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Towards Probabilistic Quantitative Precipitation WSR-88D Algorithms: Preliminary Studies and Problem Formulation

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EXECUTIVE SUMMARY

The main objective of the project is to develop a scientifically substantiated method for operational probabilistic quantitative precipitation estimation (PQPE) based on the WSR-88D measurements. During the first year of the project, the authors accomplished the following goals: (1) performed an extensive research of the existing quantitative results about the major error sources in radar rainfall estimates; (2) formulated the PQPE problem in scientific terms and defined the conditions that must be fulfilled by any viable method applied to its solution; (3) designed and documented three possible mathematical approaches to estimating the PQPE products based on the operational data; and (4) organized a workshop of several experts in radar hydrology to discuss the PQPE problem, possible solution methods, and the development strategy.

The authors define a radar PQPE product as a set of situation-dependent parameter values in a model describing the probability distributions of the uncertainties in the radar-estimated rainfall. The distributions quantify the available probabilistic knowledge about the true spatial rainfall that is likely, given current radar measurements and other available information. The model parameter values determine unambiguously the uncertainty distributions for each operationally useful distance from the radar and spatiotemporal averaging scale. This allows generating different user-specific outputs demanded by various operational applications. Among these outputs are the uncertainty bounds and probabilities of exceedence. Generating an ensemble of the probable rainfall maps to provide the input for the ensemble forecasting schemes is also possible.

Three possible approaches to the PQPE problem were considered. The first is an error propagation scheme using static models of rainfall and the observational uncertainties. The second is error propagation using stochastic-dynamic models of precipitation and the radar observations. The third consists of empirically based scale-dependent modeling of the final effect of all the errors at different distances from the radar and for different synoptic conditions. As a result of the research and discussions carried out in this project, the authors recommend basing the final PQPE algorithm on a combination of the first and third approach. The first approach provides a conceptual and mathematical basis to understand and quantify the effects of various error sources. The third approach provides empirical justification of the necessary modeling assumptions, the large-sample estimates of the model parameters in different situations and a statistical framework for dealing with the ground reference errors during the parameter estimation.

The authors describe the strategy necessary to accomplish the project objectives. The strategy requires an extensive data analysis of a large (5-8 years) data set based on the unique facilities available in Oklahoma. These resources include four standard WSR-88D stations (KTLX, KINX, KVNX and KFDR), an experimental polarimetric WSR-88D station (KOUN), and the Oklahoma Mesonet, the Little Washita Micronet and the EVAC PicoNet. The data collection for this project has already started.

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A. BACKGROUND INFORMATION

Flood and flash-flood forecasting as well as other hydrologic and water resources services performed for the public by the National Weather Service (NWS) require high space and time resolution precipitation input. Currently, these needs are being addressed by use of observations from the network of weather radars WSR-88D combined with rain gauge data and satellite information. The current operational NWS multi-sensor rainfall algorithms produce deterministic (i.e. single-valued) fields of precipitation accumulations. However, it is well-known that rainfall estimates are notoriously uncertain owning to high space and time variability of the relevant physical process and the limitation of the observational systems. Catastrofic events of the recent years are a good illustration of that (Smith et al. 2000; Smith et al. 2001; Ogden et al. 2000). Yet, forecasters and other water management agency users of these products have no quantitative information on rainfall products uncertainty or accuracy. Users would be better able to make informed decisions if they knew not only the best rainfall estimate but also the associated uncertainty and/or range of most likely values.

The Office of Hydrologic Development of the NWS intends to address this shortcoming of the existing algorithms by preparing a comprehensive plan for development of a new generation of algorithms for the precipitation estimation. These algorithms are referred to as *probabilistic quantitative precipitation estimation*, or PQPE. The purpose of this report is to lay out an early formulation of the problem, identify conceptual, methodological and technological issues, and propose a feasible plan of action.

Our focus will be on radar-rainfall estimation but certain aspects of the discussion are applicable to other observing systems, satellite-based in particular. In this report we review the state-of-the-art of uncertainty estimation of precipitation observing systems, formulate the problem of providing probabilistic quantitative estimates of precipitation, and discuss three approaches to delivering it operationally. We also formulate the research, technical, and funding requirements necessary to accomplish the goal of operational implementation of PQPE algorithm with 3-4 years.

In the next section, we summarize the current state-of-the-art in RR uncertainty estimation paying particular attention to those aspects of the past works that are potentially useful for our problem at hand. In our discussion we try to distinguish research and operational applications but the distinction is not always clear.

B. State-of-the-art in Radar-Rainfall Uncertainty Research & Operations

From the statement of the PQPE problem, it is clear that its central issue concerns all the uncertainties in RR estimates. Thus, it is crucial to understand the major sources of these errors and their relative importance. Some information on these questions can be obtained from the numerous studies that investigated the uncertainties in RR estimates from different points of view. In this section, we review the major published results about the subject. However, before we proceed with the review, let's first enumerate the major sources of the uncertainties in the reflectivity-based RR products:

1. Radar miscalibration
2. Variable Z-R relationship
3. Vertical air motions
4. Hail contamination
5. Vertical variability of the precipitation system
6. Beam overshooting of low clouds
7. Ground clutter and AP
8. Beam blockage.

The radar miscalibration has the simplest structure. It is constant for the entire radar umbrella and can persist for long periods of time, until the radar reflectivity measurements are properly calibrated. The next three error sources (2 to 4) are variable in space and time, but are independent of the distance from the radar. One can assume with some degree of confidence that, in most situations, their characteristics are homogenous under the radar umbrella. This assumption, however, does not apply to radar locations with complex topography where the orographic effects can force strong inhomogeneities in the microphysics and dynamics of a precipitation system. The two error sources listed above as 5 and 6 exhibit strong range dependence. This dependence is pronounced in both the large-sample averages as well as in other distributional characteristics of the errors. It is a direct result of the geometry of radar measurements combined with the variability of the spatial structure of the precipitation systems. Finally, the last two error sources (7 and 8) have vastly different spatial characteristics depending on the surrounding topography, presence of obstacles and current atmospheric propagation conditions. The above list is not exhaustive and there are many other error sources like radar navigation errors, distortions due to the polar to Cartesian grid transformation, advection effects, temporal sampling errors and others. Since our scope concerns the operational products that are averaged over at least 1 hour interval and 16 km^2 area, we assume that these additional errors average out to a large degree and become insignificant in comparison with the major uncertainties that we enumerated. Still, how this assumption applies to different space and time scale remains to be verified.

The following review of published analyses on RR uncertainties is limited to reflectivity-based RR estimates, with particular focus on the currently available operational WSR-88D rainfall products (Fulton et al. 1998). From this literature review, we will try to obtain some estimates of the probable range of magnitude and possibly other characteristics of the uncertainties. Our review is roughly organized according to the different error sources listed above. Since we are mostly interested in the actual RR error levels estimated in comparison with accurate reference data, here we only rarely mention the analyses that are based on analytical and/or simulation models only. Due to complexity of the precipitation and its radar observational process, the models are always highly idealized and their results can be far from being operationally applicable.

B.1. Radar miscalibration

One of the most notorious errors often encountered in the RR products is severe underestimation of rainfall at all ranges that is apparently caused by the radar miscalibration. In the early stages of NEXRAD development, such problems were reported by Lott and Sittel (1996) in their study of five extreme rainfall events that resulted in damaging floods. The storms occurred during the years of 1994-95 and were covered by different WSR-88D stations. The authors compared the storm totals from altogether 220 rain gauge stations with the corresponding operational NEXRAD estimates. In 80% of the cases the radar totals were underestimated, often as much as 2-3 times, and the errors were independent of the distances from the radars. One of these events, the catastrophic storm near Houston, Texas, in October 1994, was later analyzed by Vieux and Bedient (1998). They concluded that using the "tropical" Z-R relationship ($Z=250R^{1.2}$), instead of the standard NEXRAD relationship ($Z=300R^{1.4}$), dramatically improved the rainfall estimates. On the other hand, a study by Bedient et al. (2000) of two events that occurred over the same area in 1997 and 1998 demonstrates significant overestimation of radar accumulations obtained using the tropical Z-R. The authors blame the possible rain-gauge failures for these discrepancies. However, it is also likely that the possible reflectivity bias of the Houston WSR-88D was corrected in the meantime rendering the tropical Z-R ineffective.

In general, based on rain gauge data, it is impossible to distinguish the radar reflectivity miscalibration from the Z-R biases. One way to overcome this difficulty is comparing measurements of the same storm from two radars in the overlapping area. Such comparisons carried out by Smith et al. (1996) revealed systematic difference of about 30% between Oklahoma City (KTLX) and Tulsa (KINX) radars. Both radars used the standard Z-R so the difference in radar calibration was evident. Baeck and Smith (1998) report that in 1996 this difference was reduced. Statistical analysis of concurrent reflectivity data from two radars in equidistant areas is becoming an operational tool in NORDRAD (Joe 2001). This technique, however, can only check the relative systematic differences between radars. More objective information about the possible miscalibrations of the radar constant can be provided by an accurate, independent and concurrent measurement of rainfall reflectivity. Large sample comparisons with disdrometer estimates of reflectivity was applied by Ulbrich et al. (1997) to test the calibration of the Greer (KGSP) radar station in South Carolina. They report underestimation of the WSR-88D reflectivities by 4 dBZ that coincides with systematic underestimation of rainfall by a factor of two in comparison with a well maintained rain-gauge network. Radar-disdrometer comparisons are difficult due to the inherent area-point differences and the instrumental uncertainties of the disdrometers. More promising seems to be comparisons with the stable precipitation radar (PR) on the TRMM satellite. Recently, Anagnostou et al. (2001) performed such large-sample comparisons for several radars, including nine selected WSR-88D stations at the South-East of the USA. They report calibration differences in the range from –3 to +2 dBZ in these radars. Additionally, they observed occasional large jumps in the biases over a long period of time that might be the results of periodic radar calibration procedures. Although the mathematical approach used in Anagnostou et al. (2001) seems to be oversimplified and their quantitative results might be questionable, they at least were able to demonstrate a promising idea of using the TRMM PR data to deal with the WSR-88D miscalibrations.

Summarizing this topic, systematic albeit unpredictable biases in the radar constant still poses a severe problem for quantitative RR estimation, despite multiple steps of thorough electronic calibration performed in all the WSR-88D stations (Crum 1998; Serafin and Wilson 2000) and mean-field bias adjustments based on rain gauge data (e.g. Anagnostou et al. 1998). Hopefully, with the advance of new technologies more effort will be devoted to satisfy a basic demand for measuring the radar reflectivities accurately.

B.2. Variable Z-R, Vertical Air Motions, and Hail Effects

Large part of the uncertainties in RR estimates is caused by the lack of one unambiguous Z-R relationship that could be used to convert the radar-measured reflectivities into rainfall estimates. This problem has been attributed to the unknown variability of the drop size distribution (DSD) in the radar-observed precipitation systems. Although numerous experimental and theoretical studies have been performed on the DSD variability in different rainfall regimes, their application to improve the RR estimates is still questionable. This might be due to the fact that classification of the rainfall regime based on the radar information does not have to be closely related to the DSD structure. For example, Ciach et al. (1997) showed that using radar-based classification into convective and stratiform echoes proposed by Steiner et al. (1995), with their corresponding Z-R relationships, does not bring noticeable reduction of the mean-square differences between the RR estimates and rain-gauge accumulations. Most likely, the problem of the DSD dependence on precipitation regime is much more complicated. A study by Atlas et al. (1999) based on disdrometer measurements confirms this opinion. They distinguished three rainfall regimes and showed that several Z-R relationships could be fitted for each of the regimes. Also Uijlenhoet et al. (2003) studied disdrometer data from one event and showed that the multiplicative constant of the Z-R relationship changes from 200 to 400 within the storm. However, what we need for the PQPE, an assessment of the RR uncertainties caused by this Z-R variability is a complex problem. The results based on disdrometer data are not directly applicable for this purpose because of the huge difference in spatial resolution of the two sensors. It is probable that the storm-to-storm biases of the radar-estimated accumulations are mostly caused by the systematic differences in the Z-R relationship and can provide relevant data about the magnitude of this error in rainfall products. One of the most informative studies in this respect was performed by Brandes et al. (2002). They compare area-averaged storm totals based on the S-POL radar data with the corresponding accumulations from two dense local networks of rain-gauges in Florida. Their results are based on data from 17 rainfall events collected during August and September of 1998. For the reflectivity-based estimates, the storm-to-storm bias factors (rain-gauge over radar totals) ranged from 0.62 to 1.56 for the smaller network (about 80 km^2) and from 0.63 to 1.17 for the larger network (about 500 km^2). Much larger data-sample would allow estimating the distributional properties of this error that are needed for the PQPE, however, such an extensive analysis has not been performed yet.

Strong updrafts and downdrafts are another source of uncertainties in RR estimation. Austin (1987) showed that in convective downdrafts rainfall rates can be even two times higher than in stagnant air, for the same reflectivities. The vertical air motions cause an additional significant increase of the Z-R variability. Atlas et al. (1995) demonstrated large variations of the multiplicative constant in the Z-R relationships due to the drafts. Similar results were obtained recently by Dotzek and Beheng (2001) in a simulation study based on a fine-resolution model of convective precipitation systems. The multiplicative constant in the computed Z-R relationships changed in the range from 100 to 300. They also noted that these uncertainties are considerably reduced when the spatio-temporal averaging scale of RR estimates is increasing. It is worth mentioning that the draft-related effects will remain a source of serious errors also in the polarimetric rainfall products since polarimetry cannot deal with this specific problem. Perhaps, systematic quantification of their probable magnitude and spatio-temporal structure for both reflectivity-based and polarimetric rainfall estimates might be worth additional experimental effort.

Occurrence of hail in a convective system leads to dramatically high reflectivities that result in unrealistic apparent rain-rates of thousands of mm/h, if substituted to a Z-R relationship. For example, a case of hail related reflectivity peaks of 76 dBZ was reported by Baeck and Smith (1998). If unsuppressed, such high reflectivities would cause instances of huge overestimation in the RR products by an order of magnitude and more. In the NEXRAD precipitation processing system (PPS), the hail contamination problem is reduced by using the so called "hail cap." It is a reflectivity-based rain-rate threshold, equivalent to a reflectivity threshold selected between 51 and 55 dBZ, and any rain-rates above it are replaced with this threshold value (Fulton et al. 1998). In a case study of a catastrophic storm in Colorado, Fulton (1999) showed that the RR estimates can be fairly sensitive to the "hail cap" selection. Changing the threshold from 51 to 55 dBZ increased the radar estimated storm totals from 72 mm to 104 mm. On the other hand, Baeck and Smith (1998) demonstrated a case of substantial underestimation causes by using a typical threshold of 53 dBZ in a hail-free albeit extreme storm. Thus, quantification of the hail-related uncertainties is a complex problem. It must account for both the effectiveness of reducing the large reflectivities caused by the hail stones, as well as the negative effect of suppressing the extremely strong rain-rates that can occur without hail contamination. Also the spatio-temporal structure of the hail effects might be extremely variable. They can probably extend from short and localized incidents in single convective cell, up to the extreme convective super-cells that can persistently produce hail over large areas. In our opinion, based on a few case studies described in the literature, quantitative probabilistic modeling the RR uncertainties induced by hail and the "hail cap" would be difficult. To avoid quite arbitrary assumptions, a thorough large sample study on these specific questions is required.

