October 2005; Figure 2 shows an example of the output.

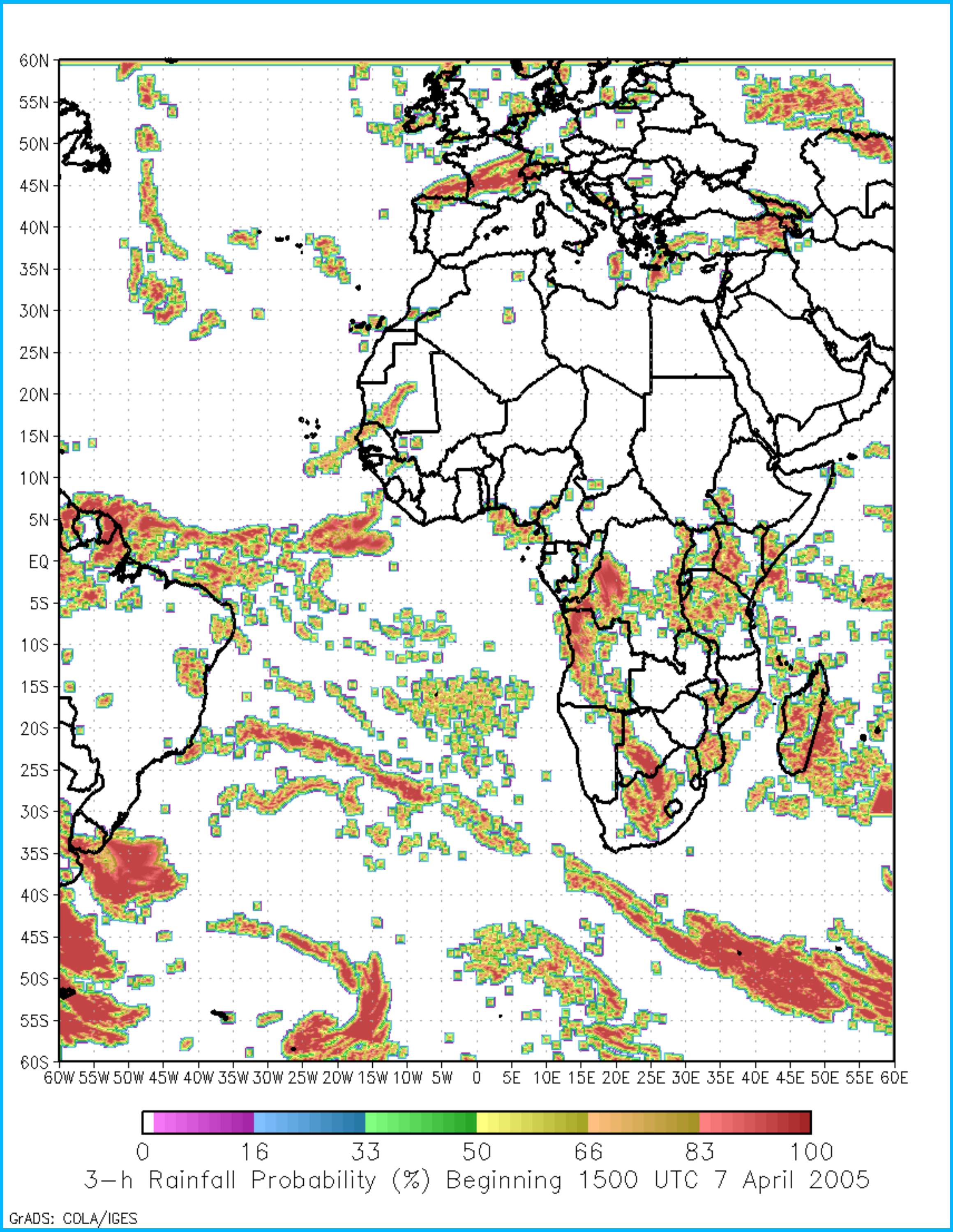

Figure 2. Probability of Rainfall for the 3 hours beginning 1500 UTC 8 July 2005 derived from Rainfall Potential and Rainfall Rate fields based on SEVIRI data.

4.3.1 Precisions and Accuracy Estimates

To estimate the performance and accuracy of the Probability of Rainfall Algorithm, we will have to compare the output against available rain gauge data and radar data. However, such data are very difficult to obtain over Europe and Africa. Comparisons will be made against Nimrod radar data over Western Europe, and, if possible, data from the Convective and Orographically-induced Precipitation Study (COPS) and NASA African Monsoon Multidisciplinary Analyses (NAMMA) field campaigns over Europe and West Africa, respectively. This section will present the analysis methodology for estimating the precision and accuracy, followed by the quantitative results in terms of the F&PS specifications.

