The Distributed Model Intercomparison Project (DMIP):

An Overview

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Abstract

The Distributed Model Intercomparison Project (DMIP) was formulated as a broad comparison of many distributed models to a lumped model used for operational river forecasting in the US. DMIP was intended to provide guidance on research directions for the US National Weather Service as well as to address unresolved questions on the variability of rainfall and its effect on basin response. Twelve groups participated, including groups from Canada, China, Denmark, New Zealand, and the US. Numerous data sets including 7 years of concurrent radar-rainfall and streamflow data were provided to participants through web access. Detailed modeling instructions specified calibration and verification periods and modeling points. Participating models were run in ‘simulation’ mode without a forecast component. This paper presents a thorough discussion of the motivations for DMIP as well as the major project elements.

Key words: distributed, rainfall runoff, model comparison, lumped, forecast, simulation.
1. Introduction

The Distributed Model Intercomparison Project (DMIP) arose out of the convergence of several factors. First, the National Oceanic and Atmospheric Administration’s National Weather Service (NOAA NWS) realized the need to infuse new science into its river forecasting capability. Second, the continued proliferation of geographic information system (GIS) data sets and exponential increases in computer capabilities have largely removed historical barriers from the path for development of complex distributed models. Finally, but certainly not the least important, large questions remain regarding the effect of the variability of precipitation and basin properties on runoff response. Related to these questions is the choice of model or approach to best exploit variability information to generate improved outlet simulations and potentially useful information at ungaged interior points. In this section, we begin with a brief discussion of the specific motivation for the NWS to forge ahead with distributed models. After this, we will discuss several scientific motivations for launching DMIP. Subsequent sections of this paper will describe the DMIP goals, design, data, participants, and modeling instructions. A companion paper (Reed et al., this issue) presents the analyses, conclusions, and recommendations of the DMIP project. Beyond presenting the motivations for DMIP, the purpose of this paper is to discuss the major project elements so as to avoid needless repetition in subsequent contributions in this issue.

1.1 The NWS Motivation

The NWS is uniquely mandated among US federal government agencies to provide river and flash flood forecasts to the entire US. To accomplish this challenging mission, the NWS has employed its NWS River Forecast System (NWSRFS) at 13 River Forecast Centers (RFC)
across the nation. Daily river forecasts are currently being provided at over 4,000 points, with high resolution flash flood forecasts being generated as needed. Traditionally, forecasts have been generated through the use of lumped conceptual models. The Hydrology Lab (HL) supports the NWS mission by conducting scientific research, software development, and data analysis and archival for the RFCs. Interested readers are referred to Glaudemans et al., (2002), Fread et al., (1995), Larson et al., (1995), and Stallings and Wenzel (1995), for more information regarding the NWS river and flood program.

Beven (1985) outlined the benefits of distributed modeling, including the forecasting of land use change, the effects of spatially variable inputs and outputs, pollutant and sediment movement, and the hydrological response at ungauged sites. The NWS recognizes these advantages and has the conviction that distributed modeling provides a key pathway to infuse new science into its river forecast operations (Carter, 2002; Koren et al., 2001). In addition to the scientific attention focused on distributed modeling, the NWS was also motivated to expedite its research in this area based on guidance from the National Research Council (NRC, 1996).

Given the scale of the NWS mission and the recommendations from external reviewers, it was clear that an accelerated program was needed to move the NWS research in the proper direction for operational distributed modeling. While numerous distributed models exist and indeed some are moving into the operational forecasting environment (e.g., Koren and Barrett, 1994; Turcotte et al., 2003) it is not clear from the literature which distributed model or modeling approach is best to improve the NWS forecasting capabilities. With guidance from several outside organizations, the NWS formulated DMIP as a method to capitalize on the formidable
distributed modeling research being conducted at academic institutions and other organizations around the world.