B.3. Vertical Variability and Beam Overshooting

In the vertical, the lowest radar beam extends from its lower to its upper edge (half power boundaries) approximately from 0.6 to 2.3 km at the distance of 100 km, from 1.3 to 3.9 km at 150 km, and from 2.4 to 5.6 km at 200 km distance. This geometry has a tremendous impact on the relation between radar measurements above and the rainfall at the surface because of the variable vertical structure of the precipitation systems. As the altitude of the radar sampling volume increases, the relation becomes more and more uncertain. There are several factors that contribute to these uncertainties (Zawadzki 1984; Fabry et al. 1992) and most of them are reflected in the vertical profile of reflectivity (VPR). The VPR depends on the precipitation regime and its dynamics, the altitude of the zero (Celsius) isotherm, evaporation (or condensation) conditions under the clouds, and other less predictable factors (Fabry and Zawadzki 1995). As a result, the reflectivities measured at higher altitudes differ from the reflectivities close to the surface below the radar sampling volume. Advection adds to these differences making the rain-drop paths deviate from straight vertical lines. The advection effects, most likely, can be considerably reduced by increasing the spatio-temporal averaging scales.

Although the precipitation VPRs are highly variable in space and time (Vignal and Krajewski 2001), on the average they result in well pronounced range dependent biases in RR estimates. A large sample analysis of these biases is presented in the already mentioned study by Smith et al. (1996). For the warm season, they show a broad maximum of the mean hourly rainfall products around the distance of 100 km from the radar. For the cold season, this maximum is narrower, more pronounced and occurring around the distance of 60 km. In both seasons the peaks are an evidence of the “bright band” that often accompanies the melting layer, especially in the stratiform precipitation systems. The probability of rainfall detection drops with the distance beyond the range of 100 km, which indicated an increasing number of clouds that are below the radar sampling volume (the “beam overshooting”). This drop is especially strong for the cold season. The conditional means (conditioned on the nonzero rainfall) of the radar estimates starts dropping beyond 150 km because the radar beam at these ranges is mostly in the region in which the reflectivity decreases with the altitude. The regular range dependent behavior of the RR products is consistent with the typical VPR shapes in the same geographical region shown in Vignal and Krajewski (2001).

Since the range dependent bias is a strong and to some degree systematic effect, there exist well developed methods for its correction. A method based on solving a discrete inverse problem is presented in Andrieu and Creutin (1995) and in Andrieu et al. (1995). They retrieve an approximation of the mean-field VPR from the radar reflectivities measured at the two lowest elevation angles. This method was later generalized by Vignal et al. (1999) to use the full volume-scan data and to estimate the VPRs in more localized area of an approximate size of 20 km. This increases the efficiency of the correction in the typical situations when the VPR shape varies across the radar observation field (Vignal and Krajewski 2001). An operationally oriented real-time correction scheme of the VPR-related biases was developed by Seo et al. (2000). Their procedure follows in principle the method by Andrieu and Creutin (1995) and additionally provides an estimate of the maximum distance of the radar measurement applicability in a given situation. They conclude that, for the correction method to be operationally useful, it must also account for the spatial variability in the VPR shape.

Although all the published reports show that the correction procedures result in significant reduction of the systematic range-dependent biases in RR estimates, the residual uncertainties are still high. For example, in a case examined by Seo et al. (2000), the root-mean-square (RMS) radar-gauge difference of the hourly accumulations drops only by 10% after applying their VPR adjustment procedure. Thus, the random errors in RR are difficult to reduce and still have strong effect on the hydrological applications of the products. From the PQPE perspective, we need to know the distributions of the uncertainties remaining after different corrections. Unfortunately, there are no published results on this difficult subject. Obtaining reliable quantitative information about these distributions demands extensive large-sample research. Such analysis would allow us to progress beyond the crude simplifications based on arbitrary assumptions that might have very limited practical relevance.

B.4. Ground Clutter, AP and Beam Blockage

Efficient elimination of ground clutters that originate from the earth surface is a long standing although still relevant problem. Especially troublesome are “false echoes” that appear in the anomalous propagation (AP) conditions. In the NEXRAD PPS the AP echoes in clear sky situations are detected through a comparison of the reflectivity coverages at the two lowest elevation angles. In situations of mixed clutter and precipitation echoes, methods based on the Doppler signal can be used to suppress echoes with radial velocities close to zero (so called "notch filter"). A reflectivity-based procedure for pixel-by-pixel discrimination of the ground clutters (including AP) is described in Grecu and Krajewski (2000a). Their method, based on an artificial neural network scheme, was calibrated and tested on the so called "clear cut" cases: situations with either only rainfall echoes, or solely clear sky echoes. Currently, a new algorithm to classify radar echoes on a pixel-by-pixel basis is being developed at the National Center for Atmospheric Research (Kessinger et al. 2001). This method is based on fuzzy-logic and its evaluation based on two events (Robinson et al. 2001) showed its good performance.

None of these clutter filtering procedures is perfect. Regardless of the method applied to the WSR-88D reflectivity measurements, there still remains the question of the residual clutter that remains unrecognized, as well as the precipitation echoes that is erroneously classified as clutter. These uncertainties seem to pose an especially difficult problem in mixed situations when both the precipitation and clutter echoes are present in the same area (Smith et al. 1996). Serafin and Wilson (2000) allege that the "notch filter" method can suppress as much as 20% of the precipitation echoes that have their velocity perpendicular to the radar beam. This can result in severe underestimation of the RR estimates in some situations. Although the published studies provide information of the performance of the respective procedures, it is given in terms of the percentage of the correctly and erroneously classified echo points. This is not sufficient to infer the resulting error distributions on the level of the RR products conditioned on different situations.

The radar beam blockage is a specific case of the topography-induced errors that results in complete or partial suppression of the precipitation echoes in the affected areas at the lower elevation angles. The technique that is applied in the WSR-88D data processing to identify the obstructed parts of the radar volume scans is described in Westrick et al. (1999). The method, called the "terrain-based hybrid scan," is based on a high-resolution digital elevation model and assumes standard propagation conditions. If the beam blockage is 50% or larger, data from higher scans are used for the RR estimation. As a result of this procedure, the blockage-related rainfall underestimation is considerably reduced (O'Bannon 1997). Using higher elevation angles, however, increases the uncertainties due to the VPR effects that we discussed above.

C. PQPE: PROBLEM FORMULATION

C.1. Basic Definitions

We begin with brief definitions of a few basic notions and acronyms that will be used throughout this report:

- *True rainfall*: The amount of rain-water that has fallen on a specified area in a specified interval of time.

- *Radar-rainfall (RR)*: A radar data-based approximation of the true rainfall that corresponds to the same spatio-temporal domain.

- *RR uncertainties*: All systematic and random differences between RR and the corresponding true rainfall.

- *Ground reference (GR)*: An approximation of the true rainfall used to evaluate RR products, usually based on rain-gauge measurements.

The evolution of the operational RR products has been mostly determined by the attempts to quantify and to reduce the uncertainties in the RR estimates. The traditional RR map is just an array of numbers describing the spatial distribution of approximate rainfall values that are obtained based solely on weather radar measurements. On the other hand, introduction of the term radar QPE implies that the RR maps are completed with quantitative information about the product uncertainties. Without this additional information about the relation of the RR product to the corresponding true rainfall, both the notion of "quantitative" and the mathematical term "estimation" would be meaningless in this context. However, despite a wide use of this term, the operational WSR-88D rainfall products are devoid of their uncertainty information.

C.2. Problem Description

The probabilistic products, both in meteorology and hydrology, convey the inferred information about the unknown true value of a physical quantity in terms of its probability distribution rather than its one "best" estimate (e.g. Krzysztofowicz 2001).

Thus, the radar PQPE product can be defined as a parameterized mathematical model describing (somehow) the probability distribution of the uncertainties in the RR estimates. To formulate the PQPE objective more precisely, first we need to answer the following question: “What exactly should this distribution represent?” It is our view, that the radar PQPE model should express probabilistic knowledge about the true rainfall maps that are likely, given the current radar measurements and other available information. From such probabilistic RR product one can derive and display any specific characteristics (standard errors, probabilities of exceedence, or an ensemble of probable rainfall maps, for example) that can be required for operational applications.

We envision three possible alternative approaches to the PQPE problem that can potentially realize the above-stated objective. The first approach is based on the error propagation using static models of rainfall, rainfall measurements, and their uncertainties, the second is error propagation using stochastic-dynamic models of precipitation processes and their observations, whereas the third consists of empirically based modeling of the final effect of all the errors. These proposed approaches will be presented in detail in the next Sections. They can be briefly summarized as follows:

Error propagation approach using static models: The first step is identifying the most important error sources in the RR products. The second step is modeling their error structure and estimating the model parameters. This is followed by propagating the joint distribution of the errors through the specific WSR-88D precipitation estimation algorithm. This approach is equivalent to what is known in hydrology as derived distribution.

Error propagation approach using stochastic-dynamic models: The first step is formulating a physically based model of the involved processes. The model is formulated as a system of partial differential equations. The second step involves modification of this deterministic system into its stochastic form. This allows taking into account the uncertainty in the input and mode structure. The third step is formulating a relationship between the model states and their observations. The model can be used as both a forecasting tool as well as an estimator of the current conditions right after updating the model states with the current observations.

Product-error-driven modeling approach: The first step is collecting large samples of reliable data about the relation between different RR products and the corresponding true rainfall. The second step is developing a flexible mathematical model of the relation that can be applied in the operational WSR-88D precipitation estimation process. This is followed with developing empirically based generalizations of the model for different rainfall regimes and radar locations.

Regardless of the particular approach that will be applied to reach the PQPE objective, each method has to satisfy several key requirements that we briefly summarize below:

1. The method has to be "verifiable" using available information. Results of the method will be systematically evaluated to assess degree to which the method provides probabilistically meaningful rainfall estimates.

2. The method has to be adjustable by its model parameter calibration using available information.

3. The method has to include procedures that link spatial and temporal scales in a consistent manner. In other words, the method has to be able to provide PQPE at different scales.

4. The method has to work both for the current reflectivity-only WSR-88D algorithms as well as for the multi-parameter (differential reflectivity and differential phase-shift) algorithms available after the upcoming upgrades of the operational radars.

5. The method has to take into account the local characteristics of topography, vertical profile of reflectivity, ground clutter and anomalous propagation patterns, etc.

6. The method has to take into account the characteristics of the precipitation regime.

7. The method has to provide information in a format appropriate for hydrologic usage of the results.

D. ALTERNATIVE SOLUTIONS

In this section we discuss the two major approaches: (1) uncertainty propagation; and (2) uncertainty parameterization. The first approach can be conveniently divided into one that uses static models and one that uses dynamic models. In our discussion we point out the information required for application of the particular method, its conceptual basis, implementation difficulties, etc.

D.1. Uncertainty Propagation Using Static Models

The main concept of the method has firm basis in probability theory and statistics. It essentially constitutes what is known as derived distribution (e.g. Kottegoda and Rosso 1998) or function of random variables. It requires that physical variables and sensor measurable quantities be conceptualized and modeled as random variables. If probability distribution of input random variables are known, the probability distributions of their functional transformations can be found by following well-establish procedures. For example, if random variable X has probability density function f(x), variable Y that is a monotonic function of X, Y=g(X) with the inverse function X=h(Y), has the probability density function

$$f_1(y) = f[h(y)]|h'(y)| = f[h(y)]\left|\frac{dx}{dy}\right| \tag{D.1.1}$$

In most practical situation relevant to our problem the situation is not as simple as in the above example. The function h(·) is often non-monotonic and, more importantly, variable of interest Y may depend on several input variables. Thus, joint probability functions of the input variables have to be considered.

To illustrate the approach let us consider a generic radar-rainfall estimation algorithm. We assume a single parameter (i.e. radar reflectivity) based rainfall estimation. Multiparamater method based on polarimetric measurements (Ryzhkov and Zrnic 1995;

Zrnic and Ryzhkov 1996; Ryzhkov et al. 2000) will be implemented beyond the three-year timeframe we address in this report. Considering an actual operational algorithm, such as the Precipitation Processing Subsystem (Fulton et al. 1998), would unnecessarily complicate the analysis obscuring the important concepts. A generic algorithm consists of the following steps:

1. Radar system acquisition of radar-reflectivity measurements, typically as a volume scan, i.e. a set of 360 degree sweeps of the atmosphere taken at several antenna elevation angles. The WSR-88D reflectivity data are processed in such a way that the input to any following algorithms is in the form of values with resolution of 1 km in range, and 1 degree in azimuth at some 9 antenna elevation angles. Operational access to higher resolution data is not available. No such data are archived either.
2. Radar data quality control. In this step ground clutter from permanent echoes and from the anomalous propagation conditions has to be detected and eliminated. One way of doing this is by classifying the echo into rain or non-rain (e.g. Moszkowicz et al. 1994; Grecu and Krajewski 1999; Grecu and Krajewski 2000a; Steiner and Smith 2002; Robinson et al. 2001; Kessinger et al. 2001).
3. Correction of the radar-reflectivity for gaseous attenuation, attenuation by precipitation, bright band and vertical profile non-uniformity. For the WSR-88D systems reflectivity attenuation by precipitation is usually ignored as negligible and the vertical profile of reflectivity correction will be implemented operationally soon (Seo et al 2000).
4. Conversion of radar reflectivity to rainfall rate. In most operational systems around the world this is accomplished using a power law type two-parameter relationship (Z-R). For other options see Rosenfeld et al. (1994) and for recent discussions of Z-R parameter estimation issues see Ciach and Krajewski (1999a) and Krajewski and Smith (2002).
5. Calculations of rainfall accumulations and coordinate conversion. With frequent temporal sampling (scanning) by radar the accumulation calculations are accomplished by simply assuming constant rainfall between the volume scans. If the sampling is less frequent (e.g. once every 15 minutes), this assumption leads to often significant errors, particularly in presence of storm advection (e.g. Fabry et al. 1994; Liu and Krajewski 1996).

In the above brief description we only hinted on some sources of uncertainty that contribute to the final estimates of radar-rainfall accumulation maps. We will elaborate as we discuss the various components.

The uncertainty propagation using static models can be performed through derived probability distribution framework as discussed above, or using Monte Carlo simulation. The simulation approach is often much simpler to implement but suffers from significant computational requirements. There are several studies described in the literature that use this approach in an off-line mode designed to improve our understanding of the quantitative impact of certain error sources on rainfall estimates and the subsequent hydrologic predictions (e.g. Krajewski et al. 1996; Sharif et al. 2002).

D.1.1. Accuracy of Radar-Reflectivity Observations

Accuracy of the basic data clearly is the first step in propagation of the various uncertainty sources. The basic data constitute observations associated with measurement error. We define this error as the difference between the physical quantity, called radar reflectivity, and the measured quantity, called radar reflectivity factor Z (in the following discussion we will refer to Z as simply radar reflectivity.) The physical quantity is a characteristic of the atmosphere and it involves summation of the back scattering cross section (σ_i) within an elemental volume ΔV of the atmosphere, as

$$\eta = \frac{1}{\Delta V} \sum_{\Delta V} \sigma_i \qquad \text{(D.1.2)}$$

while its relationship to the measured quantity, Z_m, depends on the characteristics of the scatterers (i.e. rain and cloud droplets), the radar and the processing of the data. Both quantities are associated with a specific sampling volume in the atmosphere, roughly centered on the beam axis and extending around the axis according to an antenna pattern. In range the sampling volume is described by an approximately uniform function over a few hundred meters span and available for further processing after averaging to 1 km scale.

