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Towards Probabilistic Quantitative Precipitation WSR-88D Algorithms: Preliminary Studies and Problem Formulation: Phase 2

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Principal Investigators:

Witold F. Krajewski and Grzegorz J. Ciach
IIHR-Hydroscience & Engineering
The University of Iowa
Iowa City, Iowa 52242

Report Authors:

Witold F. Krajewski and Grzegorz J. Ciach
IIHR-Hydroscience & Engineering, The University of Iowa
Dusan Zrnic and Alexander Ryzkhov
National Sever Storms Laboratory, NOAA

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EXECUTIVE SUMMARY

The report sets forth plans for developing a scientifically rigorous methodology for operational probabilistic quantitative precipitation estimation (PQPE) for hydrologic applications. The methodology will be based on the WSR-88D measurements complemented with rain gauge and satellite data. It is flexible enough to allow a smooth transition to the polarimetric era after the planned upgrade of the operational network of radars. This report formulates plans for future research and development with respect to three main objectives: (1) demonstrating hydrologic utility of the probabilistic information of the precipitation estimates; (2) developing a theoretical and operational framework for probabilistic multisensor precipitation estimation; and (3) preparing for operational use of polarimetric information in the PQPE framework.

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.

The hydrologic utility of the PQPE methodology will be demonstrated in two ways. The first concerns agricultural application with irrigation water allocation and scheduling. The second one concerns the flash flood problem. In both cases the probabilistic rainfall maps based on radar data only will be input to distributed hydrologic models and decision models. This part of the project will be performed in close collaboration with the Hydrologic Research Center (HRC) which will run the hydrologic and decision models. The demonstration will be limited geographically to the Oklahoma region.

The multisensor PQPE will involve combining multiple radar-rainfall maps, bias adjustment, and use of satellite information. The relevant research includes spatial sampling of rain gauge fields, error properties of the operational bias adjustment procedures, and validation of the multisensor PQPE products. The validation strategy extends beyond the Oklahoma region.

The transmission to the polarimetric era involves switching from the current Precipitation Processing System (PPS) to the Enhanced PPS (EPPS), developing the probabilistic polarimetry-based precipitation products, and merging these into the multisensor PQPE framework. The authors formulate two major tasks: (1) modeling the error structure of the polarimetric multisensor PQPE, and (2) use of polarimetric information in the development work of the PQPE models based on the current generation of the WSR-88D radars. This will be possible as the only polarimetric WSR-88D is currently located in Oklahoma which is the major test bed for the PQPE developments. Further validation of the polarimetric PQPE is recommended in Iowa where extensive ground based facilities exists. This requires early scheduling of the Davenport, IA WSR-88D for polarimetric upgrade.

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A. BACKGROUND INFORMATION

Many hydrologic and water resources services performed for the public by the National Weather Service (NWS) require high space and time resolution precipitation input. 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 (e.g. Fread et al. 1995; Stallings and Wenzel 1995). The current operational NWS multi-sensor rainfall algorithms produce only deterministic fields of precipitation intensity and 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 limitations of the observational systems. Yet, forecasters and 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. Krajewski and Ciach (2003) developed a comprehensive plan for nation-wide development of the PQPE algorithms. Their report lays out an early formulation of the problem, identifies conceptual, methodological and technological issues, and proposes a feasible plan of action. However, because the plan calls for considerable expenditures of resources, the PQPE Advisory Team suggested preceding it with a geographically focused effort of an end-to-end demonstration of the utility of the PQPE approach.

In this report we will address three aspects of the PQPE project: (1) hydrologic applications chosen to demonstrate the benefits of the PQPE information; (2) plans for providing PQPE information for the current and future Multisensor Precipitation Estimation (MPE) algorithms; and (3) plans for developing PQPE algorithms for the polarimetry based WSR-88DP products. We consider two hydrologic applications. They involve analyzing the benefits from improved irrigation scheduling and enhanced flash flood guidance procedures. The MPE algorithms include those currently used by the River Forecast Centers (RFCs) and the algorithms under development for the Weather Forecast Offices (WFOs) at the Office of Hydrologic Development (OHD).

In the next section, we discuss a general framework for demonstration of the utility of the PQPE algorithms. In section C we summerize our mathematical and statistical approach to developing the PQPE for different precipitation products, in section D we discuss the plans for the probabilistic MPE enhancements, and in section E we present summary of the development plans for the polarimetry based radar PQPE. We close the report with discussing general requirements for the next phase of the project.

B. UTILITY OF PROBABILISTIC RAINFALL ESTIMATES: GENERAL FRAMEWORK

B.1. General background

Value of improved weather forecasting, both in terms of extended forecast lead time as well as increased accuracy is widely acknowledged (see Katz and Murphy 1997). Value of hydrologic forecasting has been demonstrated clearly in operation of multipurpose reservoirs (Georgakakos et al. 1998; Georgakakos et al. 2000). Such demonstrations for rainfall estimates are not well-documented although there is recognition within the research and operational community that estimates of uncertainty of precipitation are needed for improved data assimilation schemes. Some researchers also investigated the propagation of uncertainty in rainfall estimation onto hydrologic predictions with a conclusion that interpretation of the hydrologic forecast uncertainty is difficult if the input uncertainty is unknown (Krajewski et al. 1991; Borga 2002; Carpenter et al. 2001; Sharif et al. 2002; Sharif et al. 2003.) If one takes the view that estimates are essentially very-short-term forecasts, the same arguments that justify the value of probabilistic forecasts apply to rainfall estimation. What is different is their economic value as this depends strongly on the specific application, time scale, and space scale.

In Figure 1 we present a general context for uncertainty propagation and its relationship to various aspects of water resources systems operation. Observations of the natural system are fed into forecasting models and the forecasts are used as a basis for making operational decisions. The decisions result in economic benefits or losses. It is easy to accept the notion that better decisions translate into higher benefits or lower losses. It is also easy to accept the notion that better observations lead to better forecasts. Thus, estimates of forecast model inputs characterized by lower uncertainty lead to lower forecast uncertainty. In principle, it should be possible to associate the improved forecast benefits (or, alternatively, reduction of losses) with the improvements of the observational system. However, counter examples exist. For instance, better forecasts may produce bad decisions in a reservoir system that is based on climatological rule curves. Thus, whether for a specific application the benefits of better forecasting are realized depends on how the forecasts are utilized for making decisions and how sensitive the decision space is to forecasts (e.g. Krzysztofowicz and Long 1990). Linking benefits with forecasts and with observations constitutes a system design problem and is outside of the scope of our considerations in this report. Also outside of the scope of our project is the use of observation for updating of the initial and boundary conditions for improved forecasting (i.e. updating or data assimilation problem.)

Our focus is on quantifying the benefits of the uncertainty information (e.g. Krzysztofowicz 2001). In other words, if we acknowledge that our input to hydrologic forecast and system control models is uncertain, is it important to characterize this uncertainty correctly or not? Intuitively, it seems that if the specification of the uncertainty is too optimistic (under estimated), the decision based on such uncertain information might be too risky and result is additional net losses. If, on the other hands, the uncertainty is overestimated, the decisions might be too conservative, also resulting in unnecessary losses. For example, Krajewski et al. (1993) demonstrated this for a river water temperature forecasting/control problem. It is also well known in the theory of optimal estimation and control (e.g. Gelb 1974; Schweppe 1973) that correct specification of the model and observational error (input uncertainty) is required for optimal prediction.