With the advent of 4km spatial resolution Next Generation Radar (NEXRAD) rainfall estimates in many parts of the US, the NWS and the research community at large have access to gridded rainfall estimates at unprecedented spatial and temporal resolution. Other parts of the world have similar quality radar data available (e.g., Moore and Hall, 2000). Also, the proliferation of GIS data sets and ever-increasing capabilities of computer systems have continued to push distributed modeling to the forefront of hydrologic research and application. In light of these developments, the major question facing the NWS and perhaps other operational organizations is: what is the best way to exploit the information in high resolution radar rainfall estimates and GIS data sets to improve river and flash flood forecasting? Or, in the words of Beven (1985), under what conditions and for what type of forecasting is it profitable to implement a distributed model?

A review of the scientific literature did not provide clear guidance for the NWS. A coherent comparison of lumped and distributed modeling techniques has not been published. It is encouraging that in the development and testing of their distributed models, several authors have included a comparison of their results to those using lumped inputs or from simpler lumped approaches (Bell and Moore, 2001; Boyle et al., 2001; Smith et al., 1999; Michaud and Sorooshian, 1994b; Obled et al., 1994; Pessoa et al., 1993; Naden, 1992; Loague and Freeze, 1985). In addition, Carpenter et al., (2001), and Carpenter et al., (this issue) used Monte-Carlo analysis to evaluate distributed versus lumped model gains in light of parametric and radar rainfall data uncertainty.
However, we feel that a more organized and controlled comparative effort is required to guide NWS distributed modeling research and development. The emergence of high resolution data sets, GIS capabilities, and rapidly increasing computer power has maintained distributed modeling as an active area of research. While the utility of distributed models to predict interior hydrologic processes is well known, few studies have specifically addressed the improvement of distributed models over lumped models for predicting basin outflow hydrographs of the type useful for flood forecasting. As a consequence, the hypothesis that distributed modeling using higher resolution data will lead to more accurate outlet hydrograph simulations remains largely untested.

More specifically, the requirements of the NWS are as follows:

a. The distributed model should perform at least as well in an overall sense as the current operational lumped model. Simulation improvement should be achieved in cases of non-uniform rainfall patterns.

b. The distributed model should be operationally feasible in current and anticipated computational environments.

c. The distributed model should have procedures for parameterization, calibration, and state updating.

1.2 Scientific Background.

Major scientific issues also point to the need for DMIP. Among these are the continuing questions regarding the effects of rainfall variability on runoff hydrographs and the level of model complexity needed to achieve a specific objective. Numerous studies in the past three
decades have investigated the sensitivity of runoff hydrographs to spatial and temporal variations in precipitation. Singh (1997) provides at least one comprehensive overview, and a brief review is provided here to show that mixed results have been documented.

Several of these studies examined the effects of rainfall spatial variability in light of raingauge sampling errors. Using data from five recording raingauges, Faures et al., (1995) concluded that distributed modeling on small catchments requires detailed knowledge of the spatial rainfall patterns. These results agreed with those of Wilson et al., (1979), who showed that the spatial distribution of rainfall had a marked influence on the runoff hydrograph from a small catchment. On the other hand, Beven and Hornberger (1982) stated that rainfall patterns have only a secondary effect on runoff hydrographs, while a correct assessment of the global volume of rainfall input in a variable pattern is more important in simulating streamflow hydrographs. Troutman (1983) investigated the effect of rainfall variability on estimating model parameters. He concluded that improperly representing the rainfall over a basin due to sampling errors would lead to overestimating large runoff events and undersimulating small events.

Subsequent research with radar rainfall estimates also contributed to these mixed results. On a small watershed, Krajweski et al., (1991) found a greater sensitivity to the temporal resolution of precipitation than to spatial resolution. Ogden and Julien (1994) performed synthetic tests that identified when spatial and temporal variability of precipitation is dominant.

It is interesting to note that some of these and other studies were based on synthetically generated precipitation and streamflow records (e.g. Watts and Calver, 1991; Troutman, 1983; Wei and Larson, 1971). In many cases, comparisons were made against a reference or ‘truth’ hydrograph generated by running the hydrologic model at the finest data resolution (e.g., Shah et al., 1996b; Ogden and Julien, 1994; Ogden and Julien, 1993; Krajewski et al., 1991;
Chadrasekar, et al., 1990; Troutman, 1983; Hamlin, 1982). Synthetically generated data were
often used due to the lack of appropriately long periods of observed data.