The reflectivity measurement error has a certain probability distribution, largely unknown. This distribution can be characterized by its mean and variance. The mean is a reflection of the radar system calibration and the variance is a reflection of the data processing attributes such as pulse length, pulse repetition frequency, electronic stability of the transmitter and receiver, as well as the target attributes, such as hydrometeor phase, size and shape distribution, and their distribution within the sampling volume.

Let us discuss the calibration issue first. A well-calibrated radar provides, on average, true reflectivity values. As radar is a complex system, calibration is a complicated process that has to include the integrated effect of transmitter, waveguides, antenna, and receiver calibration. As discussed at a recent workshop devoted to the topic during the 2001 Annual Meeting of the American Meteorological Society, and summarized by Atlas (2002), there are no standards for the end-to-end integrated calibration of the weather radar systems. Metal sphere calibration and sun calibration are perhaps two most popular approaches, each associate with its own problems. It is a popular opinion of the radar experts that a well-calibrated radar provides, on average, reflectivity values that are within 1 dBZ.

Operationally, within the NEXRAD there is a built-in frequently performed calibration of the receiver and once a month solar calibration of the antenna positioning system. Transmitter calibration is performed on a regular schedule, approximately once every three months. Despite these efforts, there are many well-documented cases where the disagreement between neighboring radar is on the order of 2-4 dBZ.

The differences from the true values (errors) are due to the above mentioned factors. Even for the best circumstances of uniformly distributed over the sampling volume spherical liquid water droplets, there will be small radar-reflectivity errors dues to finite pulse number averaging and the electronic noise. In expert opinion, the reflectivity measurement error standard deviation for a perfectly calibrated radar would be on the order of 0.5 dBZ.

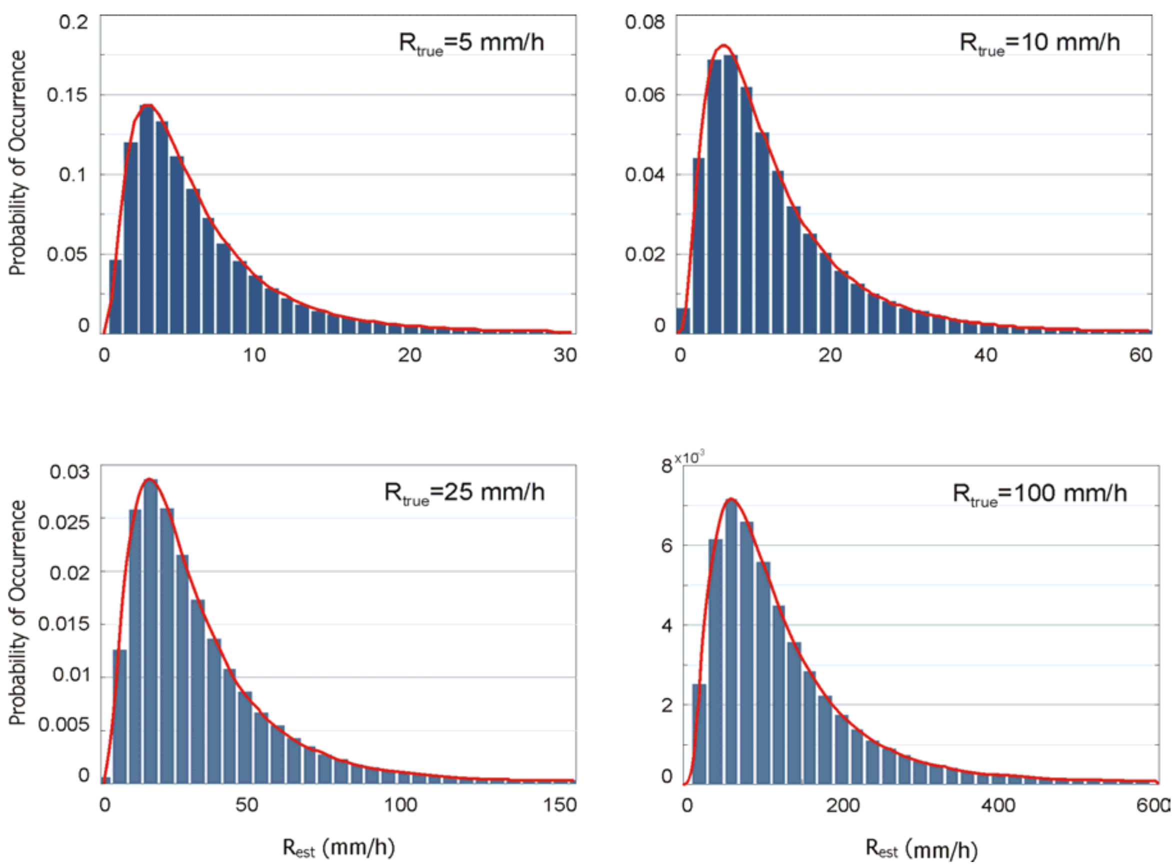

Figure D.1. Error distribution in radar estimated rainfall for the case when the sole source of uncertainty is the measurement error in radar reflectivity. The radar is assumed perfectly calibrated and the measurements of Z have standard error of 1 dBZ.

Thus, what is the bottom line of this discussion in the context of uncertainty description? If for arbitrary operational radar we know its calibration status, we could propose the following error model for the measured Z:

$$Z_{mes} = Z_{true} + \varepsilon_Z \quad \text{with } \varepsilon_Z \propto N(0, \sigma_Z) \tag{D.1.3}$$

where the Z values are given in dBZ units, and N(·,·) denotes Gaussian distribution characterized by the mean and standard deviation, respectively. The above model also implicitly assumes multiplicative nature of the radar-reflectivity measurement error. Clearly, this implies that the measured values were adjusted by adding the Z_{bias} value, resulting in unbiased measurements of Z.

If, we have no information on the calibration status, this leads to the following model of reflectivity uncertainty:

$$Z_{mes} = Z_{true} + \varepsilon_Z \quad \text{with } \varepsilon_Z \propto N(Z_{bias}, \sigma_Z) \tag{D.1.4}$$

Again, these models are based on several assumptions that are difficult to verify independently. For the sake of illustration only, let us demonstrate the effect of these models on rainfall estimation. Assuming, for illustration only, that the rainfall on the ground is the result of the reflectivity measurements in a sampling volume above the ground, and that the Z-R relationship is deterministic and known, and there are no other sources of uncertainty, the estimated rainfall can be described as a random variable whose distribution depends on the probabilistic properties of the measurement error. If we assume a multiplicative error model for radar reflectivity, i.e.

$$R_{est} = \alpha \left(Z_{true} \varepsilon_Z \right)^{\beta} \tag{D.1.5}$$

where α and β correspond to the a and b parameters of the Z-R relationship, and ε_z is lognormally distributed with the mean μ_z and the standard deviation σ_z, the estimated rainfall is also a lognormally distributed random variable with the mean

$$E\{R_{est}\} = R_{true}\mu_Z^{\beta}\left(\frac{\sigma_Z^2}{\mu_Z^2}+1\right)^{\frac{\beta(\beta-1)}{2}} \tag{D.1.6}$$

and the variance

$$V\{R_{est}\} = R_{true}E\{R_{est}\}\left[\left(\frac{\sigma_Z^2}{\mu_Z^2}+1\right)^{\beta^2} - 1\right] \tag{D.1.7}$$

As the multiplier of R_{true} in (D.1.6) is not equal to 1, the measurement error in Z leads to multiplicative bias in the estimated rainfall. The effect is quite significant, assuming the error standard deviation of 1 dBZ, the estimated rainfall distribution for a few values of R_{true} are presented in Figure D.1. In Figure D.2 we show the results over a wide range of rainfall rate. Note that even a small error in Z (as standard error of 1 dBZ is considered a small error) results in considerable uncertainty in the estimated R.

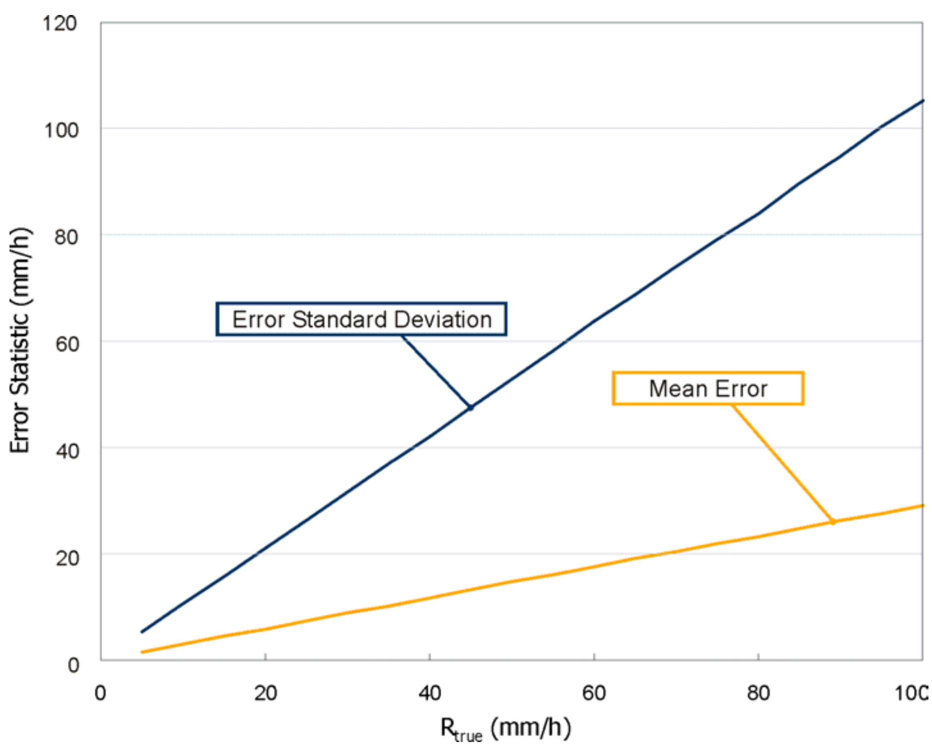

Figure D.2. Error mean and standard deviation of the radar estimated rainfall as a function of the true rain intensity for the same case as that described in Figure D.1.

These results were obtained assuming no uncertainty in the Z-R parameters. It is clear that uncertainty in a and b will increase the error variance. For example, assuming that our lack of knowledge about the parameter a and b can be modeled using uniform distribution, with a~U(200,400) and b~U(1.2,1.6), the distribution of the estimated rainfall is as presented as in Figure D.3. Note the increase of the estimation error bias and variance due to added uncertainty. We will elaborate on the uncertainty due to Z-R relationship parameters in the next sections.

The main conclusion thus far is that modeling the uncertainty of such a basic variable as radar reflectivity measurement error requires information that is not easily obtainable. What complicates the situation further is that gradients of reflectivity within sampling volume contribute additional uncertainty with increases with radar range. At present, we do not know the statistics of such gradients for different rainfall regimes in different climatological settings. Certain polarimetric measurements are more immune to these effects (Ryzhkov and Zrnic 1998a), but again, the main focus of our discussion here is on single parameter radars.

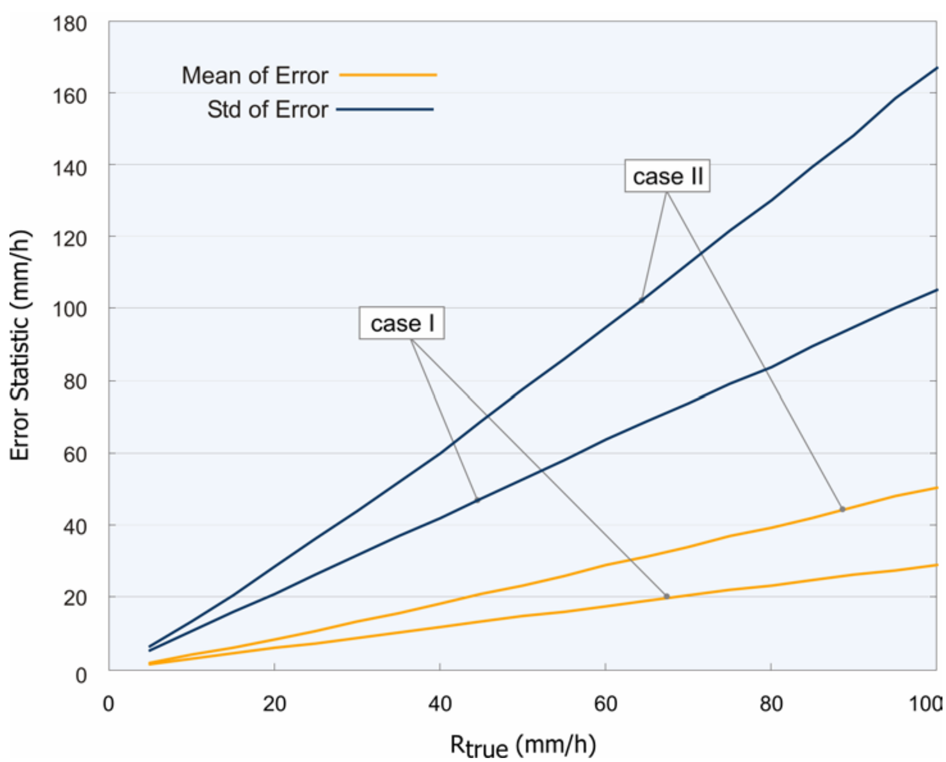

Figure D.3. Error mean and standard deviation for Case 1 as described in Figures D.1. and D.2. and Case 2, where uncertainty of the Z-R relationship parameters is taken into consideration as well.

D.1.2. Radar Data Quality Control

The second step in developing radar-rainfall estimates is quality control of reflectivity data. The main and most difficult issue here is detection of the echo due to anomalous propagation of radar waves. Under certain atmospheric conditions the radar beam propagates in a non-standard way, and may reflect of the terrain (e.g. Doviak and Zrnic 1993). Often the spatial topology of the resulting patterns is difficult for non-experts to discern from those of rainfall systems thus automation of the radar echo classification into rain and non-rain echo has been a subject of continuing research (e.g. Moszkowicz et al. 1994; Grecu and Krajewski 1999; Grecu and Krajewski 2000a; Krajewski and Vignal 2001; Steiner and Smith 2002).

In the PPS system the problem is addressed on a scan-by-scan basis. Checks for vertical and temporal continuity lead to classification of the entire scan as rain or non-rain. Occasionally, this strategy leads to erroneous classification, in particular when part of the scan is covered by a rain system, and contributes to increase in uncertainty in radar-rainfall estimates. A new algorithm developed at the National Center for Atmospheric Research (Kessinger et al. 2001) will perform the classification on a pixel-by-pixel basis. The algorithm will soon be implemented operationally, but its performance in varied climatological and topographic conditions is not well known. As a pixel may be wrongly classified, the severity of such an error depends on the pixel's reflectivity value and the hydrometeorological context.