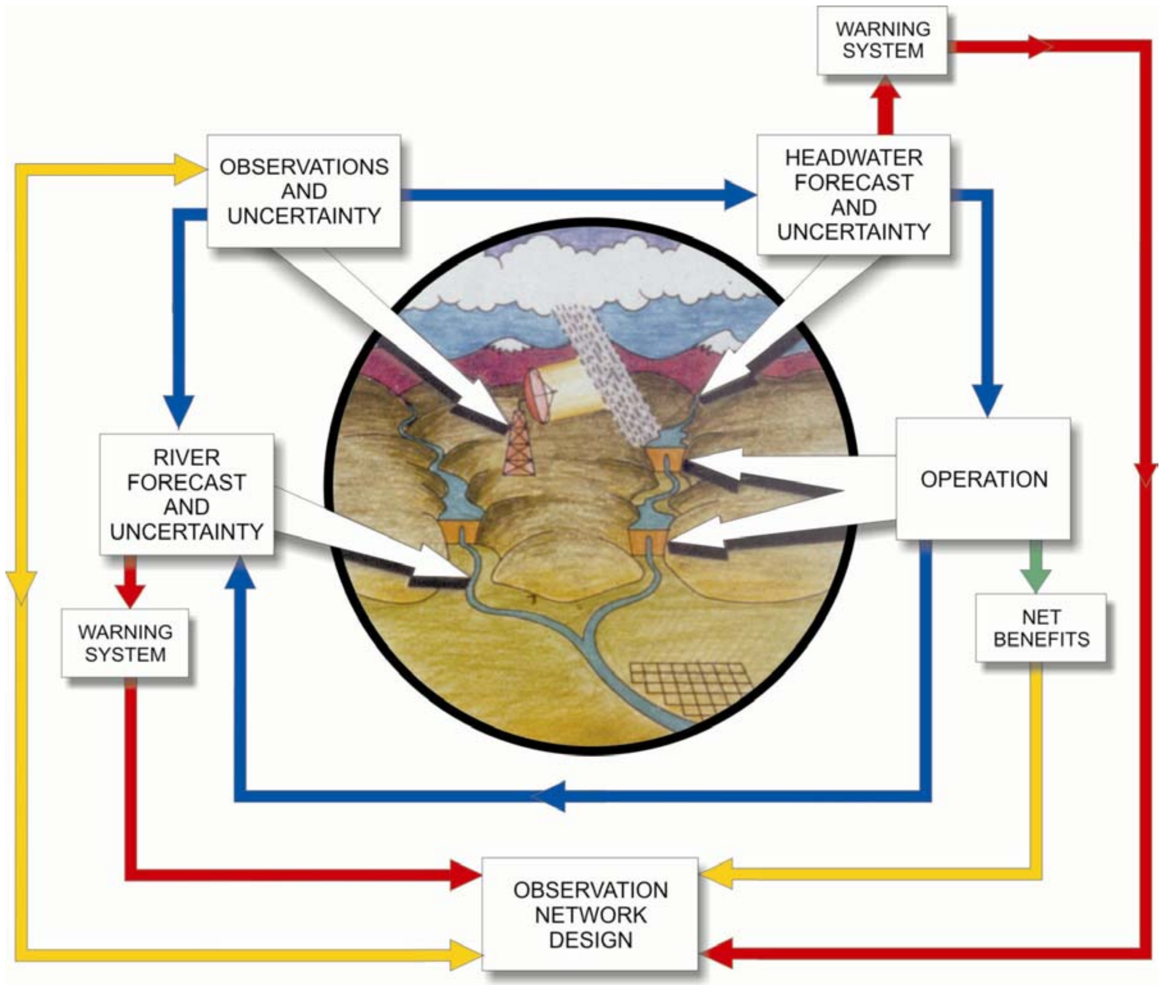

Figure 1. Conceptual illustration of different elements of a water resource system and the associated components of uncertainty (adopted from Georgakakos 1992).

However, we do not know of any such illustration, either theoretical or empirical, for the case of utility of radar-rainfall or multisensor precipitation estimation (MPE) uncertainty. In the next section we describe two potential hydrologic applications and research plans necessary to conduct such a quantitative demonstration.

An important issue in selecting a proper application that would allow demonstration of the utility of quantified uncertainty associated with MPE estimates is the choice of temporal and spatial scale. For example, considering benefits from operation of large reservoirs is probably not a good choice as the operators are interested in seasonal forecasts of inflows. From their point of view estimates of current rainfall are not most relevant. Also forecasting floods of large rivers is more sensitive to the measurements and modeling of the channel routing rather than accurate estimation of a localized storm.

We propose to consider two hydrologic applications. The first is the benefit of rainfall estimation in irrigation scheduling and control. Clearly, irrigation is a costly activity affected by the fluctuating prices of energy and to a lesser extends of water. Farmers who make decision on watering crops can save considerable amount if they can take advantage of knowing how much water their plants received due to rainfall. The second application is flash-flood prediction (Carpenter et al. 1999) and the associated potential for minimizing losses. A flash-flood prediction and warning system quickly loses credibility with the public if the warnings are issued too often and are not followed by a real treat. On the other hand, ignoring or failing to detect flash-flood danger leads to considerable economic and human life loss (e.g. Ogden et al. 2000). We discuss both applications in more detail in the following section.

B.2. Irrigation scheduling and control

Irrigation water is delivered to crops grown on large scale farm via several different systems which include sprinklers and irrigation canals. Water is supplied from small storage reservoirs or from groundwater aquifers. We plan to base our demonstration application in Oklahoma for reasons discussed in Krajewski and Ciach (2003). Several WSR-88D radars cover the region (Figure 2.)

The Oklahoma Mesonet provides relatively high quality surface data and operational hydrologic models are well calibrated for many subbasins of the Arkansas River. In Oklahoma, under the Oklahoma City WSR-88D (KTLX) there is considerable fraction of cultivated land that uses irrigation (Figure 3). In particular, we plan to use the case of the Illinois River and Blue River basins in Oklahoma, for which the appropriate hydrologic models are calibrated and all relevant data exist (see below). Note, that large extents of irrigated land are located in the Upper Washita basin, west of Oklahoma City.

The demonstration of the benefits of the PQPE for irrigation will be a collaborative effort with the Hydrologic Research Center (HRC). The role of the IIHR team will be to provide rainfall estimates and their associated error distribution for the required regions and with the required spatial and temporal resolution. The HRC research staff will use the data provided by IIHR and perform the benefit analysis. Below we elaborate on some details of the approach, the data sets we plan to compile and anticipated results.

B.2.1. Approach

The main necessary element for the demonstration is a distributed hydrologic model, the primary role of which will be to keep track of the temporal evolution of the soil moisture conditions in the root zone relevant to the crop of interest. The model will also partition the observed rainfall into surface runoff and infiltration components, route the water through the channel network, and propagate the input uncertainty through model components.

Another necessary element is a model of irrigation water delivery. This is essentially a hydraulic type model of water flow through a system of irrigation channels or pipe (sprinkler) network. The role of the model is to properly account for the time delay of water delivery and to properly link the cost of satisfying the plant water demand. It seems that at this stage it is sufficient to use a much simplified (parameterized) model. The conveyance part could be taken into consideration as an application delay parameter only and not based on the detailed hydraulic network, because the latter one requires sub-grid scale description for the model. Uncertainty with respect to conveyance of irrigation water should be considered however. Also the cost of irrigation water should be specified as a gross figure that includes delivery.