Perhaps some of the mixed results from the early studies arose out of the use of synthetic
data, numerical studies, and the choice of the rainfall/runoff models itself. Many of the studies
emphasizing the importance of rainfall spatial variability used models containing the Hortonian
runoff generation mechanism. It is now recognized that runoff results from a complex variety of
mechanisms and that in some basins, a significant portion of runoff hydrographs is derived from
slower responding subsurface runoff (Wood et al., 1990). Obled et al., (1994) commented that
numerical experiments in the literature were based on the use of models which may be only a
crude representation of reality. Furthermore, they argued that the actual processes at work in a
basin may not be those predicted by the model, a caution echoed by Michaud and Sorooshian

Thus, the research in the literature may have highlighted the sensitivity of a particular
model to the spatial and temporal variability of (at times synthetic) precipitation, not the
sensitivity of the actual basin. The work of Obled et al., (1994) is significant in that they were
perhaps the first to examine the effects of the spatial variation of rainfall using observed
precipitation and streamflow data. In addition, the model used in their studies focused on
saturation excess runoff as the main runoff generation mechanism. In simulations against
observed data, they were unable to prove the value of distributed inputs as they had intended. A
semi-distributed representation of the basin did not lead to improved simulations compared to a
lumped basin modeling scenario. The authors reasoned that the runoff mechanism may be
responsible for the lack of improvement, noting that in runoff generation of the Dunne type, most
of the water infiltrates and local variations in input will be smoothed. As a result, this type of
mechanism may be much less sensitive to different rainfall patterns. Loague (1990) concluded that revised data did not lead to significant improvement in a physically based distributed model because the model used the Hortonian mechanism while the basin appeared to function with a combination of Hortonian and Dunne overland flow. Michaud and Sorooshian (1994a) recommended that more comparative work be performed on Hortonian versus Dunne overland flow.

Winchell et al., (1998) and Winchell et al., (1997) extend this theme by noting that there has been a bias towards the use of infiltration-excess runoff mechanisms as opposed to the saturation excess type. Their work with both types of runoff generation mechanisms found that saturation-excess and infiltration excess models respond differently to uncertainty in precipitation. They suggest that generalizations concerning the effects of rainfall variability on runoff generation and variability cannot be made. Koren et al., (1999) came to a similar conclusion based on simulation results from several different rainfall-runoff partitioning mechanisms.

In the midst of these efforts to understand the importance of the variability of precipitation, a large volume of research continues to emerge that addresses the possibility of improving lumped hydrologic simulations by using distributed and semi-distributed modeling approaches containing so-called physically based or conceptual rainfall-runoff mechanisms. Indeed, at least one book chapter (Beven, 1985) followed by two entire books have been published on such models (Abbot and Refsgaard, 1996; Vieux, 2001). Recently, the availability of high resolution precipitation estimates from different weather radar platforms has intensified these investigations. Most efforts have focused on event-based modeling and again, mixed and somewhat surprising results have been realized.
Refsgaard and Knudsen (1996) compared a complex distributed model, a lumped conceptual model, and an intermediate complexity model on a data sparse catchments in Zimbabwe. Their results could not strongly justify the use of the complex distributed model. Pessoa et al., (1993) found that adequately averaged gridded precipitation estimates from radar were just as viable as fully distributed estimates for streamflow simulation using a distributed model on an 840 sq. km basin with low intensity rainfall. Conversely, Michaud and Sorooshian (1994a) compared their results with high intensity rainfall and found that simulated runoff is greatly sensitive to space-time averaging. Kouwen and Garland (1989) investigated the effects of radar data resolution and attempted to develop guidelines for the proper resolution of input rainfall data resolution. They noted that spatially coarser rainfall data sometimes led to better hydrograph simulation due to the smoothing of errors present in finer resolution rainfall information. Continuing this theme, Carpenter et al., (2001) examined the gains from distributed versus lumped modeling in view of radar data and parametric uncertainty. In several cases a spatially lumped model response proved to be statistically indistinguishable from a distributed model response.