A major improvement of the permanent and anomalous propagation ground clutter detection will be operational implementation of the polarimetric measurements in the NEXRAD system (Ryzhkov and Zrnic 1998c). Polarimetric measurements allow much easier classification of the radar echo, for example discrimination of different types of precipitation and non-meteorological echoes (Ryzhkov and Zrnic 1998b). It is likely that at that time the contribution of the ground clutter contamination to the uncertainty of rainfall estimates will be negligible. However, this is still 5-10 years away as the operational implementation must be followed by a period of "fine-tuning" of the QC algorithms.

The main point of the above discussion for our purposes of uncertainty propagation is that the performance of the new algorithm has to be monitored and its uncertainty quantified and documented. We expect that the algorithm will perform well and in the following discussion we will ignore this source of uncertainty. Clearly, this is a simplification that has to be further justified.

D.1.3. Vertical Profile of Reflectivity Correction

Nonuniformity in space and time of the vertical profile of reflectivity (VPR) has been known as a major source of radar-rainfall uncertainty (see discussion in Section B.1.3). Several corrective schemes have been proposed and documented in the literature (e.g. Andrieu and Creutin 1995; Vignal et al. 1999; Vignal et al. 2000; Vignal and Krajewski

2001; Seo et al. 2000). In the WSR-88D PPS a correction scheme will not be implemented until 2004.

The effect of the VPR on uncertainty of the radar-rainfall estimates depends on several factors. The most important ones include distance from radar, antenna elevation angle; rain type; and rain climatology. Vignal and Krajewski (2003) attempt to quantify the first two moments (mean and variance) of the error distribution due to VPR. The main assumption of their approach is that the VPR is the main source of error. We outline the procedure below.

Let us formulate the radar rainfall estimates as follow:

$$R_{est}(D,\alpha) = B \cdot R_{true}(D) \cdot I_{VPR}(D,\alpha) \qquad \text{(D.1.8)}$$

where $R_{est}(D,\alpha)$ is the rainfall estimate deduced for radar reflectivity (through the use of a simple Z-R relationship) at the distance D from the radar, α is the antenna elevation angle, and B is the mean field bias. $R_{true}(D)$ is the true rainfall intensity at the ground level for the same location. According to (D.1.8), two factors that link $R_{est}(D,\alpha)$ and $R_{true}(D)$ are I_{VPR} and B. The first one,

$$I_{VPR}(D,\alpha) = \left[\int_{H^-(\theta_0,\alpha,D)}^{H^+(\theta_0,\alpha,D)} Z(h) f^2(\theta_0,h)\,dh \right]^{\beta} \qquad \text{(D.1.9)}$$

quantifies the VPR influence, where Z(h) is the VPR at this location, H^- and H^+ are respectively the lower limit and the upper limit of the radar beam, and f is the one-dimensional power distribution of the radar beam at altitude h, which depends of the beam width, θ_0. The coefficient $\beta=1/b$, where b is the exponent of the Z-R relationship. This parameter can be assumed to be known and constant over time and space. Andrieu and Creutin (1995) or Vignal et al. (1999) discussed this formulation of the VPR influence in detail.

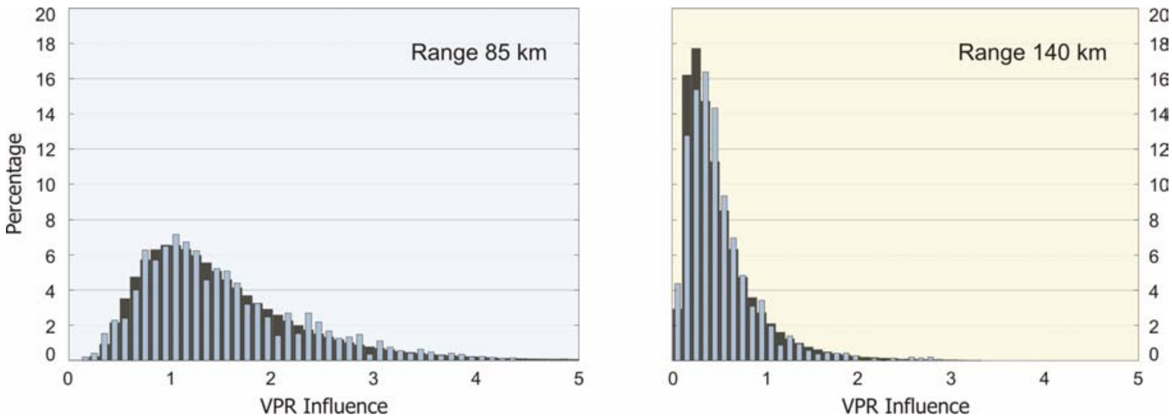

Figure D.4. Empirical distribution (in blue) of the VPR influence at 85 km and 140 km from the Tulsa, OK, WSR-88D radar for an elevation angle of 1.48º. The theoretical lognormal distributions with the same mean and variance are shown in dark gray.

We defined the Range Dependent Error in radar rainfall estimate, RDE(D,α), function of the distance to the radar D and the elevation angle α, as the ratio of radar estimates versus true rainfall. From (D.1.8), the expression for this error is then:

$$RDE(D,\alpha) = \frac{R_{est}(D,\alpha)}{R_{true}(D)} = B \cdot I_{VPR}(D,\alpha) \qquad \text{(D.1.10)}$$

For each distance D and elevation angle α, following the assumption of log-normality of RDE(D,α), the first and second-order statistics are sufficient to characterize the time-variations of the radar error. This assumption can be supported by analysis of the VPR influence for the Tulsa, OK data (Figure D.4). We also assumed that B and $I_{VPR}(D,\alpha)$ are independent. Using data from the Tulsa, Oklahoma, WSR-88D, Vignal and Krajewski (2001) described the evaluation of two methods to correct radar data using VPR. Additional results dedicated to the analysis of corrected radar rainfall estimates show that there is no significant correlation (as the correlation coefficient is between -0.2 and 0.1) between the mean field bias and the VPR influence whatever the distance D.

At a distance D, the time-averaged mean E{RDE} and variance V{RDE} of the range dependent radar error can be expressed as follow:

$$E\{RDE(D,\alpha)\} = E\{B\} E\{I_{VPR}(D,\alpha)\} \qquad \text{(D.1.11)}$$

$$
\begin{aligned}
V\{RDE(D,\alpha)\} = {} & V\{B\}V\{I_{VPR}(D,\alpha)\} \\
& + V\{B\}(E\{I_{VPR}(D,\alpha)\})^2 \\
& + (E\{B\})^2 V\{I_{VPR}(D,\alpha)\}
\end{aligned}
\tag{D.1.12}
$$

As we mentioned earlier, in this discussion, we define the error in radar rainfall estimates as the ratio between radar estimate and true rainfall. These ratios are only defined for non-zero true rainfall. Thus, a threshold on true rainfall has to be introduced. In this case, the frequent conditions of low rainfall intensities would strongly influence our results.

The error can also be defined as the difference between radar and true rainfall. Use of a threshold is not required. In this case, (D.1.8) shows that the error in rainfall estimates depends on the true rainfall [$R_{true}(D)$]. One should also consider possible correlation between B and $R_{true}(D)$. More importantly, the time-averaged mean and variance of the range dependent error will depend on the mean and the variance of the true rainfall. Vignal and Krajewski (2001) showed that for the data from Tulsa, Oklahoma, due to the rainfall climatology of the region, $E\{R_{true}\}$ is not homogeneous in space and therefore in range. For a given direction, the expected value of the true rainfall varies significantly versus distance. The variance displays a similar behavior. This point is the major argument in favor of using ratio versus difference in the error definition.

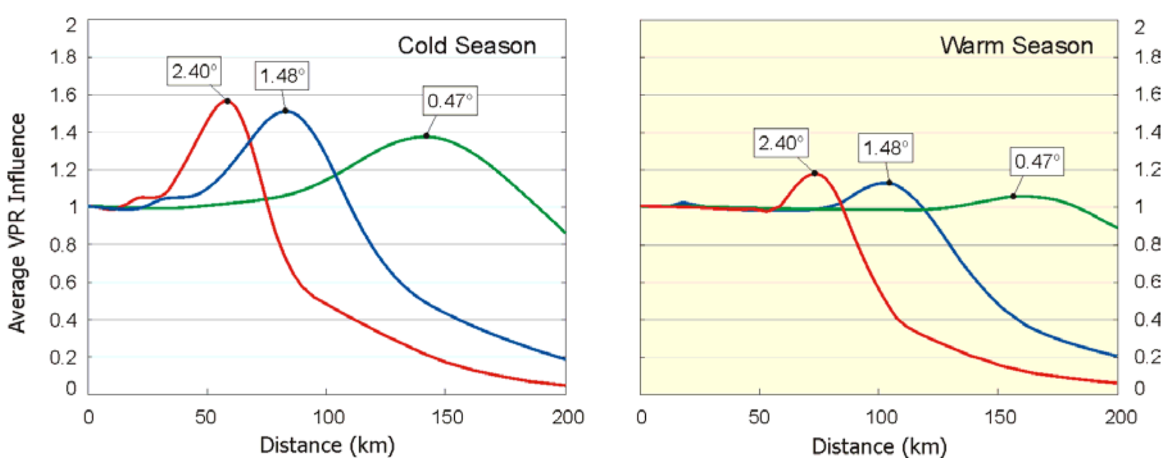

Figure D.5. Evolution of the time-averaged VPR influence versus distance from radar for both cold and warm season and three antenna elevation angles.

At a given distance D, the time-averaged range dependent error is the product of the time-averaged mean field bias and the time-averaged VPR influence. We want to find an appropriate model for the time-averaged VPR influence deduced from the VPR dataset. Figure D.5 displays the evolution versus distance of the time-averaged VPR influence for both cold and warm seasons and the three lowest elevation angles. The curves have several features in common. First, when the VPR influence is equal to 1, the VPR contributes little error. Second, when the VPR influence is greater than 1, the bright band affects the radar data and rainfall intensities are over-estimated. Third, when the VPR influence is lower than 1, the radar beam is above the bright band, and the rainfall intensities are under-estimated. Fabry et al. (1992), for instance, obtained similar results.

The parameterization of Vignal and Krajewski (2003) is based on a simple conceptual model of the VPR. In the model, at low altitudes, the reflectivity is assumed to be constant. Above the bright band enhancement, the decrease of the reflectivity (in dB) with height is assumed to be approximately linear:

$$z(h) \approx \exp\left[-\frac{\ln 10}{10} S(h-h_{bb})\right] \qquad \text{(D.1.13)}$$

where S is the slope of the decrease of the reflectivity with height (in dB/km) and h_{bb} is the bright band altitude (altitude where the reflectivity is maximum). The height h_{bb} is related to the average level of the freezing level, slope to the average condition of the growth of ice particles. The hypothesis of linear decrease of the reflectivity with height above the bright band is supported by several studies (e.g. Joss and Lee 1995).

The bright band influence is addressed considering that it is characterized by a given altitude interval where the reflectivity increases first with increasing altitude and decreases after that. We chose:

$$Z(h) \approx 1 + Z_{\max} \exp\left[-\left(\frac{h-h_{bb}}{e_{bb}}\right)^2\right] \qquad \text{(D.1.14)}$$

where Z_{max} is the maximum reflectivity and e_{bb} is the vertical extension of the enhancement of the reflectivity. This function is maximum when $h = h_{bb}$. Z_{max} is related to the average enhancement of the reflectivity associated with the melting of ice particles;

and e_{bb} is related to the distribution of h_{bb} and the typical vertical extension of the bright band at hourly scale (typically about 0.6 km).

The conceptual VPR model is then expressed as follow:

$$Z(h) = \left\{ 1 + Z_{\max} \exp\left[-\left(\frac{h - h_{bb}}{e_{bb}} \right)^2 \right] \right\} \exp\left[-\delta_h \frac{\ln 10}{10} S(h - h_{bb}) \right] \qquad \text{(D.1.15)}$$

where δ_h is defined by $\delta_h = 0$ if $h<h_{bb}$, $\delta_h = 1$ otherwise.

We obtain indirectly a model of time-averaged VPR influence with four different parameters (h_{bb}, e_{bb}, Z_{max}, and S). To model the time-averaged range dependent error, a fifth parameter (the time-averaged mean field bias) has to be included. Thus, our model can be compared to the four parameter model of the range correction algorithm proposed by Ahnert et al. (1983). This algorithm was designed to reduce the magnitude of error in rainfall estimates at far range associated with incomplete beam filling and the decrease in storm of the reflectivity with height. The parameters of the model are fitted using a least square criterion applied to the VPR influence simulated using the conceptual VPR and the time-averaged VPR influence directly obtained using the VPR dataset.

The final illustration of the VPR error parameterization is shown in Figure D.6 where we compare the time-averaged VPR effect with rain gauge data (error mean). It is clear that the major features of the VPR effects are well captured by the above parameterization. The question is whether the remaining discrepancies between the uncertainty model and the data can be quantitatively explained by the other sources of uncertainty. This issue should be addressed by a research project.

D.1.4. Reflectivity to Rainfall Rate Conversion

The issue here is description of uncertainty of the Z-R relationship. Since the most popular approach to radar rainfall estimation is through use of a power law Z-R function, we will discuss the uncertainty in the a and b parameters. Ciach and Krajewski (1999a) developed a simple model of the uncertainties involved in estimation of the Z-R parameters from radar and rain gauge data. Their analysis shows how uncertainties in the measurement error of Z, area-average rainfall using gauges, and true rainfall variability are reflected in the estimation error uncertainty of the exponent parameter.