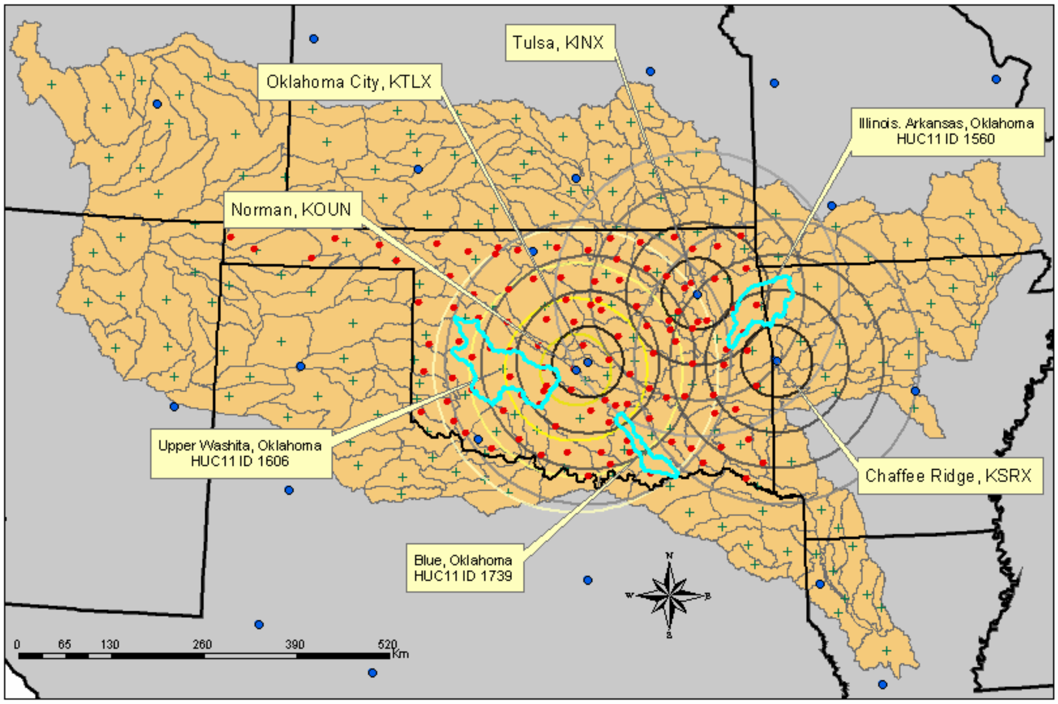

Figure 2. Arkansas River Basin with its radar coverage (blue dots and 50 km spaced rings), Oklahoma Mesonet (red dots), polarimetric WSR-88D (yellow rings), and basins selected as potential study sites.

The final element is a model of water consumption by plants throughout the growing cycle. The model has to take into account the atmospheric conditions such as air temperature and humidity, solar radiation, canopy growth and root growth.

The above elements will be used by a control module that will keep track of the water availability, and the plants condition. The module will make decision of the irrigation scheduling and calculate the associated expected costs. The benefits will be calculated assuming fair market prices for the crops based on predicted yield.

All these elements are either available or will be developed by the Hydrologic Research Center.

B.2.2. Data

We plan to perform the demonstration study in Oklahoma. Based on information we have received from the Hydrologic Research Center, historical hydrologic data are available for the Illinois and Blue River basins, which were among several basins in Oklahoma used for the

Distributed Models Intercomparison Project (DMIP) (Smith et al. 2004). Agricultural data consists of vegetation type and acreage, consumptive water use, and yield functions of water availability.

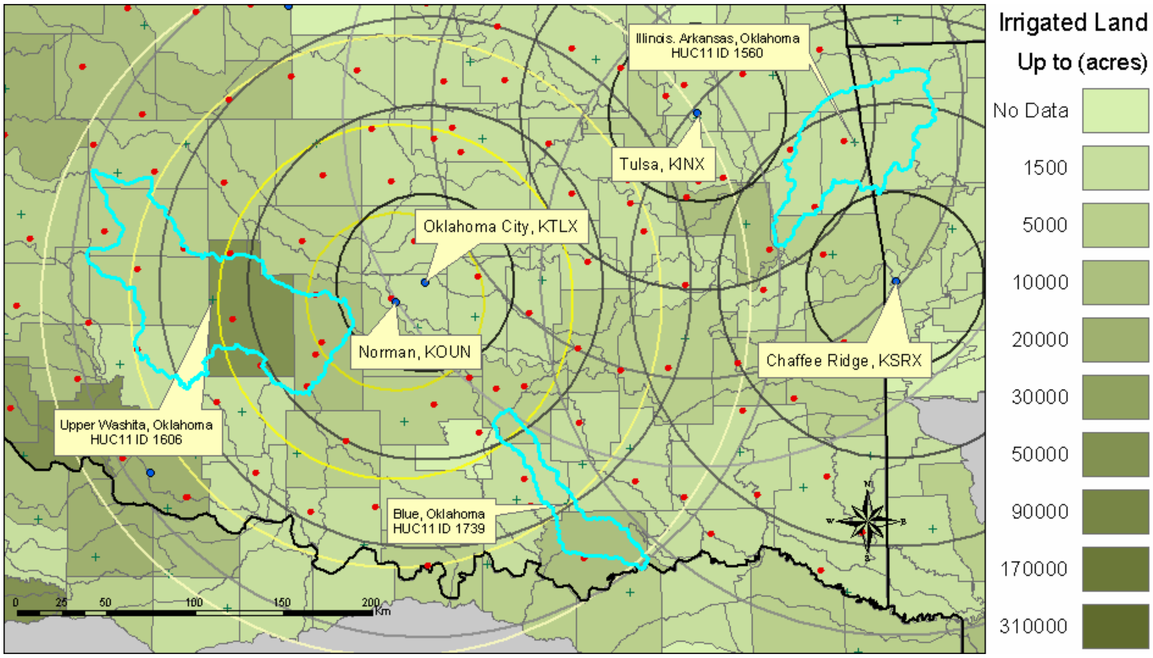

Figure 3. Total (per county) irrigated land under the coverage of the Oklahoma City and Tulsa WSR-88D radars.

Rainfall data include Level II reflectivity data from the Oklahoma City (KTLX), Tulsa (KINX), and Chaffee Ridge, Arkansas (KSRX) radars, Oklahoma Mesonet surface observations, and other operational data. The basins are also under the coverage of the polarimetric WSR-88D in Norman, Oklahoma (KOUN). The reflectivity data are available from the National Climatological Data Center (NCDC). We have developed software for downloading, quality controlling, and organizing large databases of radar observations (Kruger and Krajewski 1997; Kruger and Krajewski 2003). We will interface the data with the Open System Radar Product Generator (OPRG) software for generation of radar-rainfall products according to a pre-specified scenario (i.e. set of PPS options and parameter values).

B.2.3. Anticipated results

The final results of the demonstration will be in the form of the expected benefits (since the actual benefits are unknown.) Given real rainfall data, models of real basins, actual land use, crops properties, and water delivery costs we will propagate the probability distribution function of the input data (PQPE) into a distribution of the benefits associated with irrigation. We will attempt to show that decisions based on the probabilistic information are better than decisions based on deterministic information (i.e. corrupted with unknown uncertainty). We classify our study as data driven simulation (see Krajewski et al. 1993 for an example of a similar demonstration in the field of power plant cooling water release control.)

B.3. Flash-flood warning

Demonstration of the benefits from improved prediction of flash-floods is the second hydrologic application we will focus on. Here the main challenge is the timely issuing of the flash-flood warnings (e.g. Georgakakos et al. 1997). The current technology used by the NWS is based on the concept of threshold rainfall (Carpenter et al. 1999; Reed et al. 2002), i.e. rainfall amount that will cause flooding (exceedence of bank-full discharge). This amount depends on static variables (i.e. changing slowly with time) such as land use, topography, channel network, etc. and dynamic variables (fast changing in time) that include soil moisture, snow melt, ground temperature. The threshold value that corresponds to the average (i.e. typical) conditions and determined based on the static variable, is adjusted in real time based on the monitoring of the dynamic variables. Collectively these are know as flash flood guidance (FFG) procedures and are used on a basin by basin basis. They are used operationally by the NWS Weather Offices around the country using hydrologic models operated by the River Forecast Centers. When rainfall amount integrated over the basins exceeds the threshold value warning to the public is issued. Although the analysis is done based basin delineation (i.e. in a hydrologically meaningful way) the warnings are issued on a county basis with which the public is more familiar. Typically the basins that are subject to FFG analysis are smaller that a typical county.

Clearly, since rainfall amount estimated over the basin is subject to uncertainty, wrong decisions about issuing the warnings are sometimes made. These have social as well as economic consequences. Our concern will be the economic aspects only.