In preliminary testing limited to a single extreme event, Kenner et al., (1996) reported that a five sub-basin approach produced better hydrograph agreement than a lumped representation of the basin. Sub-basin rainfall hyetographs revealed spatially varied precipitation totals for the event. Smith et al., (1999) attempted to capture the spatial variability of precipitation using sub-basins for several watersheds in the southern Great Plains of the US. Using a simple semi-distributed approach with spatially uniform conceptual model parameters, they were unable to realize significant improvement over a lumped model. For a basin in the same geographic region, Boyle et al., (2001) concluded that eight subdivisions of a basin
provided no gain in simulation accuracy compared to a three sub-basin representation. However, both simulations were superior to those from a lumped model. Naden (1992) found that lumped modeling was appropriate for even a large 7,000 sq. km. basin.

Refsgaard (1997) illustrated the concepts of parameterization, calibration, and validation of distributed parameter models. Noting that hydrologists often assume that a distributed model calibrated to basin outlet information will adequately model interior processes, he realized poor simulations of discharge and piezometric head at three interior gaging stations. In contrast, Michaud and Sorooshian (1994b) found that a complex distributed model calibrated at the basin outlet was able to generate simulations at eight internal points that were at least as accurate as the outlet simulations. These results underscore one of the mains advantages of distributed parameter hydrologic modeling: the ability to predict hydrologic variables at interior points. They also concluded that a simple distributed model proved to be just as accurate as a complex distributed model given that both were calibrated and noted that model complexity does not necessarily lead to improved simulation accuracy. Studies such as this may have caused Robinson and Sivapalan (1995) to comment that further work is needed to fully exploit the connection between conceptual and physically-based models to advance the science of hydrologic prediction. The distributed modeling work of Koren et al., (2003) is one attempt to follow this recommendation.

Bell and Moore (1998) compared a simple gridded distributed model and its variants to a lumped model used operationally in the UK for flood forecasting. They concluded that a well designed lumped model is preferred for routine operational purposes on the basins studied. Yet, a distributed model run in parallel to the lumped model would provide meaningful information in the cases of significant rainfall variability.
Seyfried and Wilcox (1995) commented that many have even questioned the usefulness of complex physically based models outside of strictly research applications, especially in light of the effort required to parameterize, calibrate, and implement such models.

In light of these concerns, DMIP was formulated as a focused venue to evaluate many distributed models against both a calibrated lumped model and observed streamflow data. Compared to some of the earlier studies on the effects of rainfall variability, DMIP has the advantages of multi-year hourly time series of high resolution radar rainfall estimates as well as hourly discharge measurements at both basin outlets and several interior points. Over seven years of concurrent radar rainfall and streamflow data were available. Another aspect of this venue is that researchers would have the opportunity to evaluate their research quality models with data typically used for operational forecasting. The availability of these data sets had already attracted several researchers to set up and run their models on these basins (e.g., Vieux and Moreda, 2003; Carpenter et al., 2001; Finnerty et al., 1997; Bradley, 1997). In addition, several evaluations and studies of the radar rainfall data in this area have been performed (Young et al., 2000; Johnson et al., 1999; Finnerty and Johnson, 1997; Smith et al., 1996). Moreover, the study basins are free of major complications such as orographic influences, significant snow accumulation, and stream regulation, which may mask the effects of precipitation and feature variability. The basins selected for DMIP range from 65 sq. km. to almost 2,500 sq. km., removing the temptation to extrapolate conclusions from small scale hillslope studies to larger basins of the size typically used for operational forecasting.

2. Project Design
DMIP identified the following science questions. Some questions were explicitly addressed through the design of the simulation tests discussed in section 8 and Appendix B, while for others, it was hoped that inferences could be made given a broad range of participating models.

**Can distributed models produce increased simulation accuracy compared to lumped models?** This question would be addressed through the use of multiple distributed model simulations compared to lumped simulations for a number of basins. In the absence of data sets such as spatial fields of soil moisture observations, model calibration and validation would use observed streamflow data. Improving simulations at the outlet of basins is the focus of this effort.