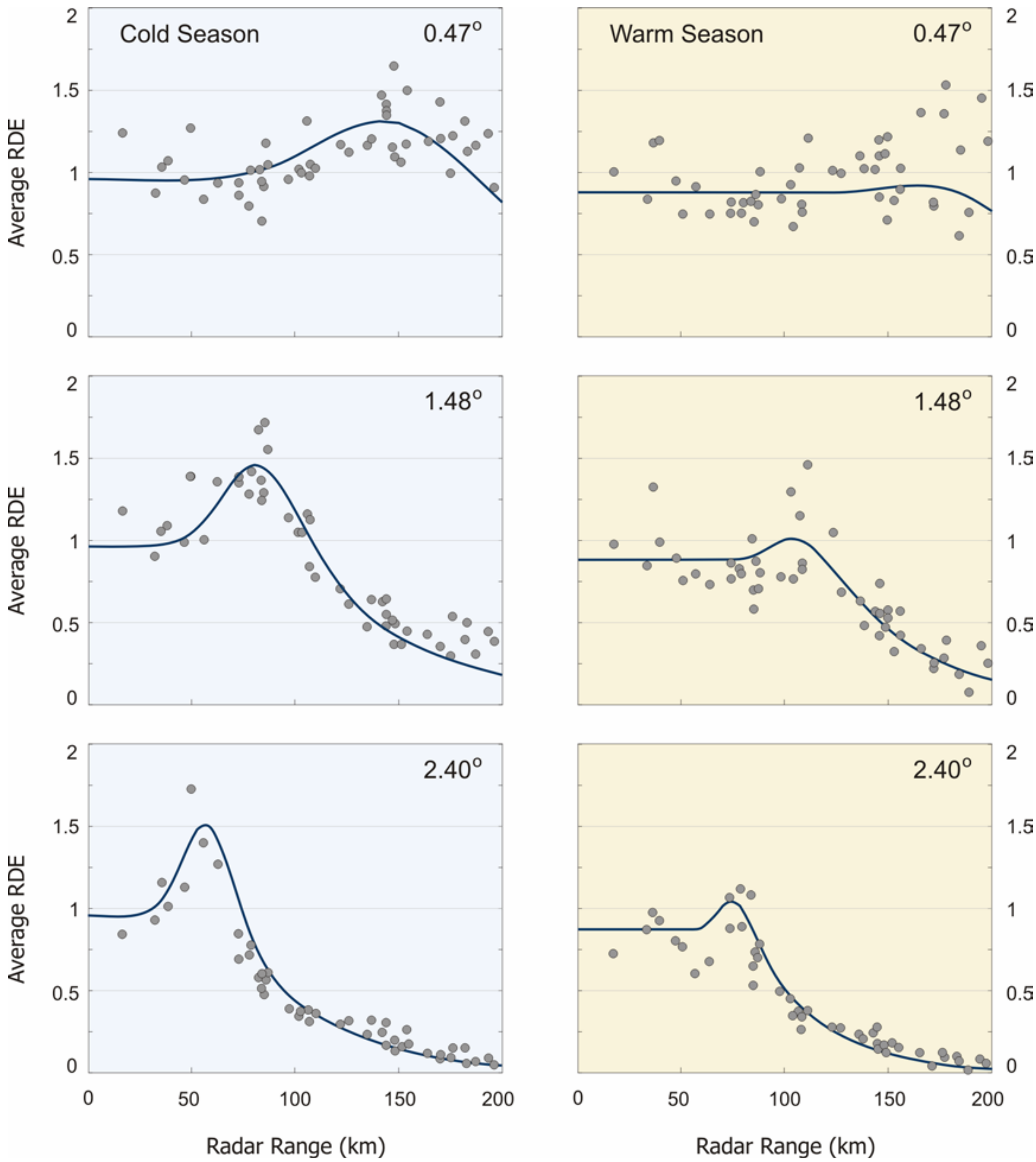

Figure D.6. Time-averaged radar range dependent error (RDE) for different antenna elevation angles computed from the VPR model (line) and the rain gauge data (dots).

In a recent study by Steiner et al. (2003), the authors present a link between the microphysics of rain as described by a gamma distribution of the drop size parameters, and the values of the Z-R parameters. They point out that identification and estimation of the theoretically existing relationships suffer from uncertainties due to lack of our observational capabilities. Thus, at this point in time, only much simplified and crude models of a and b uncertainty are possible.

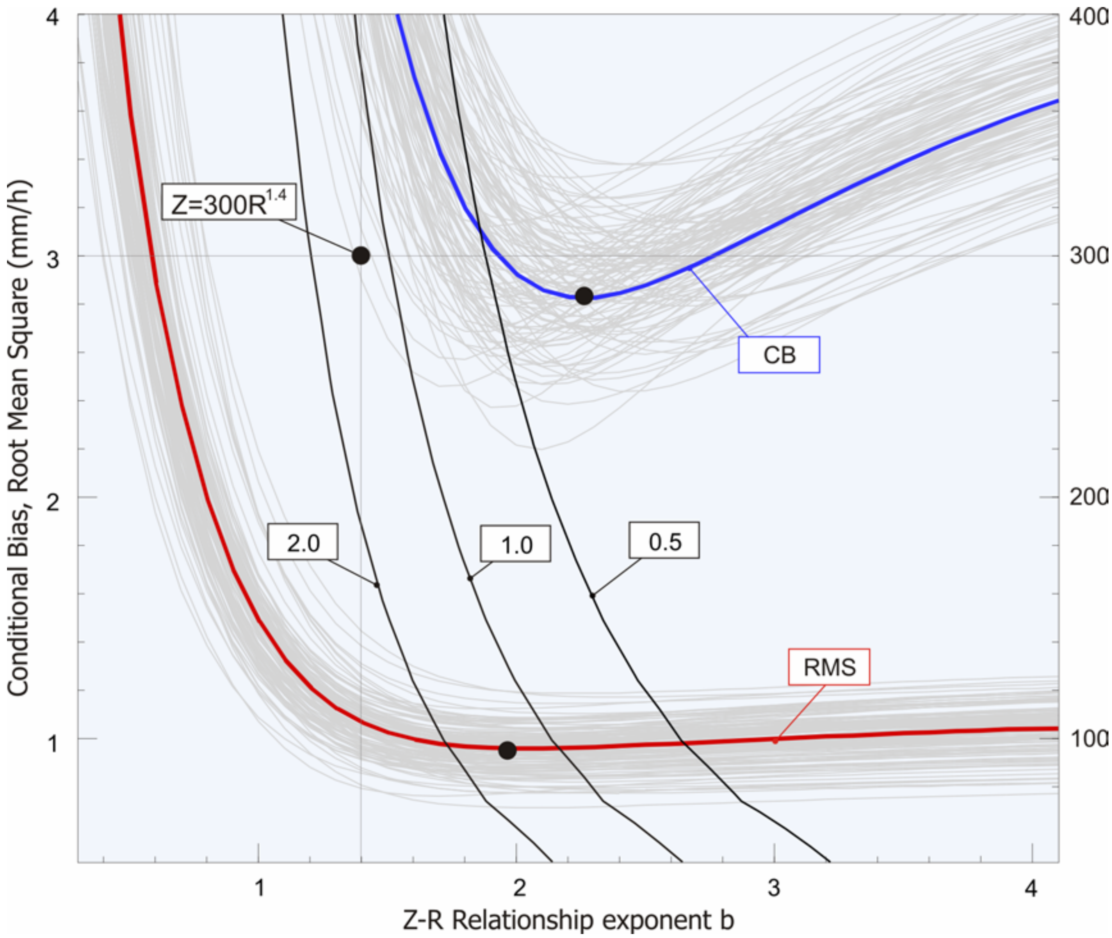

Figure D.7. Calibration of Z-R relationship using Oklahoma Mesonet data (Nelson et al. 2003). Five year (1996-2000) sample is used. The light gray lines correspond to individual lines.

An interesting result was obtained by Nelson et al. (2003) who used the Oklahoma Mesonet data to calibrate their five-year radar rainfall product. In Figure D.7 we show the results of their calibration using two criteria (1) minimizing the root mean square difference (RMSD) between radar and rain gauge estimation of rainfall, and conditional bias as defined in Ciach et al. (2000), both at the spatial scale of 2 km by 2 km. Also the lines of constant bias are shown. Analysis of the plot leads to several interesting conclusions. First, different criteria result in different estimates of the Z-R parameters. Second, there is considerable variability from gauge to gauge although a period as long as five has been used. Third, the parameters a and b are not independent. There is lack of sensitivity in the RMSD criterion for values of b greater than about 1.2.

The analysis above ignores the differences in the values of a and b due to different rainfall type (e.g. stratiform vs. convective) or intensity. Previous attempt to classify radar data prior to converting reflectivity into rainfall rate resulted in failures to demonstrably improve rainfall estimates. This is probably because of the lack of resolution in radar data, particularly at far range.

Our main conclusion is that the current state-of-the-art of rainfall estimation using radar does not support any obvious model of uncertainty of the Z-R parameters. Therefore, an ad-hoc model such as the one we used in Section D.2 is as good as any other. Research is required to answer the questions of sensitivity of the radar-rainfall propagation with respect to the choice of the model.

D.1.5. Grid Conversion

Grid conversion is often treated as an afterthought in radar-rainfall studies and application. Yet, it is an important step that results in modifying the uncertainty associated with the products based on the polar grid. In principle, the grid conversion should reduce the uncertainty if averaging is involved. This reduction decreases as the range from radar increases. However, an often used method of grid conversion is the nearest neighbor interpolation. It is a computationally fast method but will not result in random error reduction as it involves no averaging.

We do not know what is the approach implemented in the PPS system of the WSR-88D radars. In any case though, propagation of the uncertainty through this step of radar-rainfall estimation is straight forward using a simulation approach.

D.1.6. Rainfall Accumulation Calculations

Rainfall accumulation maps are constructed by simple stepwise interpolation of the rain rate maps. The main source of error is the temporal sampling. With sparse sampling and in presence of advection it is possible that some locations on the path of a moving storm may not receive any rainfall. This happens when the product of the advection velocity and the inter scan interval is greater than the size of the pixel. The result is a "choppy" looking pattern of the accumulation map. Note that the error reaches some maximum value that depends on the combination of the velocity and the rain intensity. When either is small the error is small. When the velocity is high, the error is also small as there is not enough time for the storm to produce much accumulation.

The effect has been discussed is greater detail by Bellon et al. (1991), Fabry et al. (1994) and Liu and Krajewski (1996). The authors of the latter study, performed using space-time rainfall models and simulation, concluded that the effect is not very important for the temporal scanning frequency of the WSR-88D systems (about 6 minutes). Still, it does contribute some errors to the overall estimates. Also, as the NWS is moving toward the higher spatial resolution of the precipitation products, the effect will be more pronounced.

The effect of advection on error of rainfall accumulation is fairly easy to understand and it seems that it should not be very difficult to parameterize its effect. The main parameters of a parameterization should be the advection velocity that can be estimated, for example, by correlation maximization of two consecutive scans, the temporal frequency (known and constant), and the rain intensity and its temporal gradient. Still, to the best of our knowledge such parameterization has not been described in the literature.

D.2. Stochastic-Dynamic Formulation

This approach can also be classified as a propagation of uncertainty method. It includes a dynamic model of rainfall and its uncertainty. The approach is attractive in that it provides a consistent framework for rainfall estimation and forecasting. Models of this type have been proposed in the past (e.g. Lee and Georgakakos 1990; Lee and Georgakakos 1996; French and Krajewski 1994; French et al. 1994; Andrieu et al. 2003).

In principle, the model is a set of partial differential equations that need to be integrated in space and time given certain input. If the model is setup in the form of an equivalent system of ordinary differential equation updating the model states from observations related to the states of the model becomes possible using the framework of method similar to Kalman filter (e.g. Bras and Rodriguez-Iturbe 1993). The updating state provides the best-in some sense-estimate of the state of the model. The framework allows acknowledging both the uncertainty of the model structure and input as well as that of the observations.

Formulation of complex models of atmospheric systems such as clouds and rain is difficult. The models we mentioned above were much simplified as compared to the state-of-the-art mesoscale models such as MM5. Updating of the states of the mesoscale models using volume scan radar reflectivity data has not been developed yet although there are several groups that have worked towards this goal (e.g. Sun and Crook 1997, Sun and Crook 1998, Crook and Sun 2002; Grecu and Krajewski 2000b,c; Georgakakos 2000; Protat and Zawadzki 2000). The approach of updating the models from real-time observation has also been referred to as data assimilation.

Although radar data assimilation into mesoscale models may one day provide the best estimate of current and future rainfall (as it combines dynamical and microphysical models of our understanding of the precipitation process with detailed observations of the atmosphere from in-situ and remote sensing data), today this approach represents a frontier of basic research in hydrometeorology and is not a viable for us to pursue within the time frame of the PQPE project. We will not discuss it herein any further.

Another approach to rainfall estimation is based on combining estimates from different sensors (Chou et al. 1994; Tustison et al. 2003) according to their spatial scaling and error properties. However, in the context of radar-rainfall estimation this approach requires the information that we are trying to provide, i.e. quantification of uncertainty.

Thus, we will not consider it here, although it may be a viable alternative for the broader problem of operational rainfall estimation using satellite, radar, and rain gauge information.

D.3. Product-Error-Based Approach

The fundamental feature of this approach is that it is focuses on the combined effect of all the error sourced discussed in Section B1. We acknowledge the fact that in practice it is impossible to delineate these errors based on the available measured quantities. We propose to develop a fully empirically-based framework for quantification of the probability distribution of the RR error process defined through the discrepancies between the RR products and the corresponding true rainfall. The general methodology of this approach can be summarized as follows:

1. Collect a large sample of the WSR-88D Level-2 data and reliable ground reference (GR) data. The GR should include rainfall measurements at small scales as well as data from sparse rain-gauge networks covering the radar umbrella.

2. Generate several versions of fine resolution precipitation product samples using different setups of the NEXRAD's PPS.

3. Apply the GR error filtering method to the radar-gauge verification samples at different spatiotemporal scales. The result is to approximate the theoretical verification sample of RR and true rainfall values.

4. Create a flexible mathematical model of the relation between the RR products and the corresponding true rainfall in different situations.

5. Apply the model to parameterize the probability distribution of the RR uncertainties and its dependence on the distance from a radar, space-time averaging scale, rainfall regime and the PPS setup.

6. Verify transferability of the method for different radar locations.

Below, we present a more detailed outline of this approach. We start with the GR error filtering method, which is the first necessary step in the analyses of the RR error properties.

D.3.1. Ground Reference Error Filtering

If we want to estimate the dependence of the RR error distribution parameters on the distance from a radar, we have to use the ground reference (GR) data based on sparse single-gauge networks covering the whole radar umbrella. If, additionally, we want to know this dependence over a span of spatial averaging scales, we have to account for the inevitable rain-gauge representativeness errors. As shown in Ciach and Krajewski (1999b), the area-point differences are comparable with the RR errors at the 4 by 4 km scale. Obviously, they are even more significant, if one wants to estimate the RR error distribution at the larger spatial scales. To obtain meaningful results, we need to filter-out the rain-gauge errors from the radar-gauge verification samples.

This task can be formalized as follows. Let R_g, R_r and R_a be the corresponding (concurrent and collocated) rain-gauge, radar and true rainfall values, respectively. Assume that, for given spatio-temporal resolution (*A,T*) and distance (*d*), we have a large sample of corresponding (R_r,R_g) pairs and the additional information about spatial rainfall variability in this sample. The goal is to apply this information to retrieve the verification distribution (R_r,R_a) of the RR and corresponding true rainfall values. To accomplish this, we have developed an efficient GR error filtering procedure that is called the conditional distribution transformation (CDT) method. The scheme comprises of the following steps:

1. Divide the range of R_r into a number of intervals.

2. Estimate spatial correlations of R_g in each interval.

3. Apply a special point-to-area transformation of the distributions of R_g conditioned on the R_r intervals.

4. Synthesize the full bivariate distribution from the family of the transformed conditional distributions.

As a result of this procedure, we obtain a fairly accurate approximation of the (R_r,R_a) probability distribution. The above point-to-area distribution transformation is based on a method proposed by Journel and Huijbregts (1978). Their scheme was expanded to a conditional framework by Morrissey (1991) for verification of satellite rainfall. We have recently implemented their development and tested it on RR data (Habib et al. 2003). Our results indicate that the GR error filtering based on the CDT method can be applied to PQPE development and validation. However, its implementation requires concurrent data on spatial rainfall correlations over a range of scales from a few hundred meters to a few tens of kilometers. This additional information can be obtained based on combinations of nested rain-gauge networks covering different spatial scales. Such resources can be found in Oklahoma, for example, where the Oklahoma Mesonet can cover large distances, the Little Washita Micronet can cover the medium scales (Ciach at al. 2003), and the EVAC PicoNet can monitor the rainfall variability at the scales below 3 km (see Figure D.8).