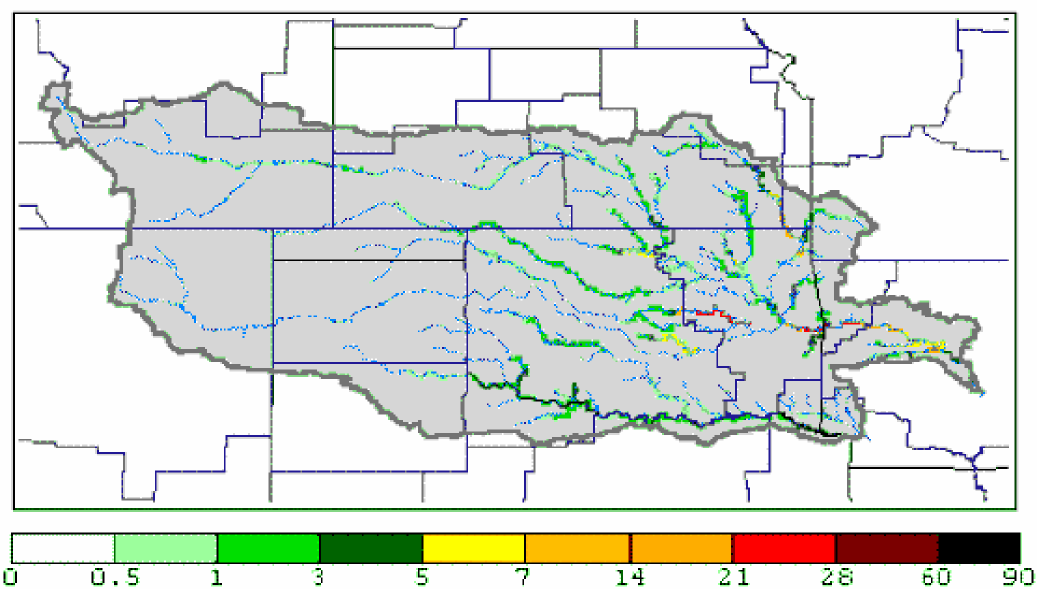

Figure 4. Average annual number of days with discharge exceeding the flood stage in the Arkansas River basin.

In close collaboration with the Hydrologic Research Center we will conduct a data based simulation of the potential decrease of economic losses due to providing probabilistic information about the mean area rainfall averaged over a basin. As in the case of the irrigation benefits, we will provide the PQPE products to HRC which will apply the FFG procedures to the selected basins. It seems that the data-rich Oklahoma will be an adequate test bed for this procedure as well. Based on Figure 4 the region in Oklahoma east of Oklahoma City experiences frequent flooding thus should provide a good test of our methodology.

C. Formulation of the PQPE Methodology

During the Phase II of this project, we continued our analysis and refinement of the methodological framework for the PQPE problem that was initiated in Phase I (Krajewski and Ciach 2003). For the completeness of this report, we briefly summarize the proposed methodology for the PQPE algorithm development as we understand it now.

C.1. Basic Definitions

The four fundamental notions defined below are used throughout this report:

- *True rainfall*: The amount of rain-water that has fallen on a specified area in a specified time-interval.
- *Radar-rainfall (RR)*: An approximation of the true rainfall based on radar data corresponding to the same spatio-temporal domain.
- *RR uncertainties*: All systematic and random differences between RR and the corresponding true rainfall.
- *Ground reference (GR)*: Estimates of the area-averaged rainfall accumulations based on rain-gauge data that are used to evaluate RR products.

C.2. Problem Description

The progressive evolution of the operational RR products has been guided by the attempts to quantify and to reduce the uncertainties in the RR estimates. The currently existing RR maps produced operationally by the NWS (the Stage II and III products) are just arrays of numbers describing the spatial distribution of approximate rainfall accumulation values that are obtained based on the WSR-88D reflectivity measurements corrected with the available concurrent rain-gauge data. Application of the term “quantitative precipitation estimates” QPE to such products implies that the maps are completed with quantitative information about the product uncertainties. Without such 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 QPE products are devoid of their uncertainty information. We believe that the development of the probabilistic quantitative precipitation estimation (PQPE) products based on sound empirical evidence will be the optimal comprehensive solution for this pathological situation.

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 mathematically defined through the conditional probability distributions of the likely true rainfall, given the current radar measurements and other available information. These distributions can be determined by specific parameter values of a general uncertainty distribution model developed in this project. The model parameters have to determine unambiguously the uncertainty distributions of given RR estimates in different rainfall regimes for each operationally useful distance from the radar and spatio-temporal averaging scale. From such a general PQPE product, one can directly derive any specific uncertainty characteristics (for example, the RR expectation, standard errors, probabilities of exceedence, or an ensemble of probable rainfall maps) that can be required for different operational applications.

C.3. Basic Requirements

During the discussions with the panel of experts engaged in the Phase I of this project (Krajewski and Ciach 2003), it was agreed that any method that will be applied to generate the PQPE products has to satisfy several key requirements. These requirements were further analyzed and refined in the course of the Phase II of the project. We summarize them briefly below:

1. The method has to be empirically "verifiable." Conditions have to be assured to systematically evaluate the degree of agreement between the PQPE results and the RR uncertainties estimated based on reliable GR in selected "validation sites."

2. The method has to be adjustable to different synoptic and topographical situations, and to the changing operational environment, by its model parameter calibration using available information.

3. The method has to account for the spatio-temporal dependencies in the errors process to provide the PQPE products over a broad range of spatial and temporal scales used in different hydrological applications.

4. The method has to work with the current reflectivity-only WSR-88D algorithms, the multi-parameter (MPE) algorithms using the available concurrent rain-gauge and satellite data, and the polarimetric algorithms (using differential reflectivity and differential phase-shift) available operationally after the upcoming upgrades of the WSR-88D radars.

5. The method has to provide the PQPE products in a format appropriate for their efficient usage in different hydrological applications.

C.4. The Proposed Solution

In the Phase I of this project (Krajewski and Ciach 2003), we analyzed various possible alternative approaches to the PQPE problem that can potentially realize the above-stated objectives. The methodology that was finally chosen for possible further development consists of empirically based mathematical modeling of the cumulative final effect of all the errors in different RR estimates over a broad range of spatio-temporal scales. It reflects our acknowledgement of the fundamental fact that, in practice, it is impossible to delineate all the important error sources, and to quantify their effects separately, based on the available measured quantities. This methodology, called the product-error-driven (PED) modeling, can be briefly summarized as follows. The first step is collecting large samples of reliable data about the relation between different types of RR products and the corresponding true rainfall in different situations. The second step is developing a flexible mathematical model of the relation that can be applied to the operational WSR-88D precipitation estimation process. This is followed with developing empirically based generalizations of the model and its calibration for different types of RR products, rainfall regimes and radar locations. The mathematical framework of the proposed PED method and the empirical basis necessary for its development are described in detail in the report of the project's Phase I (Krajewski and Ciach 2003).

The mathematical framework for the PED approach is general and, in principle, can be applied to characterize the probabilistic properties of any type of RR products, including the multi-sensor products (MPE) and the polarimetry-based rainfall estimates. This flexibility, the broad scope of scales and precipitation regimes considered, and the proposed sound empirical basis of the mathematical modeling enable the fulfillment of the basic requirements for the viable PQPE development and implementation methodology stated in the previous section. This approach also provides sound empirical justification of the necessary modeling assumptions, the large-sample estimates of the model parameters in different situations, and an efficient framework for dealing with the ground reference errors during the model parameter estimation. The total uncertainty is determined by observations of rainfall on the ground, which is fundamentally important for hydrologic applications. The PED method is feasible both as far development of the model and its operational implementation are concerned. It is also technically straightforward in that it uses the currently available surface rainfall measurement technologies and can account for their errors.

D. MULTISENSOR PQPE

Here we describe our planned strategy to upgrade the multi-sensor precipitation estimation (MPE) algorithms implemented by the NWS to the relevant probabilistic framework. This part of the planed PQPE development is a considerable extension of the initial plan developed in Phase I of this project (Krajewski and Ciach 2003) that was limited to the radar only precipitation products. In Phase II, we performed additional studies of the available documentation and literature reports regarding the MPE algorithms and applications. Apart from that, we visited the North Central RFC in Minneapolis, Minnesota, to get acquainted with various practical aspects of the operational interactive data processing based on current implementation of the MPE software. During this visit, we also discussed the demand for the uncertainty information that should accompany both the input data used in the MPE algorithms as well as the final MPE products ("the best estimates"). It was impossible, during a one-day visit, to cover all the practical problems related to the PQPE project in different situations and their possible operationally viable solutions that can be achieved within the PQPE development process. We recommend a longer visit (2-3 weeks) of Dr. Grzegorz (Greg) Ciach to the North Central RFC that would allow him to participate in the real-time MPE operations and to get detailed insight in current MPE applications and the way the PQPE algorithm should be implemented in the operational environment. The optimal timing for this visit would be the Spring of 2004.