**What level of model complexity is required to realize improvement in basin outlet simulations?** Included in this are questions regarding the use of conceptual versus so-called physically based models and the size of computational elements or the use of semi-distributed approaches. Given a group of participating models with a wide range of complexity and modeling scale, it was hoped that inferences could be made about model complexity and scale.

**What level of effort is required for distributed model calibration? What improvements are realized compared to non-calibrated and calibrated lumped models?** Participants would provide an overview of the process to calibrate their models. Modeling instructions explicitly called for uncalibrated and calibrated simulations, so that the gains by calibration could be weighed against the level of effort. Reed et al., (this issue) discuss the gains provided by calibration.

**What is the potential for distributed models set up for basin outlet simulations to generate meaningful hydrographs at interior locations for flash flood forecasting?** Inherent
to this question is the hypothesis that better outlet simulations are the result of accurate
hydrologic simulations at points upstream of the gaged outlet. Interior simulations are one way to
validate distributed models. Moreover, the NWS is interested in the concept of a distributed
model for forecasting both outlet hydrographs as well as smaller scale flash floods upstream of
the gage. As noted in the modeling instructions, calibrated and uncalibrated simulations at
various gaged and ungaged locations at basin interior were required. Reed et al., (this issue)
evaluate these interior point simulations.

What characteristics identify a basin as one likely to benefit from distributed
modeling versus lumped modeling for basin outlet simulations? Can these characteristics
be quantified? Prior research on the DMIP basins had shown that distributed modeling to
capture the essential variability of precipitation and model parameters did not significantly
improve simulations in the Illinois River basin. (Carpenter et al., 2001; Smith et al., 1999). On
the other hand, another basin in the same geographic region did benefit from one level of
distributed modeling (Zhang et al., 2003; Boyle, et al., 2001). What is different about these two
cases? Through additional simulations from a number of distributed models in DMIP, these prior
results could be verified. Given the validated conclusion that certain basins benefit from
distributed modeling, research could investigate potential diagnostic indicators that might be
used without the expense of setting up a distributed model.

How do research quality models behave with forcing data used for operational
forecasting? DMIP provided a realistic opportunity for developers to test their research quality
models in a quasi-operational environment. Such exposure would hopefully identify needed
model improvements or further tests to bring such models closer to public use. Conversely,
DMIP could highlight the need for continued research for improving radar or multi-sensor methods of precipitation estimation.

**What is the nature and effect of rainfall spatial variability in the DMIP basins?** The seven years of gridded radar rainfall values presented in DMIP would provide modelers an opportunity to investigate the dominant forms of rainfall spatial variability. Moreover, through the application of multiple distributed models, we hoped to refine our understanding of the effects of rainfall spatial variability on simulated basin outlet hydrographs.

In addition to these identified issues, the participants investigated other relevant questions using the DMIP data sets. These efforts are presented in this special issue.

3 Operational Issues

As with the science questions surrounding DMIP, issues that need to be addressed before a model can be implemented in NWSRFS for operational use were identified. Explicit experiments were not designed in DMIP to address these issues. Rather, general concepts were discussed at the DMIP workshop.

1. Computational requirements in an operational environment. To be effective in an operational environment, forecast models need to be accurate, reliable, and robust. Moreover, they need to be able to run in real time

2. Run time modifications and updates in an operational forecasting setting.

3. Parameterization and calibration requirements.
4. Does ease of parameterization/calibration of a physically based distributed parameter model warrant its use, even when it might not provide improvements over simpler (but harder to calibrate) lumped conceptual models?

4. DMIP Study Area

Figure 1 presents the basins used in the DMIP comparison. The Illinois River draining to the USGS gage at Tahlequah, OK. straddles the Oklahoma-Kansas border. The Elk River flowing to the USGS gage in Tiff City, Missouri lies to the north of the Illinois basin, while the Blue River basin lies to the south near the border with Texas. These basins are typical of the size used for operational forecasting in the NWS. The numbers in Figure 1 signify the locations of US Geological Survey (USGS) streamgages at forecast locations and at interior points. Letters denote the location of ungaged points specified for the computation of simulations according to the DMIP modeling instructions. Hereafter, we will use the terms basin outlet and interior point when making general statements about the locations represented by numbers and letters, respectively.