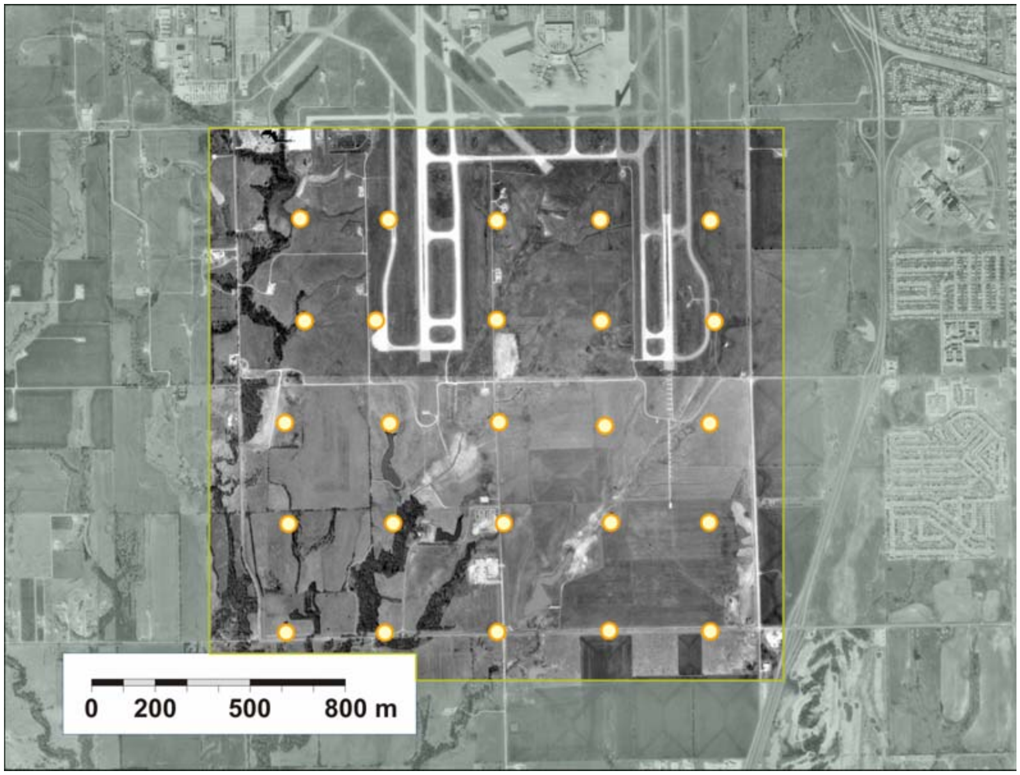

Figure D.8. Schematic configuration of the Piconet at the Oklahoma City International Airport.

D.3.2. Mathematical Modeling of the R_r-R_a Relation

The relations between RR and the corresponding truth can be described by the family of bivariate frequency distributions ("verification distributions"):

$$(R_r,R_a)_{A,T,d} \tag{D.3.1}$$

where R_r and R_a are the corresponding (concurrent and collocated) RR and true rainfall values, respectively, A is the spatial averaging scale, T is the temporal scale (accumulation interval), and d denotes the distance from a radar station. As discussed in the previous section, these distributions can be retrieved from the radar-gauge data samples, if appropriate information on the rainfall variability are available. To simplify the notation, let us focus on one resolution *(A,T)* and distance *(d)* from the radar. To model the (R_r,R_a) distribution for this situation, we can apply the following functional-statistical representation:

$$R_r=h(R_a)\ e(R_a) \tag{D.3.2}$$

where h is a deterministic distortion function and e is a random variable representing the RR uncertainty process (combined outcome of all error sources) in the form of a multiplicative error factor. This representation describes the way in which RR products approximate the true rainfall. We can assume without loss of generality that the expectation $E\{e\}=1$. For that to be true, it is enough that:

$$h(x)=E\{R_r|R_a=x\} \tag{D.3.3}$$

which is a general form of regression and indicates the straightforward way to estimate the deterministic distortion function. Although the mean of the multiplicative random error above is equal to unity for each value of R_a, its variance can vary with R_a.

We applied a more specific parameterized version of the above formula to a data sample of two warm seasons in north-eastern Oklahoma. The radar data from the Tulsa station were quality controlled and corrected for the VPR (Vignal and Krajewski 2001). After considering several possibilities, we used the following parametric model:

$$R_r = c\, R_a^{\gamma}\, e(R_a) \tag{D.3.4}$$

Our results indicate that the deterministic distortion has nonlinear character and the exponent of the power-law function, $\gamma=0.9$, for the time scaled T in the range from 6 to 24 hours. The statistical tests also show that the probability distribution of the error variable e is close to gamma and its variance $V\{e\}$ is a decreasing function of R_a. The dependence of the standard deviation of the error variable as a function of true rainfall for two time scales is shown in Figure D.9:

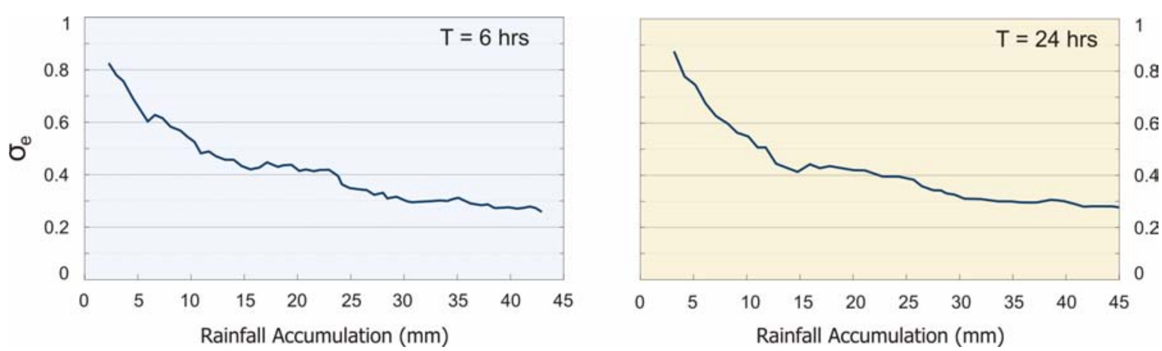

Figure D.9. The error standard deviation as a function of true rainfall for two time scales.

To be applied to the PQPE uncertainty distribution model, the above example has to be generalized to include the dependence on the spatial averaging scale and the distance from the radar. To accomplish this, a much larger data sample is required and the area-point error filtering described in the previous Section must be applied. Parameters of the full uncertainty distribution model can be estimated based on the family of verification distributions (estimated probability distributions of RR and the corresponding true rainfall):

$$(R_r, R_a)_{An,Tn,d}\ ,\quad n=1,\ 2,\ \dots\ ,\ n_{max} \tag{D.3.5}$$

where the distributions are sampled for several spatio-temporal scales and at a range of distances from the radar. Spatio-temporal dependencies in the error variable can be modeled using geostatistical methods to reproduce the dependence of $(R_r,R_a)_{An,Tn}$ distribution on the scale (A_n, T_n).

Regarding the generalization of the model to different locations, precipitation regimes and the PPS setups, we believe that, if the model is sufficiently general, only the values of its parameters will change. If the structure of the model holds, transferring it to different situations will only require estimation of a new set of the parameter values. Obviously, development and validation of such a flexible model requires strong empirical basis comprising a large (5-6 years) data sample completed with a good quality of the GR covering a broad scope of spatial scales.

D.4. Summary

Before we discuss in more detail the approach we propose to use, we would like to summarize the main characteristics of the two approaches we discussed above: the error propagation approach and the product based approach.

The error propagation approach is attractive as it allows considering different error sources separately, thus seemingly provides more insight. There exist significant "gaps" in our knowledge on the probability distribution of the major variables and parameters governing the overall uncertainty of radar-rainfall estimation. Often even simple (two moment) descriptions of this uncertainty are lacking, thus the selection of the uncertainty to propagate would be based on ad-hoc decisions. The difficulties can be illustrated with the complexities shown in Figure D.10. The figure shows a period of two hours of the vertical profile of reflectivity from vertically pointing radar located in Iowa City, Iowa. It demonstrates a plethora of complexities: from convection to stratiform rain, low level enhancement, bright band, horizontal and vertical variability on the scale of hundreds of meters and minutes. Proper mathematical modeling of these variabilities seems difficult if not hopeless. The remedy of this situation would require, of course, more research.

The approach is mathematically elegant but quickly becomes intractable. Its application requires applying extensive simulations, which may be appropriate for off-line studies but may turn out to be too expensive for real-time considerations unless extensive parameterizations are developed. The engineering approaches of using Taylor series approximation to the involved functions do not apply since the present uncertainties are significant. If applied, these approaches lead to significant errors (Figure D.11).

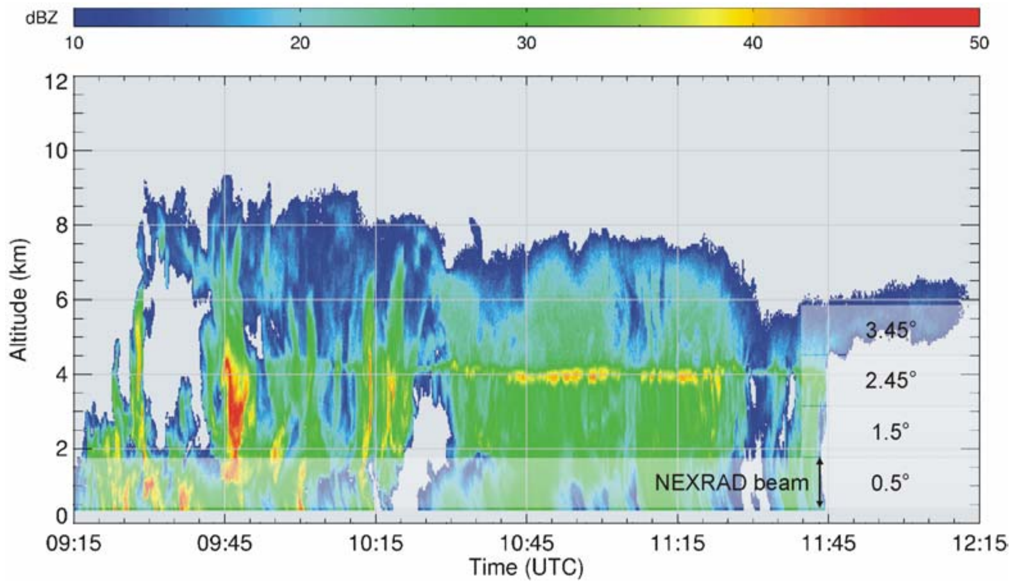

Figure D.10. An example of a vertical profile of reflectivity from vertically pointing radar. The plot illustrates typical variabilities present in radar-rainfall estimation. The storm shown is from June 19, 2002 in Iowa City, Iowa. The shaded region corresponds to the height of the Davenport, Iowa (KDVN) WSR-88D located some 80 km east of the profiler. On the right hand side the widths of other antenna elevation angles are indicated as well.

Therefore, the error propagation approach requires an additional evaluation to verify its correctness. The only independent way to achieve this would be by using a product based approach.

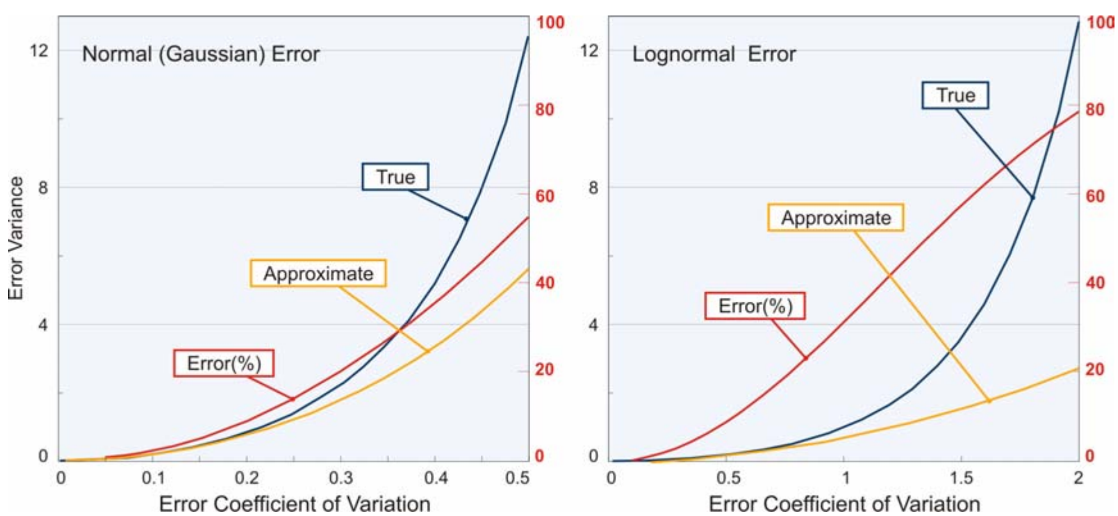

Figure D.11. Approximation error in computing error variance from a Taylor expansion for normal and lognormal variables transformed through an exponential function.

The product based approach we discussed requires extensive, specialized, high-quality data. It also requires solving a few theoretical and technical problems of parametric model identification and estimation. Overall though, it seems that it offers a quicker path to an operational implementation of the PQPE.

E. PROPOSED APPROACH

From the three approaches outlined above, we recommend the product based approach. Perhaps the main reason for our recommendation is that this approach addresses the problem in an integrative sense: the estimated errors include all sources of uncertainty. The total uncertainty is determined by observations of rainfall on the ground, which is fundamentally important for hydrologic applications. The approach is feasible both as far development of the model and its operational implementation are concerned. It is technically simple in that it uses familiar observational technologies. Below we discuss the plan of action we propose the Office of Hydrologic Development.

E.1. Requirements

There are several important requirements for the project that include research, technical, and operational implementation aspects. These aspects include methodological issues still remaining to be investigated, but more importantly, they involve mobilization of necessary resources. These include radar, rain gauge, and other data (e.g. freezing level height, synoptic summary index, etc.), software, deployment and/or modification of the experimental sites, and expert personnel. It is also important that the methodology is "verifiable" using independent data to avoid situations such as that identified by Young et al. 2000, who found lack of independent information in their attempt to evaluate operational NEXRAD rainfall products in the Arkansas River basin.

We propose to use data from the existing infrastructure in Oklahoma that consists of the Oklahoma Mesonet (Brock et al. 1995; Shafer et al. 2000) operated by the State of Oklahoma Climatological Survey (OCS), Oklahoma Micronet (Elliot et al. 1993, Ciach et al. 2003) operated by the Agricultural Research Service (ARS) in southern Oklahoma, and the Oklahoma Piconet (Ciach 2003, Ensworth and Ciach 2002; Ciach et al. 2002) operated by the Environmental Verification and Analysis Center (EVAC) of the University of Oklahoma. Figure E.1 shows the relative location of the rain gauge stations in the three networks as well as the 230 km rings from the NEXRAD radars in the region.

The three networks are characterized by different average rain gauge densities: the Mesonet has the average spacing of 30-40 km, the Micronet of 5 km and the Piconet of 0.6 km. This provides opportunities to examine several scale-related aspects as well range-dependence of the uncertainty. Also the rainfall regime of Oklahoma represents a good variety so that the results hopefully will be transferable to other regions.