4.2.1.1 Validation against Nimrod

Validation against the 5-km Nimrod composite radar product was performed for the 5th-9th of April, July, and October 2005 (January 5-9 was not available from the BADC archive). Figure 3 illustrates a comparison of the Probability of Rainfall product against the Nimrod data, where the Nimrod data indicate regions with rainfall accumulations exceeding 1.0 mm for comparison with the Probability of Rainfall product. When comparing the two panels, it should be kept in mind that the probability fields would be expected to cover much larger areas than the observed rainfall since even very low probabilities are included.

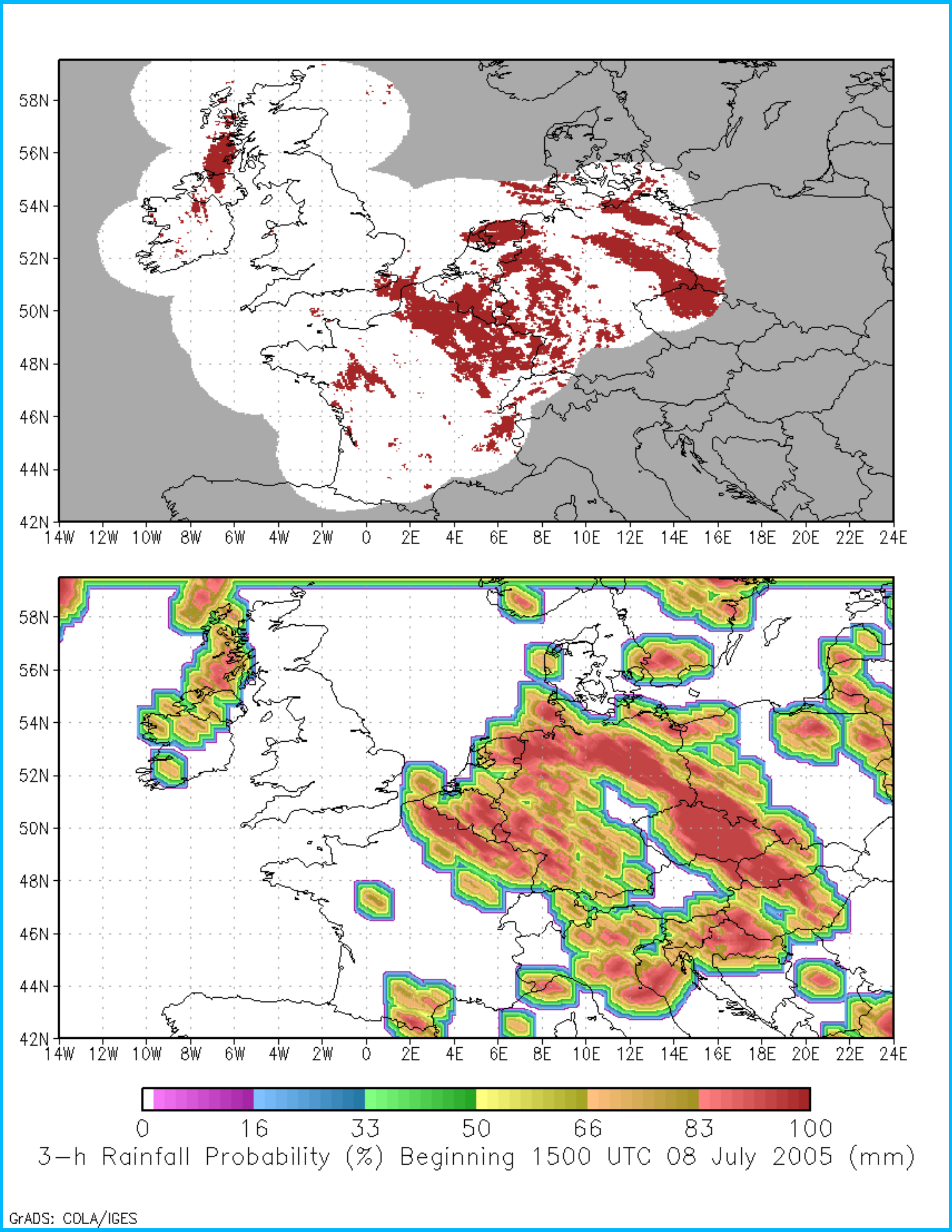

Figure 3. Comparison of Nimrod rain area (top) with the corresponding Rainfall Probability (bottom) for the 3 h begnnning 1500 UTC 8 July 2005.