Table 1 presents relevant data for the basins. The statistics in column five for the DMIP data period were computed using the radar data, while the corresponding climatological statistics were computed using raingauge data. Hereafter, and in subsequent papers (Reed et al., this issue; Smith et al., this issue), we will use the shortened names in column three to refer to be basins. A measure of basin shape is included in Table 1, generated by computing a ratio of long to short basin axes. The Blue basin has a significantly different aspect ratio compared to the other candidate basins.
Field trips were conducted on two different occasions. Personnel from the NWS and the University of Arizona examined points in the Illinois River basin in 1997, while a three day visit to the Blue River basin in November, 1999 was made by NWS scientists to collect cross section measurements. The dominant landuse in both basins is agriculture. Figure 2 shows the Baron Fork upstream of the gage near Eldon, Oklahoma. Figure 3 shows the Blue River looking upstream from the gage near the town of Blue, Oklahoma.

5. Schedule

The major activities for the DMIP effort took place according to the schedule in Table 2. One major complication was that some participants submitted their simulations by the March 31, 2002 deadline. Other participants were quite late, submitting their simulations within one week of the DMIP workshop at NWS headquarters in August, 2002. This spread of submittals allowed some participants more time to refine their results. Reed et al., (this issue) identify the submission dates of the various participants.

6. SAC-SMA and Calibration

For the NWS, one of the primary requirements for distributed modeling is that the model should equal or improve upon the capabilities of the current operational lumped approach. To examine this concern, simulations in DMIP were compared to both observed hourly streamflow and to simulations from the current NWS operational model, the Sacramento Soil Moisture Accounting Model (SAC-SMA). The SAC-SMA is a two-layer conceptual model that generates a number of runoff components. Interested readers are referred to Finnerty et al., (1997) and Burnash (1995) for more information. The SAC-SMA model was calibrated following the NWS
manual procedure outlined in Smith et al., (2003). Subsequently, the calibrations were evaluated by an independent expert. Another indication as to the quality of the calibration is that the process resulted in a logical and spatially consistent set of parameters (Koren et al., 2003). Uncalibrated simulations for the lumped model were made using the a priori parameter estimates pioneered by Koren et al., (2000) and subsequently used by Duan et al., (2001).

7. Data

Every effort was made to encourage participation in DMIP. As such, all data needed for most models were assembled and made available through a website/ftp site. A brief discussion of each data set is presented.

7.1 Digital Elevation Model (DEM) Data

Participants were free to use any DEM data available. However, to encourage participation in DMIP, DEMs of two different resolutions were provided: 15 arc-second DEM data and 1 arc-second data. DMIP did not require the use of any particular DEM or modeling resolution. The only constraint was that modelers had to discretize the basin so that simulations could be produced at the required locations.

The NWS National Operational Hydrologic Remote Sensing Center (NOHRSC) created a 15 arc-second national DEM by resampling 3 arc-second DEMs (1:250,000 scale) distributed by the U.S. Geological Survey. These data represent sampled elevations at regularly spaced, 15 arc-second (0.0041666 degrees) intervals, in geographic coordinates.

The 1-arc-second (30-m) data covering the DMIP study areas were made available for this project as an offshoot of the National Basin Delineation project underway at NOAA’s
National Severe Storms Laboratory (NSSL). The primary goal of the National Basin Delineation project is to provide small basin boundaries for the National Weather Service Flash-flood Monitoring and Prediction Program (FFMP). To produce the small basin boundaries, NSSL is cooperating with the USGS EROS data center to use the 1 arc-second DEM data available from the USGS National Elevation Dataset (NED) project. NSSL organizes their data processing efforts by eight digit USGS Hydrologic Cataloging Unit (HUC) boundaries. Initial processing steps include:

7.1.a buffering the HUC boundary of interest to allow for differences in ridgelines defined by the DEM and defined by the digitized HUCs
7.1.b merging the required 7.5 minute blocks of DEM data into a seamless data set covering the HUC of interest
7.1.c projecting the seamless data set to allow for correct analysis using Arc/Info software
7.1.d “filling” the DEM to eliminate artificial sinks (using the Arc/Info fill command)

The filled DEMs (product of Steps 1 through 4) for HUCs covering the DMIP basins were made available.