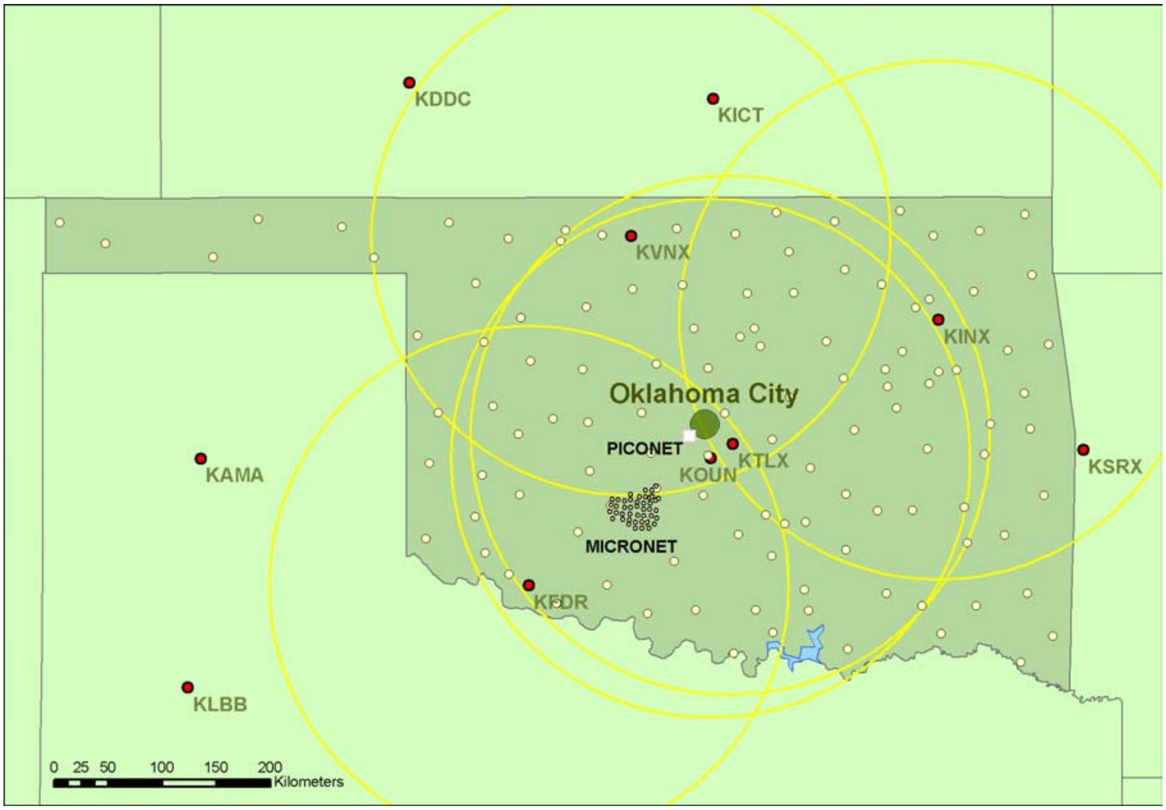

Figure E.1. Ground reference rain gauge networks in Oklahoma. The circles correspond to the 230 km radar range. Details of the Piconet are shown in Figure D.8.

The issue of transferability of the uncertainty parameterization is the focus of the second step in the plan. There are several other fairly high density clusters of rain gauges around the country providing high-resolution data that seem adequate for the purpose. For starters, IIHR operates a network of about 40 double-gauge stations around Iowa City, Iowa, that has a nested design. Average closes spacing is 5 km but in the center of the network there is a cluster of ten stations within a single Level II pixel (Figure E.2). The cluster has been in operation since 1998 but the rest of the network was deployed in the summer of 2002. The network includes a video disdrometer (Kruger and Krajewski 2002) and a vertically pointing X-band Doppler radar. There are also 12 agronomical stations in the state of Iowa operated by the Iowa State University that are being upgraded to a double gauge design.

The USGS and the City of Charlotte, North Carolina have operated a network of 73 tipping-bucket rain gauges since 1998 with one-minute data archived and available (Figure E.3). The ARS operates a network of some twenty rain gauges in Goodwin Creek basin near Oxford, Mississippi (Ogden and Dawdy 2003; Habib et al. 2003), and another one in Walnut Gulch, Arizona (e.g. Goodrich et al. 1997; Morin et al. 2003). There are dense networks of rain gauges in Florida, operated by the Florida water management districts, there is a network of about 200 rain gauges in and around the City of Phoenix, Arizona. Most likely there are many other such networks around the country. Although these networks, except the Iowa City one, were not designed for our purposes, as long as they have high spatial density and provide high-resolution data, they should be useful, perhaps with some modifications, for the transferability studies.

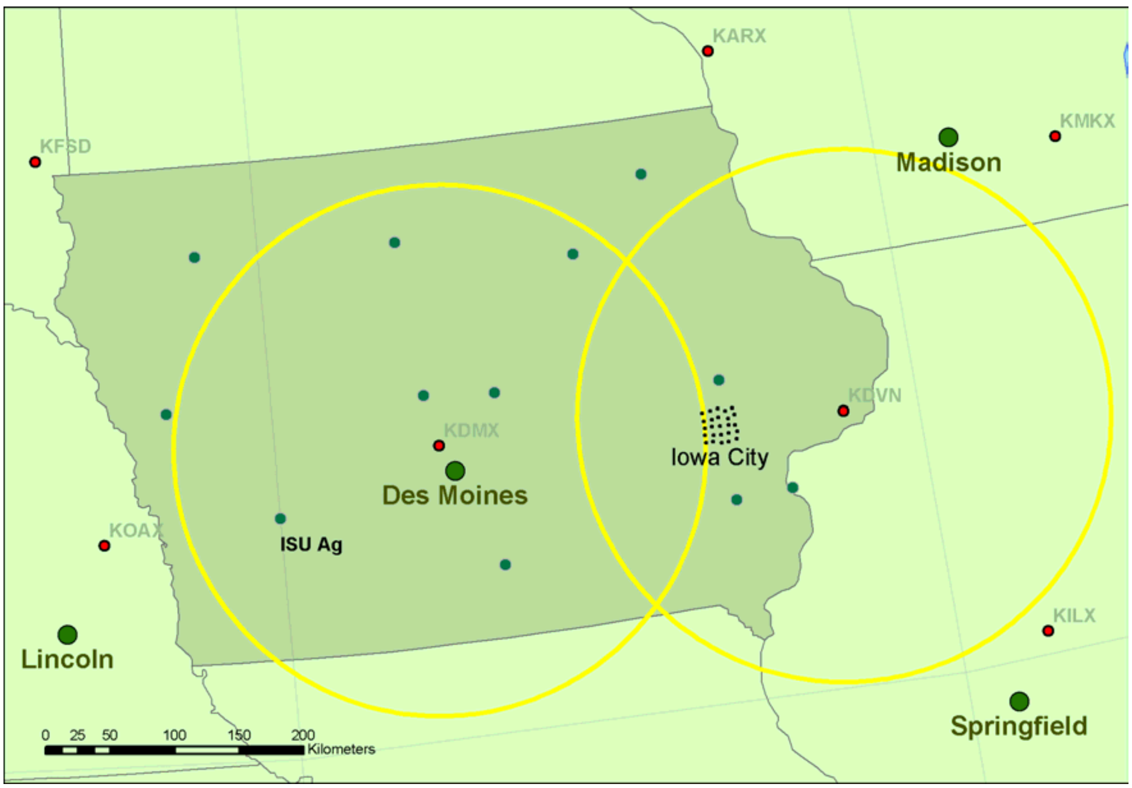

Figure E.2. Ground reference rain gauge network in the vicinity of Iowa City, Iowa.

With about ten sites organized around the country the NWS should be able to test the methodology developed in Oklahoma and “fine tune” it prior to operational tests and implementation. Considering the regional distribution of the sites we identified above (Figure E.4), there are obvious gaps along the West Coast, in Northeast, and in the North that would have to be addressed. We believe that we could organize a proper network in

North Dakota, through collaboration with Dr. Paul Kucera, a professor at the University of North Dakota, and a director of their C-band polarimetric (upgrade planned for fall 2003) radar.

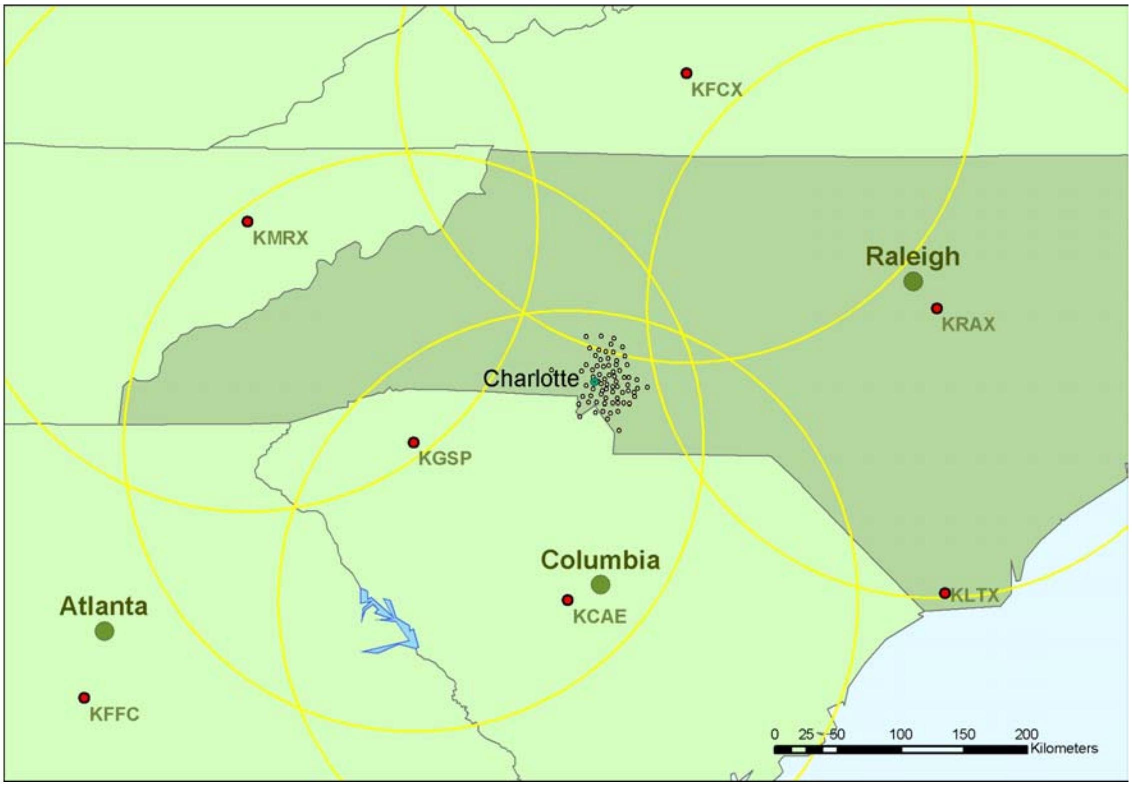

Figure E.3. Ground reference rain gauge networks around the United States.

For the above sites, radar Level II and rain gauge databases should be organized, with multiple radar data in some cases to address the range effect aspect of the uncertainty model. Extensive testing should be performed of the developed methodology with adjustments to the uncertainty model as necessary.

As the NEXRAD precipitation estimation algorithm will be transformed from a single parameter (radar reflectivity) based to multiple parameter (reflectivity, differential reflectivity, and differential phase shift) based, the uncertainty model should be sufficiently general to address the polarimetric upgrade of the radar network. We propose to begin relevant work focusing on two aspects: (1) using polarimetric radar capabilities to help with the classification of the radar echo in the uncertainty model development (for the single parameter radars); and (2) uncertainty assessment for the polarimetry based radar-rainfall products following similar framework as for the single parameter products.

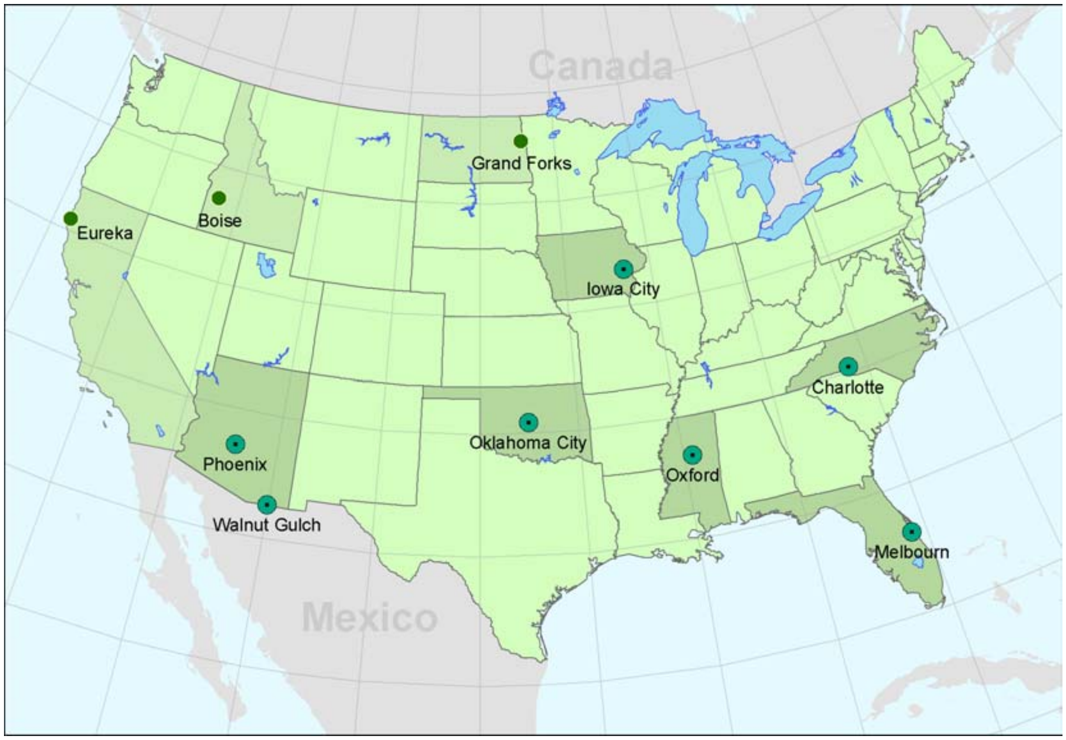

Figure E.4. Ground reference rain gauge networks around the United States.

We propose to use the NSSL facility in Norman, Oklahoma for the purpose. The radar (KOUN) is a WSR-88D upgraded for taking polarimetric measurements. It is a prototype of the future operational polarimetric radars. The main advantage of this approach is that the same facilities will be used for the uncertainty model development for both single- and multiple-parameter methods. Since the operational implementation of the polarimetric upgrade is some five years away, the transferability of the uncertainty model to other regions does not have to be addressed immediately. Still, it is clear that by examining the transferability issues of the single-parameter based product uncertainty, the lessons learned will benefit the polarimetric products in the future.

E.1.1. Research

The main focus of the scope of research activities within this project will be on the specific objective: development of a flexible and parsimonious parametric model of the

RR error distribution for different situations. This includes systematic large-sample investigation of the dependences of the error distribution on the following factors:

1. Distance from a radar location;
2. Spatiotemporal averaging scale;
3. Type of the precipitation system;
4. Height of the zero-isotherm;
5. The PPS setup.