A comparison of the observed frequency of rainfall for all pixels with a given probability in Fig. 4 shows that the forecasts are generally overconfident; that is, rainfall occurs less frequently than indicated by the PoP fields for high PoP values, though the reverse is true to some extent for lower PoP values (i.e., there is a slight wet bias.

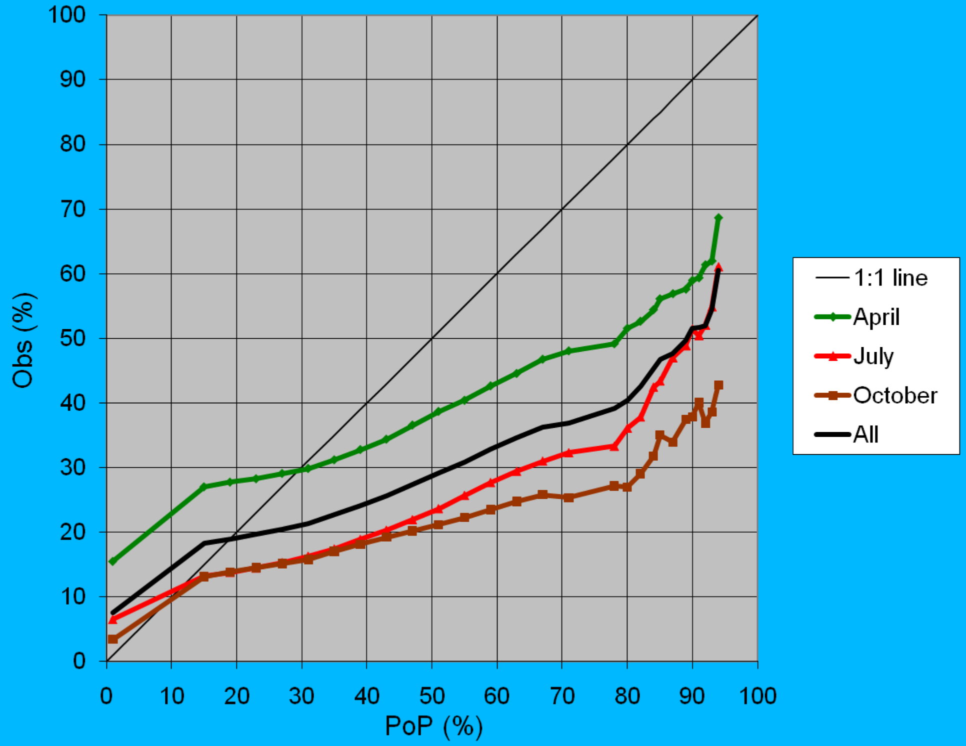

Figure 4. Observed probability of rainfall as a function of predicted probability of rainfall for the first 5 days of April, July, and October 2005.

The specific F&PS precision requirement for the Rainfall Potential algorithm is for a precision of 40%. This means that for pixels with nonzero Probability of Rainfall values, the corresponding observed value (0% for no rain and 100% for rain) should be within 40 percentage points of the predicted value 68% of the time. The evaluation of the Rainfall Potential against the precision spec value is illustrated in Fig. 4, which shows the cumulative distribution function (CDF) of the Rainfall Potential errors for 5-9 April, July, and October separately and together. The algorithm meets spec if the CDF curve reaches the 68% value at a value lower than 40% error, which as Fig. 6 shows does not occur for any season at this time.