7.2 Channel Cross Sections

Representative cross sections were provided for only the Blue River. These were derived from three sources of data:

1. Measurements taken during a site visit
2. Measurements taken from bridge plans at selected locations.
3. Data from hydraulic computations for bridge pier scour analyses.
Two types of cross section data were provided. The first type of cross section has absolute elevations expressed in feet above mean sea level (feet msl). These cross sections were compiled from sources 1, 2 and 3 above in which the elevations were derived from surveyed bench marks. In some cases, the valley section as well as the channel cross section are described in order for the user to get a more accurate picture of the surrounding terrain.

The second type of channel cross section has relative elevations. These cross sections were derived from measurements taken during a site visit and are not referenced to known elevations above mean sea level. Rather, the elevation coordinates of the section are relative and must be adjusted to fit to the elevation of the digital elevation model at that location. In all cases, the cross section data reflect a representative channel at that location. Figure 4 presents a plot of selected cross sections showing the diversity of channel and valley shapes. Photographs were provided on the DMIP web site showing the channel where the cross sections were derived.

7.3 Observed Streamflow Data

Provisional instantaneous hourly flow data were obtained from USGS local offices. Some quality control of the provisional hourly data obtained from the USGS was performed at NWS-HL. Quality control was a manual and subjective process accomplished through visual inspection of observed hydrographs. Flow values were not interpolated during this quality control. Most commonly, suspect portions of the hydrograph were simply set to missing. Hydrographs sections with (1) a sudden rise and no rain, (2) a sudden fall, or (3) a perfectly horizontal slope were candidates for correction. In many cases, the suspicious portions of the hydrographs identified at HL corresponded to missing data in the quality-controlled USGS mean daily flow record. Thus, setting the hourly data to "missing" during these periods seemed justified. In some
cases, the hourly flow data were compared to the quality controlled mean daily flow data from USGS. Also, the hourly flow data were converted to GMT to correspond to the radar data.

7.4 Radar Data

Rainfall forcing data in the form of NEXRAD gridded estimates were made available through the NWS web-accessible archive. Hourly gridded files covering the study basins had a nominal 4 km by 4 km resolution. This grid, referred to as the Hydrologic Rainfall Analysis Project (HRAP) grid, is based on the polar stereographic projection. It is a subset of the Limited Fine Mesh (LFM) grid used by the Nested Grid Model (NGM) at the NWS National Centers for Atmospheric Prediction (NCEP). For further details of this mapping, the reader is referred to Reed and Maidment (1999) and Greene and Hudlow (1982). Along with the data, software code segments were supplied to enable participants to easily extract the pertinent sections covering the basins. Examples were also provided so that participants could check their processing.

The precipitation estimates provided to DMIP were copies of the operational data sets created by the NWS river forecast center in Tulsa, Oklahoma. In this way, participants were given the opportunity to evaluate their models with operational quality data. A detailed description of the radar processing algorithms is beyond the scope of this paper. Interested readers are referred to Young et al., (2000), Seo et al., (1999), Fulton et al., (1998), and Seo (1998) for more information.

7.5 Soil Texture

Soil texture data at the study basin scale in geographic (latitude/longitude) coordinates were provided in ASCII format. The texture data provided on the DMIP site are a subset of data
grids produced at Pen State University using State Soil Geographic (STATSGO) data (Miller and White, 1999). Soil texture classes include: sand, silt, clay, and various mixtures such as sandy loam and silty clay loam. Textures can be specified for up to 11 layers.

7.6 Meteorological Data

Meteorological forcing data other than the NEXRAD precipitation estimates were provided to the DMIP effort. Two sources were used. One set of data consists of so-called reanalysis data generated from a numerical weather prediction model. The other set consisted of observed data.

The first set of energy forcing fields for the DMIP basins were obtained from the Environmental Modeling Center (EMC) of the National Centers for Environmental Prediction Climate Prediction Center (NCEP/CPC). The hourly forcing data were obtained by converting global 6-hourly reanalysis data from Gaussian grid to hourly data on 1/8th degree grid. The process involves interpolation in time and space, elevation correction (for air temperature, specific humidity, downward long-wave radiation and surface pressure), zenith angle correction for downward solar radiation, and fine tuning for air temperature using reanalysis 6-hourly maximum and minimum temperature.