Items 1 & 2. The estimation and modeling of the RR error distribution structure will be based on the mathematical methodology of the product-based approach presented in Section D3. From the description of this approach, it is clear that range and scale dependences are included as inherent components of the method. To obtain a broad span of the spatial scale, we will generate RR products of the finest possible resolution from the WSR-88D Level-2 data and up-scale them to larger spatial and temporal scales. To remove the effects of area-point errors on the RR error estimates, we will implement the gauge-error filtering method described in Section D3.

Items 3 & 4. The spatial, microphysical and dynamical structure of a precipitation system has direct effect on several of the RR error sources described in Section B1. We will stratify the data-sample according to the synoptic type of the precipitation system using information from the weather prediction models, the polarimetric radar classification results, and analyses of the three-dimensional radar Level-2 data. The height of the zero-(Celsius)-isotherm is a major governing factor of the VPR and its knowledge is necessary to narrow down the uncertainties caused by the VPR variability.

Item 5. The errors in a RR product and their distribution can obviously depend on the specific setup of the PPS that was used during the product generation. We plan to generate several versions of products from the large sample of the Level-2 data. This will include investigation of the effects of the data quality control, scanning strategy, hail cap level, VPR correction, Z-R relationship, and possibly other.

Other research will involve the error propagation approach using static models (see Section D.1.) In particular, we will study the sensitivity of the approach with respect to the degree to which we can describe the uncertainties involved in various inputs and parameters. We will investigate the interdependency of these variables and develop uncertainty models for some of the less known quantities (e.g. the spatial gradients at the scale smaller that that of the radar sampling volume, e.g. Kumar and Foufoula-Georgiou 1993; Kumar and Foufoula-Georgiou 1994.) We will also attempt to develop parameterizations of the error propagation approach as simulation based uncertainty propagation will not be feasible in real-time operation.

E.1.2. Technical

Technical requirement include data, software, and experimental activities. We discuss them below.

E.1.2.1. Data

For the proposed error distribution parameterization to be statistically meaningful, the results have to be based on large samples of radar and rain gauge data. We recommend use of five year data sample for the development of the model and 2-5 year samples for model testing and transferability studies.

We recommend using Level II data as this provides the most flexibility in testing the changing PPS algorithm structure as well as different product spatial and temporal scales. The data should be organized in a relational data base described by a set of metadata extracted from the original data. This requirement will allow convenient development and testing as it facilitates fast searches of cases of special interest, testing of different data classification (i.e. conditioning) schemes, and data aces by the collaborating parties (Kruger and Krajewski 1997; Kruger and Krajewski 2003). This is a significant technical and technological challenge but it is achievable. We estimate that the data set required will consist of up to 50 site-years. As a point of reference, at IIHR we currently maintain a 10 site-years database.

Similar requirements exist for rain gauge data. The most important issues are the availability of one-minute data (with five-minute resolution) as a minimum. The second important piece of information is the time stamp. Poor quality clocks contribute uncertainty that might unnecessarily corrupt the radar-rainfall model. Organizing rain gauge data into a relational database will facilitate studies and save time and cost.

There are other data that might be necessary or at least useful for the uncertainty model. These include the height of the freezing level as it closely determines the level of the bright band, topography with the 30 m resolution for the determination of the partial beam occlusion, and summary of the synoptic situation.

The project databases should be accessible over the Internet to facilitate active collaboration and involvement of the NWS personnel as well as others.

E.1.2.2. Software

Clearly the study has to be based on the current and future version of the Precipitation Processing System. As implementation of the new elements (algorithms) of the system follows a multiyear cycle, the project has to allow for reprocessing of the historical data for the assessment of the effect of the PPS upgrade on the uncertainty model. A good example here is the anticipated reduction of the range dependent bias due to the vertical profile of reflectivity correction.

The required software includes the PPS algorithm with the option to turn on and off certain modules. A particularly important element of the PPS software is the ground clutter detection module that can deal with both the permanent echoes as well as those due to anomalous propagation conditions. Another important module is the grid conversion as this will facilitate the scale dependent uncertainty studies. The PPS has to be interfaced with the Level II database and has to output the products and their metadata for convenient selection and analysis by independent groups.

Other software includes visualization of the input data as well as the products. The visualization software should include the tools currently and in the future used by the operational forecasters as well as research tools. Software needs to be developed for proper presentation and interpretation of the PQPE.

E.1.2.3. Experimental Activities

We do not recommend undertaking any new major experimental activities. However, we do recommend careful analysis of the sites we outlined above and taking steps towards their maintenance and improvement. For example, the Piconet has no current support. Its operation continues because of the contributions of time and effort by the people who started this activity under the funding of the NASA Epscor Program. Symbolic funding comes from the endowed professorship of the first author of this report. Piconet is a unique facility that has no precedence in the recent history of radar hydrology and is of paramount importance to the scientific credibility of the proposed PQPE project as it provides information otherwise unavailable (except for through speculations).

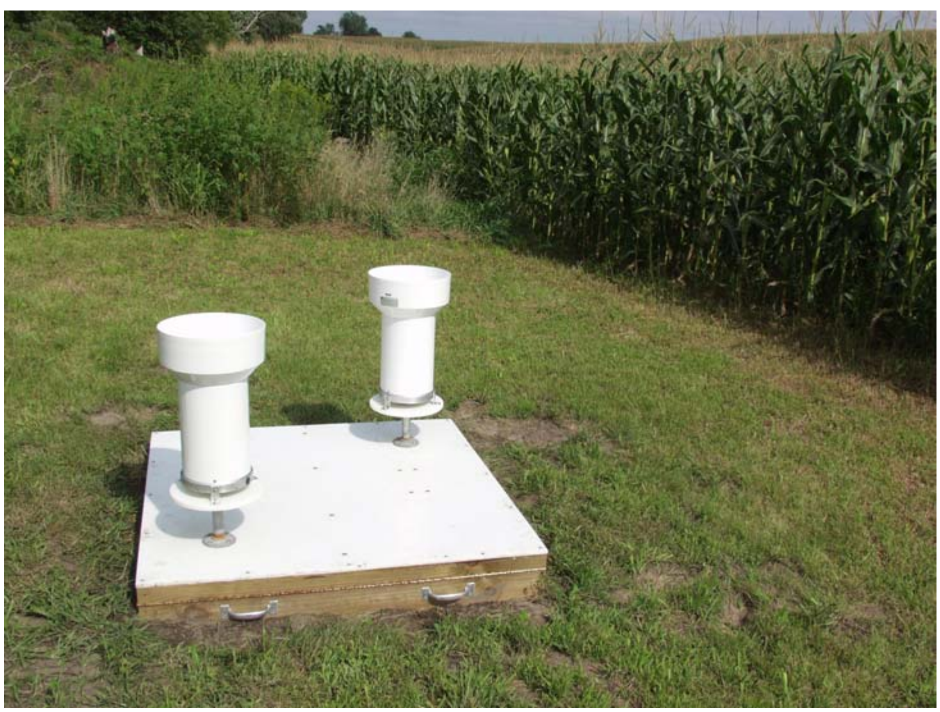

Figure E.5. Double rain gauge platforms installed at the Iowa City, Iowa, network.

As emphasized by Ciach and Krajewski (1999b), Steiner et al. (1999), Krajewski et al. (2003), the single most important modification that can significantly improve the quality of the rain gauge data is adding a second gauge right by the first (see Figure E.5 for an example of a double-gauge platform at one of the Iowa City sites.) We recommend that adding second gauges to several locations at the sites discussed above or at the locations maintained by the NWS. We claim that we have good understanding of the tipping bucket rain gauge error structure based on the studies of Habib et al. (2001) and Ciach (2003) (see Figure E.6). The point rainfall uncertainty contributes relatively small uncertainty to the overall problem of rainfall estimation. However, for the results of the above studies to apply, we must make sure that no other rain gauge data quality problems "cloud the picture." Adding a second gauge is an effective yet simple solution.

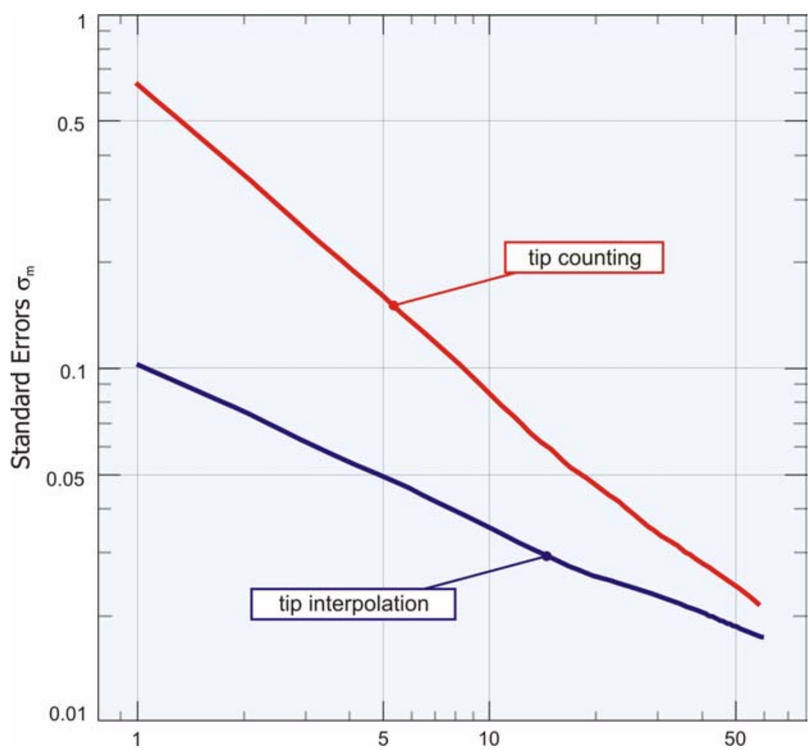

Figure E.6. Temporal scaling of tipping bucket rain gauge random errors.

Consider the sites operated by other organizations first. It is unlikely, but not impossible, that these organizations would agree to contribute the cost of the additional equipment. It is more likely, that they would agree to contribute service and maintenance of the equipment as the additional cost of doing that would be rather minimal (by collocating with the existing equipment eliminates the cost of travel, for example). Being familiar with some of the sites and the personnel operating them, we speculate positive outcome of the potential negotiations.

Although we did not say much about the operational rain gauge network operated by the NWS, the biggest concern here is the data quality. This is particularly the case with the cooperative network. The first order stations are run well and could be used as the places for doubling up the gauges. Here the strategy should be such a selection of the sites that represent the range effect of the key radar location from different climatological regions. To avoid logistical problems of finding the matching equipment and installation, we recommend simply adding stand-along platforms much like that shown in Figure E.5. The total cost for a single site that includes two rain gauges and a call phone based data acquisition system is within $4K installed.

Figure E.7. Ground reference rain gauge cluster configuration that results in point-to-area variance reduction of over 90% assuming exponential correlation function with the correlation distance of 5 km or more.

In some locations it may be worthwhile to consider installation of mini clusters of rain gauges. Since the minimum spatial resolution of the PQPE project is 1 km^2, the spatial variability of rainfall at the scale is not that high in many locations (Krajewski et al. 2003). Installing clusters of four double-gauge platforms would reduce the sampling uncertainty of such size pixel products by over 90% (Figure E.7) assuming the correlation distance as short as 5 km. Clusters of such size, with spacing by some 500-600 meters are easily feasible at all airports, where many of the NWS offices are located. Again, the proximity to the equipment by the NWS personnel will add little to the cost of maintenance of the already existing equipment (e.g. the ASOS stations). Addressing the issue of error spatial dependence would increase the requirements for the clusters and their size. Still it would be possible to do it at some locations in the country.

The data from these additional could be used operationally as the developments of the PQPE project will be done off-line starting with the Level II data.

E.1.3. Operational

The main operational requirements we foresee at this point are in the training and use of the uncertainty information in the operational environment. Prior to the operational implementation the forecasters would have to be educated about the new capability of the radar-rainfall estimation system. There are several possibilities here that include web-based training modules and/or short (1-2 days) courses to be developed. The training should include the theoretical background for probabilistic based rainfall estimation, background on methodology used in development of the error distributions, examples of proper interpretation of the PQPE data, and examples of the use of the PQPE in hydrologic forecasting.

A separate aspect of the PQPE project is its hydrologic and water resources application. Development of an adequate strategy is beyond the scope of this report but should be addressed fairly soon into the development of the PQPE project.

F. PROJECTED IMPLEMENTATION

F.1. Schedule

We foresee the PQPE project as a two tier activity: short-term with the time horizon of three years and a long-term with the time horizon of five years. The first would include data preparation, research on the uncertainty model development, and preliminary studies of the model transferability. The longer time horizon would include continuation of the model transferability studies as well as preparation for the operational implementation of the polarimetry based rainfall and its uncertainty estimation algorithms.

Below we give more details on the recommended schedule (note that the three-year horizon includes operation implementation of the PQPE for single parameter radar-rainfall estimation products):

Year 1. Continue collection of rain gauge data at the Oklahoma Piconet. Organize Level II data for the Oklahoma site and other evaluation sites. Analyze the Piconet, Micronet, and Mesonet data and formulate the uncertainty model. Continue processing the polarimetric data from the KOUN radar in Norman, Oklahoma, in cooperation with the NSSL. Install the PPS system and interface it with the Level II database.

Year 2. Continue collecting the Level II data and the rain gauge data from various sites around the country. Conduct the transferability testing of the uncertainty model. Deploy the experimental facilities in support of the PQPE project (i.e. additional gauges, mini clusters). Develop visualization tools for the PQPE.

Year 3. Continue the transferability studies. Continue data collection and database organization. Develop operational version of the PQPE software including its visualization module. Develop training materials for the PQPE.

Year 4. Continue operational monitoring of the performance of the PQPE. Develop multi-parameter radar-rainfall uncertainty model.

Year 5. Develop operational version of the multi-parameter PQPE software including its visualization module. Continue operational monitoring of the performance of the PQPE.

F.2. Cost

Since this is just a report and not a proposal our cost estimate of the PQPE project is tenuous at best. We broke the budget into several components all of which we consider necessary. We estimate the budget for the next three years only. The estimates are on a per year basis and assume 50% indirect costs.

Research & Development. The cost includes 1 year of analyst's methodology development, testing, and documenting ($100K); 3 month of computer scientist for organizing the massive data volume into a relational database ($40K); 1 month of computer support person to assist with data transfer, software installation, and computer system support ($10K); 12 months of graduate student for support with miscellaneous analysis and research tasks ($50K).

Experimental Activities. The cost includes adding 100 double-gauge platforms to different locations around the country. The cost per platform is about $4K and includes material, instruments, dynamic instrument calibration, assembly, transportation (or shipment) and field deployment. The total cost is $400K of capital investment. If support is need for the maintenance of the new facilities, we estimate that it would require $25K per site (i.e. network). This is based on our experience operating the Iowa City network. We also assume that only half of the 10 sites would require such support.

Polarimetric Radar Research & Development. We list this item separately as it is not strongly coupled with the other two. There is one radar in the country that is fully appropriate for the PQPE purpose and one group that has the expertise of using it. We estimate the budget for this item to be $75K per year.

Based on the above, we estimate the total three year cost for the PQPE project at about $600K+$525K+$225K=$1350K.

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