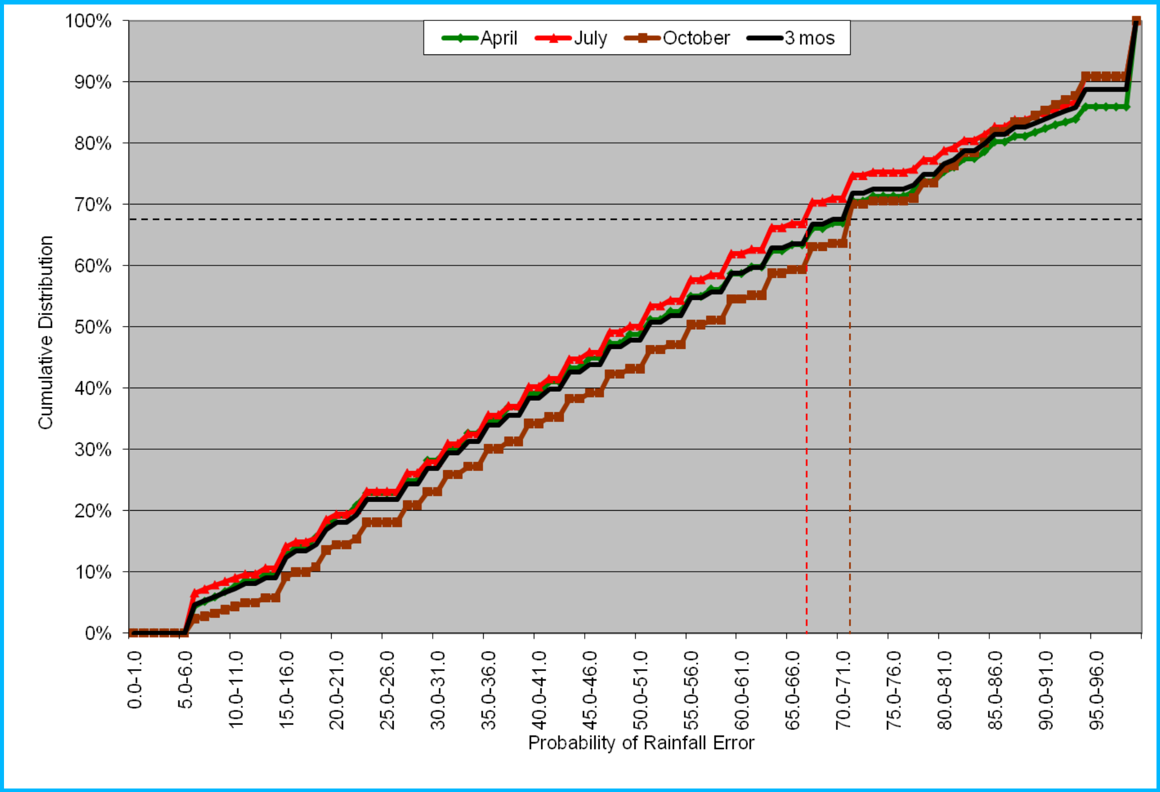

Figure 5. Cumulative distribution function of rainfall potential errors (absolute value of observation minus forecast probability) versus NIMROD data over Western Europe for the 5th-9th of April, July, and October 2005, plus the CDF curve for all data

4.2.2 Error Budget

The validation of the Probability of Rainfall derived from the intermediate Rainfall Potential nowcasts driven by SCaMPR rain rates against NIMROD data for the 5th-9th of April, July, and October 2005 indicates that the accuracy spec is generally being met over Western Europe, but the precision spec is not. For reference, the accuracy specification refers to bias—the absolute difference between the mean observed probability of rainfall and mean predicted probability of rainfall. The precision specification is the 68th percentile of the cumulative distribution function of absolute errors; i.e., 68% of the absolute forecast errors will be below the precision value. <u>It should be noted that these values exclude pixels where no rainfall was observed and the algorithm probability of rainfall was zero</u> in an effort to reduce statistical variability between relatively dry and wet regions. However, these statistics are still based on a relatively small sample, so additional baseline validation will be performed as more validation data become available. In the meantime, the results of the initial validation are summarized in Table 5.

	Accuracy (%)	**Precision (%)**	**No. of data points**
Vs. NIMROD (Apr)	0	71	3.510,244
Vs. NIMROD (Jul)	27	67	2.837,859
Vs. NIMROD (Oct)	33	71	1,993,686
Vs. NIMROD (3 mo)	11	71	8,335,860
F&PS	**25**	**40**	**-----**

Table 5. Comparison of Probability of Rainfall validation with proposed F&PS.

5 PRACTICAL CONSIDERATIONS

5.1 Numerical Computation Considerations

The Algorithm Quality fields from the Rainfall Potential algorithm that contain the forecasts of rainfall at 15-min intervals out to 3 h are needed as input to the Probability of Rainfall algorithm.

5.2 Programming and Procedural Considerations

The Probability of Rainfall Algorithm is purely a pixel by pixel algorithm and can be run for blocks rather than the full disk as desired; in addition, no temporal information is required.

5.3 Quality Assessment and Diagnostics

Quality flags will be produced, with non-zero values assigned to flags associated with pixels with missing intermediate Rainfall Potential values. These flags are described in detail in Section 3.6.

The following procedures are recommended for diagnosing the performance of the Probability of Rainfall Algorithm.