We identified several problems that should be solved in the course of the planned upgrading of the MPE algorithms into the PQPE framework. The basic development steps and components of the whole task, in their order of priority, as we perceive it currently, can be briefly enumerated as follows:

1. Developing an efficient algorithm for real-time uncertainty estimation of the currently computed mean-field-bias factors in the Stage I products.
2. Developing the probabilistic versions of the basic MPE inputs (radar, gauge and satellite precipitation data) including their realistic uncertainty estimates.
3. Quantifying the uncertainty reduction in MPE product achieved due to the real-time operations of Hydrometeorological Analysis Support (HAS) staff.
4. Developing an algorithm to deliver the PQPE version of the final MPE precipitation products that could be applied to different situations.

Operational implementation and tests of each of the above components should be an integral part of their development. In our opinion, based on our knowledge of the MPE development strategy, the new PQPE procedures have to be implemented step-by-step as integral parts of the new MPE builds.

D.1.1. Current state of the MPE system and operations

The final precipitation maps estimated using the MPE system of algorithms are obtained by combining data from several different sources that are related to the actual precipitation intensities. The four basic sources of the input precipitation information are:

- the Stage I WSR-88D radar precipitation maps;
- hourly accumulations from the available rain gauges in each radar coverage;
- satellite precipitation estimates;
- data from the lightning detectors.

Ultimately, the final products ("the best MPE estimates") are the result of many interactively guided decisions made in real-time by the HAS forecaster who is performing the MPE operations. In our opinion, the three most important decisions that directly affect the quality of the MPE product in the areas covered by the WSR-88D Stage I data are: (1) cutting-out the false precipitation in the regions of unfiltered anomalous propagation (AP) and ground clutter echoes; (2) rejecting from the analysis the rain-gauges that report suspicious data; and (3) correcting the bright-band overestimation effects in the areas where they are clearly visible. In the areas that are not covered by the WSR-88D Stage I data, the MPE maps are filled using either the interpolated rain-gauge data, or the satellite precipitation estimates. Another operation that can be based on arbitrary assumptions concerns dealing with the periods with missing data. These periods can be either filled with zero precipitation, or with a copy of the data from another period for which the data are available.

One of the drawbacks of the current MPE system is that all these decisions remain undocumented in the archived product stream. As a consequence, there is no information in the "best MPE estimates" about the data sourced that actually contributed to the final outcome over a specific area and time interval. This fact makes the estimation of the MPE product uncertainties difficult since each of the sensors has quite different error characteristics, and each decision affects the uncertainties in different way. To upgrade the MPE system into the PQPE level, it will be necessary to record the information about the decisions made by the HAS forecasters.

The rain-gauge data used in the MPE processing are subjected to several steps of automatic quality control (QC). The results of the QC are visualized by three different colors of the rain-gauge reported precipitation values, depending on the reliability level of the data assessed by the QC algorithms. The HAS forecasters use these flags to support their judgment about the eligibility of each gauge for the final MPE analysis. Additional information contributing to this decision-making process comes from the accumulated historical experience regarding the performance of each rain-gauge station. The HAS decisions are ultimately based on their intuition and operational experience.

The HAS performance and, consequently, the quality of the final MPE products are highly dependent on the time available for digesting all the available information. For example, in the area of the North Central RFC there are about 740 rain-gauges reporting hourly accumulations with various time-delays. In complex situations it can be sometimes impossible for any HAS forecaster to properly assess the eligibility of all of the "suspicious" gauges. This is another factor that makes the evaluation of the uncertainties in the MPE products difficult.

D.1.2. Uncertainties in the mean-field-bias factors

The mean-field-bias (MFB) factor is computed for each WSR-88D radar based on the hourly accumulations from the rain gauges within the radar coverage. The HAS forecaster makes the decisions about the number of radar-gauge pairs that can be used for the estimation of the MFB factors and, effectively, about the time period in the past that is included in this part of the analysis. The major drawback of the currently implemented algorithm is that the estimated MFB factors are delivered without their uncertainty bounds. The HAS decisions must be based on ad-hoc rules of the thumb (for example, "20 pairs are enough") and involve manual, experience and intuition based, modifications of the MFB factors in cases when their departures from unity are "suspiciously large". As a first step of the planned upgrading of the MPE system into the PQPE level, we propose completing it with an efficient algorithm for real-time estimation of the error bounds in the currently computed MFB factors of the Stage I WSR-88D products.

There are three major observables that affect the uncertainty of an MFB estimate. It decreases with increasing the number of the radar-gauge pairs. It grows when the time period over which the data pairs were collected increases. And, finally, it highly depends on the average amount of the accumulated rainfall. A general parametric model of these dependences, and the resulting algorithm, can be built based on our research (Krajewski and Smith 2002). However, calibration of the model parameters is necessary before the algorithm can be implemented operationally in a future build of the MPE system. This calibration process requires extensive data analysis and must be included in the PQPE development. Also, archiving systematically the decisions about the reliability of different rain-gauge stations, as assessed by the HAS forecasters, would help making this algorithm more efficient.

D.1.3. MPE products in the PQPE version

To upgrade the MPE system into the PQPE level, we propose applying essentially the same methodological framework as was proposed in Phase I of this project for the radar-only precipitation estimates, the product-error-driven (PED) framework (Krajewski and Ciach 2003). This methodology is sufficiently general and can, in principle, be applied to any type of the precipitation product. However, its application to the MPE products is much more complex and must include quantification of several new sources of uncertainties. In the areas covered by the radar data, the algorithm proposed in Krajewski and Ciach (2003), together with the MFB estimation proposed above, will constitute the core of the algorithm generating the probabilistic information. Additional uncertainty models have to be created for the situations when only rain-gauge and/or satellite estimates are available. In our opinion, the general probabilistic framework for these new algorithms can be the same as for the radar-only situation. However, estimating the specific structure of the models and calibrating the algorithm parameters requires additional verification data sets and different optimization techniques, and thus, increases considerably the scope of the PQPE project.

D.1.4. Calibration and validation of the PQPE-MPE algorithms

To build operationally viable algorithms for the MPE system, one needs a solid empirical basis for estimation of the structure of the uncertainty models for the different input sources, validation of the models, calibration their parameters, and for systematic and rigorous verification of the PQPE outcomes. The two essential components that are necessary to create such empirical basis are:

1. A long-term archive of all the input information that are applied by the HAS forecasters to generate the final MPE products.
2. A reliable, sufficiently accurate and independent ground reference (GR) data covering the same time period and area.

The long-term archive of the precipitation data from the separate sensors that are created by the MPE algorithms and presented to the HAS forecasters should be complete enough to be able to recreate the MPE-based interactively-driven processing in an off-line regime using different decision-making scenarios. This archive should be completed with the systematic record of all the HAS decisions that contribute to the final "best MPE estimates" that are currently archived. Creating such a comprehensive MPE archive is a technically simple task and could be completed by the MPE development team in the next build of the MPE system, if the decision is made quickly. Note that this archive could also serve other purposes, apart from the development of the PQPE algorithms. For example, it would enable clear identification of the problems and the sources of large errors that are possible in the final MPE products.

Collecting reliable, sufficiently accurate and independent ground reference (GR) data for the development of the PQPE algorithms for the MPE system is not an easy task. The reliability of these GR measurements has to be much better than it is in the case of the typically available operational rain-gauge data. It means that they have to contain enough redundancy to decrease the rain-gauge failure rate by at least one order of magnitude. This goal can only be achieved by careful design of the stations, application of the multiple-gauge setups at each of the stations, and their frequent inspection. The accuracy of the GR areal precipitation approximations based on reliable rain-gauge stations can only be increased by increasing the spatial density of the GR networks. And, finally, the independence requirement means that these GR data must not be used in the MPE products.