- Periodically image the individual test results to look for artifacts or non-physical behaviors.
- Periodically evaluate time series of bias statistics of the algorithm output to identify any anomalous patterns.

5.4 Exception Handling

Quality control flags will be checked and inherited from the input Probability of Rainfall fields, including bad data, missing sensor input data, and missing geolocation or viewing geometry information—thus, the algorithm expects the Level 1b processing to flag any pixels with missing geolocation or viewing geometry information. The Probability of Rainfall Algorithm also checks for any 'missing' values that are passed from the antecedent Rainfall Rate and Rainfall Potential Algorithms and assigns a 'missing' (negative) value if that occurs. Checking of the validity of the corresponding input ABI bands is performed by the Rainfall Rate Algorithms.

5.5 Algorithm Validation

Prior to launch, validation efforts will focus on Europe and Africa using SEVIRI data as a proxy for ABI given the previously discussed concerns about using simulated data for validation. The validation data will consist of Nimrod ground-based radar data over Western Europe, plus any ground-based radar data from field campaigns that can be obtained. This data set was described in Section 4.2.1.1. However, it should be noted that ground-based radars have numerous well-documented limitations, so any ground-based radar data used for validation will need to be carefully quality-controlled, including comparisons between radar-derived rainfall total fields and corresponding rain gauges to determine the extent of such errors.

During the pre-launch period, validation tools will also be developed: one set to be used by operations to monitor the performance of the algorithm in real time and identify any anomalies; the second to be used by the algorithm developers to identify systematic algorithm deficiencies, their possible causes, and potential remedies. The former will be transferred to the NOAA / NESDIS Office of Satellite Data Processing and Distribution (OSDPD) while the latter will remain at STAR for use by the algorithm developers and collaborative partners outside STAR.

The post-launch phase will consist of monitoring of the product stream by OSDPD using the aforementioned tools, and close collaboration between STAR developers and the NOAA / NESDIS / OSDPD / Satellite Services Division (SSD) Satellite Analysis Branch (SAB) analysts who are responsible for real-time monitoring of satellite rainfall. They will evaluate the performance of the algorithm both from an "eyeball" perspective of day-to-day performance and from the perspective of systematic behavior of the algorithm as identified using the statistical tools. Modifications to the algorithm to address any deficiencies will then be identified and implemented.

Additional details about algorithm validation can be found in the corresponding Product Validation Plan.

6 ASSUMPTIONS AND LIMITATIONS

The following sections describe the current limitations and assumptions in the current version of the Probability of Rainfall Algorithm.

6.1 Performance

The following assumptions have been made in developing and estimating the performance of the Rainfall Rate Algorithm. The following list contains the current assumptions and proposed mitigation strategies.

1. The region over which validation was performed (Europe and Africa) represents the meteorological regimes found in the Western Hemisphere, and hence the validation statistics for that region accurately reflect performance in the GOES-R coverage region. (No mitigation possible).

6.2 Assumed Sensor Performance

We assume the sensor will meet its current specifications. However, the Probability of Rainfall Algorithm will be dependent on the following instrumental characteristics because of their effects on the antecedent Rainfall Rate and Rainfall Potential Algorithms.

- The spatial variation predictors in the Rainfall Rate Algorithm will be critically dependent on the amount of striping in the data. Note that this will affect the retrieval only in those particular instances when they involve the small subset of predictors actually being used for the retrieval step.
- Unknown and sudden spectral shifts in some channels will affect the brightness temperature difference calculations and thus compromise some of the predictors. Note that this will affect the retrieval only in those particular instances when they involve the small subset of predictors actually being used for the retrieval step. Note that gradual spectral shift will have relatively little influence on the algorithm as long as they occur slowly enough (over the course of weeks or longer) where the spectral characteristics of the Rainfall Rate Algorithm training data set is similar to that of the real-time data.

6.3 Pre-Planned Product Improvements

Calibration will be performed on additional data to derive a more robust set of probability relationships. In addition, the actual rainfall rates from the intermediate Rainfall Potential are being considered (as opposed to just considering rain vs. no rain) and different weights for different lead times are being explored since confidence should be greater for rainfall nowcasts at short lead times than at longer lead times when retrieving the probability of rainfall for the next 3 h. Regional average Rainfall Potential values are also being explored as potential predictors. Finally, potential modifications to the antecedent Rainfall Rate and Rainfall Potential Algorithms are detailed in their respective ATBD's.

7 REFERENCES

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Klein, W. H., 1971: Computer prediction of precipitation probability in the United States. *J. Appl. Meteor.*, **10**, 903-915.