All these three conditions for an appropriate GR are currently fulfilled by the AMSR validation network (McCollum et al. 2003) that was deployed in 2002 around Iowa City, Iowa. This network covers an area of 20 km by 20 km located between 70 km and 90 km West from the Davenport WSR-88D station (KDVN). The inter-station distances are about 5 km and each station contains two accurate, regularly calibrated and carefully maintained rain-gauges. The precipitation data are recorded by data-loggers with the highest currently possible precision, in the form of the accurate tip-times of the tipping-buckets that have the resolution of 0.254 mm (0.01"). These rain-gauge data are collected about once a month, and thus, can be used only for the off-line analyses, as well as for the algorithm development and verification of the results. Their QC is by far much more reliable than for the typical operational rain-gauge data thanks to the double-gauge design and high density of the AMSR network.

We propose to base the development of the PQPE algorithms for the MPE system on the Iowa AMSR network and to include in the project its further expansion to cover larger area. Specifically, we propose to expand the network in the westerly direction to cover further distances from the KDVN station, and to finally include the Des Moines WSR-88D station (KDMX) in the development process. Including in the planned strategy about $40-50 thousands per year designated for this specific goal would allow to extend the network by about 20 km each year and to cover most of the area between the KDVN and KDMX stations in a few years. Most importantly, such a GR network would be an ideal validation site for the planned polarimertic upgrade of the operational NEXRAD network and for the future MPE builds. Since this area is within the coverage of the North Central RFC that promptly implements the new MPE builds, the proposed validation network would constitute a solid basis for close cooperation between the operational NWS staff and our research group at the University of Iowa. Additionally, it could help to overcome the currently existing opinion that the NEXRAD, QPE and MPE (and the planned PQPE) algorithms are developed mainly for the "Oklahoma weather service."

E. POLARIMETRIC RESEARCH FOR PQPE

In this chapter we discuss various aspects of adding polarimetric capabilities to the WSR-88D radars. The added capabilities are expected to improve radar data quality control procedures and accuracy of the precipitation estimates. Thus, these improvements are expected to be reflected in the future PQPE products as well. Although full operational implementation of the polarimetric upgrade is still years away, it prudent to begin preparing for the developments of the polarimetry based PQPE procedures.

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.

Herein we discuss the major steps required for evolving the Precipitation Processing System (PPS) on the WSR-88D from its pre-polarimetric stage into polarimetric era. It is on that basis that future polarimetric PQPE can be formulated. Block diagram in Figure 2 illustrates the algorithms for quantitative precipitation estimation planed for implementation in 2005 (Fulton 2003). Figure 3, adapted from Fulton (2003), shows changes that might happen to precipitation measurements after adding polarimetric capability.

We start by dissecting individual stages, identifying the common treads between the non polarimetric and polarimetric systems, and speculating on how the extra information might be utilized.

E.1. Adding Polarimetric Information to the PPS

E.1.1. Enhanced Preprocessing (EPRE)

EPRE is split into two elements (blocks): EPRE1 and EPRE2. EPRE1 is added because it deals with each polarimetric variable on the range gate by range gate basis. Clearly many steps in processing the reflectivity factor Z will still be applicable because it is also used in the polarimetric rainfall estimation and classification. Nonetheless all steps will have to be examined to establish which should remain and which will be replaced with improvements made possible by the polarimetric data. There will be additional corrections of the reflectivity data prior to application of the hybrid algorithm. We describe the main operations below.

Compensation for attenuation will be made possible from measurements of total differential phase. Compensation for differential attenuation will also use the differential phase shift Φ_{DP}. Filtering and dealiasing of Φ_{DP}, and computation of the specific differential phase K_{DP} will be performed over an adaptive range interval. Calibration of reflectivity Z and differential reflectivity Z_{DR} will be performed over the full dynamic range of the receiver. This might include self-consistency checks among the polarimetric variables.

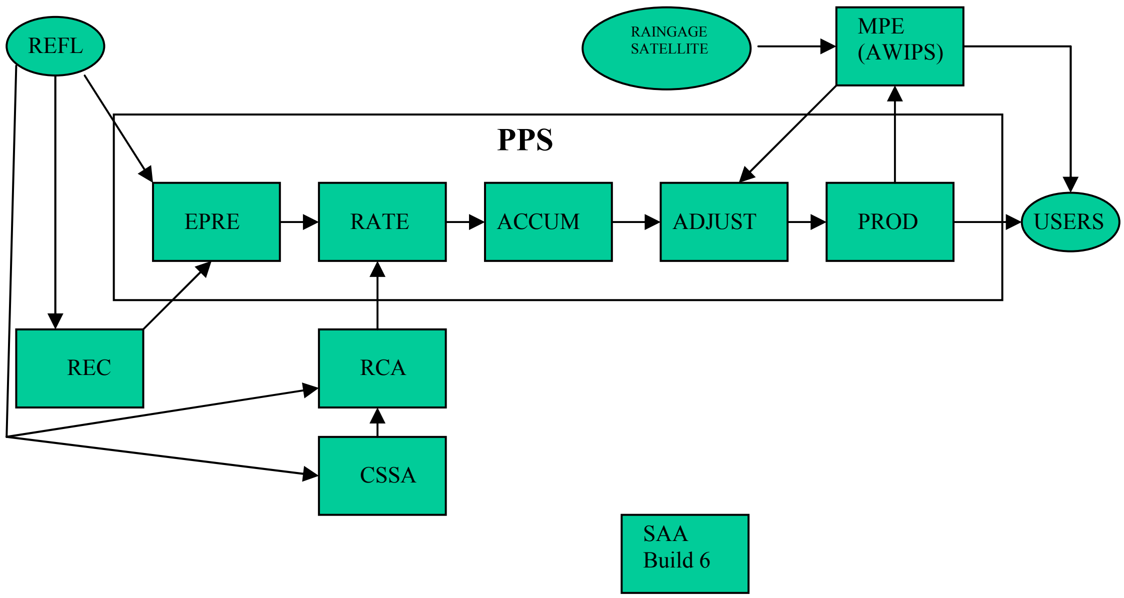

Figure 5. Future polarimetry based PPS (ORPG Build 7-8, 2005.) RCA is Range Correction Algorithm; CSSA is Convective-Stratiform Separation Algorithm; SAA is Snow Accumulation Algorithm (Adapted from Fulton 2003).

EPRE2 will be augmented by the addition of polarimetric variables and the use of Hydrometeor Classification Algorithm (HCA). In addition to texture of reflectivity computed will be texture of total differential phase. This stage of processing will be evolving continuously as our understanding of polarimetric measurements increases. For example, there will be no need to separate rain into stratiform and convective (hence the reason to eliminate CSSA in Figure 5); the hybrid rainfall algorithm (see next section) is meant to automatically adjust to the rainfall type.

Significant changes will ensue in dealing with bright band. Direct identification of bright band is possible from polarimetric measurements. Furthermore measurement of rainfall from the bright band (in cases where the lowest beam intersects it) is also possible. Also the choice of antenna tilt from which the rainfall is estimated will be made in the EPRE2. Censoring of data (precipitation vs. non precipitation) will be applied with the help of the HCA.

E.1.2. Computation of Rain Rate, Accumulation, and Adjustment

The RATE-ACCUM and ADJUST blocks in the current PPS become POLARIMETRIC QPE. This implies incorporating polarimetric variables in lieu of reflectivity factor. This should be a first step as it has been demonstrated through research (Ryzhkov 2003). In essence, the current R(Z) (both rain rate and/or rainfall accumulation) will be replaced with the polarimetric

$R(Z, K_{DP}, Z_{DR})$. At present we advocate a hybrid $R(Z, K_{DP}, Z_{DR})$ described by Ryzhkov (2003), which uses $R(Z,Z_{DR})$ at low rain rates, $R(K_{DP}, Z_{DR})$ at intermediate, and $R(K_{DP})$ at high rain rates.

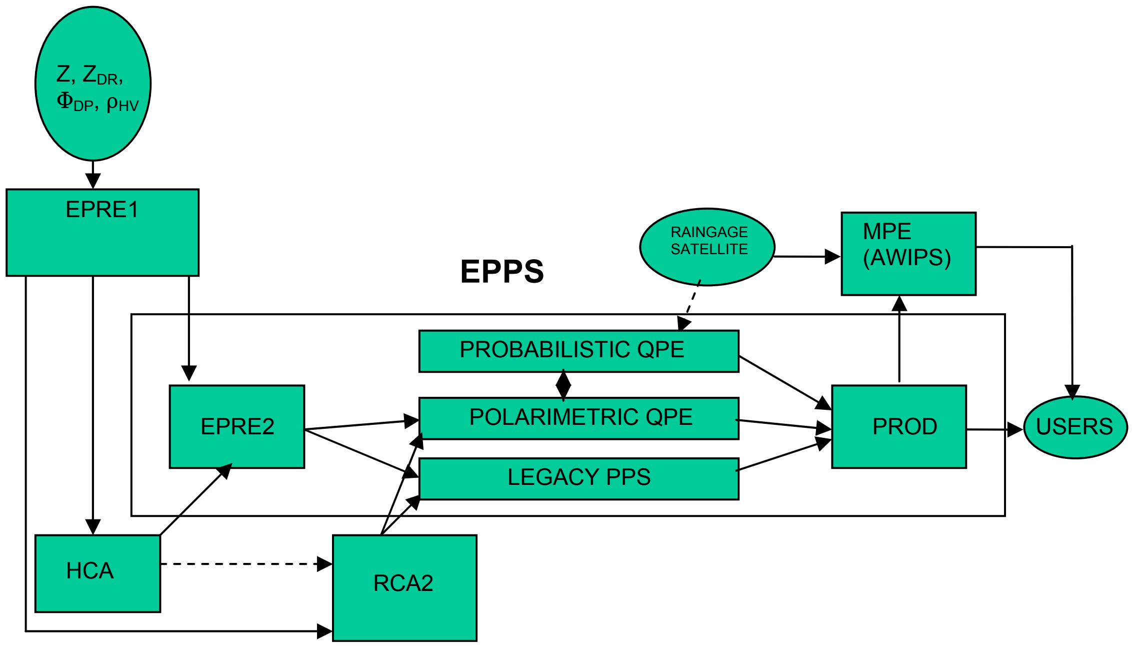

Figure 6. Polarimetric era (ORPG Build 9 and higher, 2007 and beyond). EPPS is Enhanced PPS; EPRE1 is Preprocessing and correction; EPRE2 is Enhanced EPRE; HCA is Hydrometeor Classification Algorithm; RCA2 is Enhanced RCA (Adapted from Fulton 2003).

Accumulation will be computed from rain rates. In the adjustment process some revisions will ensue. We expect polarimetric variables to lessen reliance on satellite information for identification of AP or presence of chaff.

E.1.3. Hydrometeor Classification

Current Radar Echo Classifier (REC) will be replaced with Hydrometeor Classification Algorithm which uses polarimetric variables. Note that in developing the REC scientists used the anomalous propagation and ground clutter detected with the HCA as truth for evaluating REC. Therefore, as far as detecting echoes from ground, the HCA will do better than the REC. Because it also uses principles of fuzzy logic it will quantify the likelihood of ground echo. Furthermore other non meteorological scatterers (i.e., biological, chaff, etc.) will be identified. That would leave echoes from precipitation for further processing. A pertinent output of the HCA is partitioning of echoes into rain, bright band, and snow. This will be passed to the Polarimetric QPE where a suitable procedure for quantifying precipitation will be applied. Therefore the Convective Stratiform Separation Algorithm (CSSA) has been superseded (absorbed) by the HCA.

E.1.4. Range Correction Algorithm (RCA2)

This algorithm will be augmented and improved. For one, if the lowest beam intercepts the bright band the algorithm might fine tune the $R(K_{DP})$ relation from the observed vertical profiles of polarimetric variables. In cases when the lowest beam is above bright band the HCA and vertical profiles of polarimetric variables will be used for estimation of rain below the freezing level.

E.2. Towards Probabilistic QPE

In parallel with change to polarimetric rainfall estimation, error analysis of the method will be provided and verified. That is standard errors and bias will be determined first, and later (where possible) the PDF of accumulations (and rain rates) will be determined. Errors are mainly of two type a) radar processing errors (in Z, and polarimetric variables) and physical errors (DSD variation, shape uncertainty, beam filling, height above ground etc) which can be functions of range. These we term intrinsic (per resolution volume) errors.

Three scales play a role in rainfall measurement. The smallest scale is one associated with gauges (point measurement) and update times of seconds. The next larger scale corresponds to the radar resolution volume (which is a function of range) and volume update times (5 to 6 min). The next scale up is the grid size in hydrologic measurements and models (spatial and temporal). Currently the grid is 4×4 km^2 and hourly accumulations are provided at volume update times (5 to 6 min). Error structure (correlations and variances) on the hydrologic grid scale depends on the error structure at the radar resolution scales which in turn depends on the smaller structure of unresolved scales. The errors structure of unresolved scales can be estimated by measurements with a dense (Piconet) gauge network; relating these to radar resolution volume is fraught with the basic incompatibility of a three dimensional and large radar resolution volume which is also physically displaced from gauges. Now the structure at hydrologic grid scale can be easily related to the structure of the radar resolution volume scale if the grid values are derived from radar observations. We plan to develop precisely this relation for a variety of rainfall regimes. Ultimately the rain structure will be estimated in real time and used to quantify the PQPE.

E.3. Multisensor Precipitation Estimator

Combining the radar measurement with other sensors including satellite observations will be straight forward. The values provided by the polarimetric method will have smaller bias and errors. Further, presence of artifacts such as chaff or AP, will be established from polarimetric data and that would require reexamination of the use of satellite.

E.4. Probabilistic Polarimetric QPE

Last and most difficult task is to obtain the probability density functions of measured precipitation (rain) amounts. For this, analysis of errors in polarimetric variables as well as the PDF of such errors is required. Physical properties of precipitation fields and issues concerning scales of rainfall measurement are also needed. Hence the knowledge obtained from analysis of gauge data and radar measurements will provide information about the structure of error fields.

F. PROJECT REQUIREMENTS

There are several important requirements for the project that include research, data, and software. The research requirements include methodological issues still remaining to be investigated. Large data sets need to be efficiently organized and interfaced with specialized software that includes the current and future versions of estimation and forecasting models. Additional experimental and organizational needs have to be addressed as well. In this section we discussed these requirements following the three tasks we described in the proceeding sections: (1) hydrologic utility of the PQPE; (2) multisensor PQPE and (3) polarimetric PQPE.

From the methodological requirements point of view, the focus of the development activities within this project will be on the specific objective: creating an empirically based, flexible and parsimonious parametric model of the error distribution in different precipitation products applicable for different situations. This involves large-sample analysis of the dependences of the error distribution on the following factors:

1. Type of the precipitation product (radar, gauge, satellite, MPE);
2. Distance from the WSR-88D radar covering a given area;
3. Spatio-temporal averaging scale;
4. Type of the precipitation system;
5. Height of the zero-isotherm;
6. The PPS and/or MPE setup;
7. Corrections made by the HAS operator.

As we discussed in Krajewski and Ciach (2003), data adequate for this element exist and are concentrated in Oklahoma and Iowa.

The required software includes the PPS and MPE algorithms with the option to turn on and off certain modules. A particularly important element of the 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 and/or MPE software 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 results within the MPE system.

F.1. Hydrologic Utility of the PQPE

Since in the hydrologic applications we focus on concern watersheds located in Oklahoma, we propose to use data from the existing observational 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.

Regarding the irrigation and flash-flood models, their successful application for this project depends on the existing cooperation between the Hydrologic Research Center and the NWS. Specifically, prompt availability of the calibration data for the selected basins would help timely realization of this part of the PQPE project.

F.2. Multisensor PQPE

The main issue of multisensor PQPE development and testing is availability of appropriate data in areas covered by multiple sensors. For example, although the two basins selected for the initial hydrologic studies are covered by multiple radars, the Arkansas-Red Basin River Forecast Center does not use the same multisensor QPE procedures as other RFCs. Also, the density of the rain gauge data and the rainfall regime in the south are quite different from those in other parts of the country. Thus, preparing for transfer of the uncertainty parameterization is the focus of the second step in the plan. We recommend enhancement of the research rain gauge network in Iowa covered by the Northcentral RFC. University of Iowa’s 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 6). The cluster has been in operation since 1998 but the rest of the network was deployed in the summer of 2002.

One extremely valuable improvement of the existing Iowa City network would be extending it towards the Des Moines WSR-88D radar along the range between the KDVN and KDMX radars. As discussed in Section D.4, this would allow efficient development of the algorithms to upgrade the MPE system into the PQPE level.

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 data from these stations are not used operationally by the RFC in the MPE procedures thus allowing independent evaluation of the future multisensor PQPE. We will cooperate with the ISU to acquire these data for the PQPE project.

F.3. Polarimetric PQPE

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.

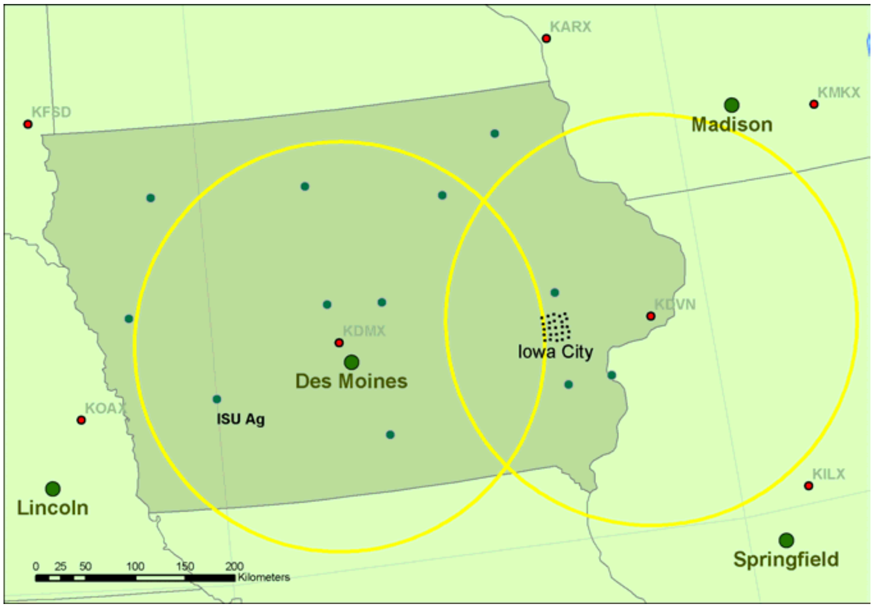

Figure 6. Ground reference rain gauge network in the vicinity of Iowa City, Iowa.

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.

To facilitate the polarimetry based PQPE research and development work, we recommend upgrading the Davenport (KDVN) and Des Moines (KDMX) radar stations to polarimetric capability as early as possible. Based on the expanding Iowa City ground validation network, such an early upgrade would provide opportunity for the transferability studies of the polarimetric rainfall estimates in an operational environment, and further algorithm development work. Also, upgrading of the KDVN and KDMX stations would provide further research opportunities on the polarimetric PQPE in a likely case if the Oklahoma Piconet could not be continued at the Oklahoma City Airport. (We have received information that the Airport will expand its facilities taking up the grounds occupied by the Piconet.)

F.4. Other requirements

Other 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 PQPE upgraded MPE system. There are several possibilities here that include development of web-based training modules and/or short (1-2 days) courses. 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. Close and direct cooperation between the University of Iowa Hydrometeorological group, the involved RFC staff and the MPE development team should be an integral part of this process.

G. PROJECT IMPLEMENTATION

G.1. Schedule

We foresee the PQPE project as a two tier activity: short-term with the time horizon of two years and a long-term with the time horizon of five or more years. In the first 2-year period, which is determined by the existing contract between the University of Iowa and the NWS, we will focus on data preparation, expansion of the Iowa City ground reference network (Section D.4), development of a general uncertainty model (Section C), demonstration of the hydrologic utility of the PQPE (Section B), and development and implementation of the MFB uncertainty estimation algorithm (Section D.2). The longer time horizon would include development and calibration of the PQPE algorithms and procedures for the whole MPE system (Section D), development of specific PQPE algorithms for the polarimetry based rainfall estimates, further work on the operational hydrological applications of the PQPE products, as well as the tests of the PQPE algorithm transferability that will be possible in the future. Below we describe the details of the recommended schedule.

First development period:

Year 1. Continue collecting and organizing the long-term archive of the Level II data for the Oklahoma and Iowa WSR-88D stations. Collect the Piconet, Micronet and Mesonet data in Oklahoma, and the AMSR and other rain-gauge data in Iowa. Start expanding the Iowa City ground validation network. Continue processing the polarimetric data from the KOUN radar in Oklahoma, in cooperation with the NSSL. Install the PPS system and interface it with the Level II database. Analyze the data and formulate the first general uncertainty model for the PQPE. Prepare sets of experimental PQPE products for the selected basin and transfer those to the HRC. Obtain the first results of the hydrologic applications and analyze them jointly with the HRC personnel. Develop an empirically based model of the MFB uncertainties.

Year 2. Continue collecting the radar and rain-gauge data from Oklahoma and Iowa. Continue the analysis of the PQPE usage in the selected hydrologic models, summarize the results of the hydrologic utility demonstration and publicize them. Obtain the first uncertainty characteristics of the KOUN experimental polarimetric precipitation products. Continue expanding the Iowa City ground validation network. Develop the operational MFB uncertainty estimation algorithm and implement it in the MPE system.

Long-term development period:

It is difficult to predict at this moment the scope of the PQPE development that would be possible after the first 2-year period. It depends on the available funds, the results of the first period and the experimental resources that will be available to us at that time. We expect that realization of the full PQPE program as presented in this report would require at least three more years of development and implementation work. Below we describe the major components of this future work as we see then now.

Develop multisensor PQPE procedures. Begin validation studies of the multisensor PQPE products. Continue data collection and database organization. Develop operational version of the PQPE software including its visualization module. Develop training materials for the PQPE. Develop plans for PQPE methodology transfer to other regions of the country.

Continue monitoring a limited operational implementation of the performance of the PQPE. Develop operational PQPE procedures for multi-parameter radar-rainfall and multisensor PQPE. Organize databases from selected regions of the country to perform additional studies on the transferability issues.

Continue development of the operational version of the multi-parameter PQPE and multisensor PQPE software including its visualization module. Continue operational monitoring of the performance of the PQPE. Document and present the results.

G.2. Cost

Our cost estimate for the above outlined schedule is approximate only and subject to changes. We broke the budget into several components all of which we consider necessary. We estimate the budget for the next three years only and cover activities to be performed at the University of Iowa only. The estimates are on a per year basis and assume 47% indirect costs (the current indirect cost rate at the University of Iowa.)

Algorithm Development. The cost per year includes 1 month of the PI (WFK) for the overall project coordination and supervision ($25K), 6 months of the Co-PI (GJC) for methodology development, uncertainty modeling and documenting of the results ($60K), 6 months at postdoc level for miscellaneous analysis, programming and testing tasks ($50K); 1.5 month of computer support staff to assist with data transfer, software installation, and computer system support ($15K); 12 months of graduate student for support with miscellaneous research and technical tasks ($50K).

Experimental Activities. The cost includes adding 10 double-rain-gauge sites to the Iowa City ground validation network each year. The cost per one site is about $4K and includes material, instruments, instrument calibration, assembly, transportation and field deployment. The total cost is $40K of capital investment per year. The maintenance of the added stations would require $10K per year, based on our current experience. (These costs could be most likely shared by other research projects that can be conducted using this expanded facility.)

Based on the above, we estimate the total cost for the PQPE project at about $200K+$50K=$250K per year, that is the total of $500K for the first 2-year phase.

The costs of the long-term continuation of this project cannot be reliably estimated at this moment. As the first guess, we can assume that they would stay at the same level of $250K per year, unless new unforeseen circumstances change it.

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