The second set of data was derived from the 1/8 degree gridded data files developed by the University of Washington (Maurer et al., 2002). These data included air temperature, incoming shortwave and longwave radiation, atmospheric density, pressure, and vapor pressure, and wind speed. Most of these variables were not direct measurements but rather values calculated from other observations.

7.7 Greenness fraction
Monthly greenness fraction files are derived based on Advanced Very High Resolution Radiometer (AVHRR) data (Gutman and Ignatov, 1997). The spatial resolution of these data is 0.144 degree.

7.8 Free Water Surface Evaporation Data (PE)

Participants were also provided climatic monthly mean values of potential evaporation demand in mm/day. These values were derived using information from seasonal and annual free water surface (FWS) evaporation maps in NOAA Technical Report 33 (Farnsworth et al., 1982) and mean monthly station data from NOAA Technical Report 34 (Farnsworth and Thompson, 1982). Summing the monthly values yields results consistent with the annual and seasonal maps in NOAA Technical Report 33. Mean monthly FWS evaporation estimates are used as potential evaporation (PE) estimates in the NWS lumped calibrations using the Sacramento model. In the Sacramento model, PE values are adjusted to account for the effects of vegetation to produce ET Demand values; however, the values provided for DMIP were unadjusted PE values.

7.9 Vegetation Data

17 categories of vegetation defined by the International Geosphere-Biosphere Program (IGBP) classification system (Eidenshink and Faundeen, 1994) were provided in a 1km. gridded data set.

8. Modeling Instructions

DMIP participants were asked to follow explicit instructions for calibrating and running their models. Appendix B lists the explicit instructions. In the analysis of DMIP results (Reed et
al., (this issue), readers will be referred to Appendix B for the naming of simulations. Other than following the modeling instructions, the only constraints were:

a. Only the archived NEXRAD radar rainfall estimates were to be used for precipitation forcing.

b. Participants had to discretize their basin representations so that the required simulations could be derived.

While not an explicit constraint, continuous rather than event simulations were encouraged as the NWS uses continuous models for all of its forecasting. Indeed, one participant submitted event simulations. Moreover, no updating was allowed, as this phase of DMIP did not include a forecast component. All model runs were generated in simulation mode. Participants were instructed to calibrate their models by comparing observed and simulated streamflow only at the designated basin outlet during the calibration period. Even though observed streamflow data existed at some interior nested locations, modelers were asked to ignore these data in the calibration process. One emphasis of DMIP was to assess how well distributed models predict streamflow at interior locations, especially at ungaged sites.

Modelers were asked to generate and submit to HL two basic types of simulations at specified points. The first type of simulation was generated using initial or uncalibrated values of the hydrologic model parameters (and any hydraulic routing parameters). This test was intended to determine how well "physically based" models perform with parameters derived from physical data. Participants submitted their uncalibrated simulations from both the calibration and verification periods. The second type of simulation was generated after hydrologic and hydraulic model parameters are calibrated at the basin outlet. This simulation is meant to show how much
calibration is required and what improvement in simulation accuracy is gained. Participants submitted their simulations (using calibrated parameters) for both the calibration and verification periods.

During the same model runs to generate the basin outlet hydrographs (with both calibrated and uncalibrated parameters), participants were required to simultaneously generate simulations at two types of interior points. The first type of interior point is where observed streamflow data are available. As stated above, there should be no calibration using these interior observed data. These "blind" simulations were used to assess how well interior processes can be simulated when calibration was performed using only basin outlet data. Not all of the basins have observed interior streamflow data. The second type of point is an ungaged location along the main channel or a major tributary of the basin. These simulations were analyzed by HL personnel to assess the variability of simulations from the various distributed models. Consequently, participants had to discretize their models in order to generate the interior hydrographs at the specified locations.

The Illinois River flowing through Arkansas and Oklahoma presented a good opportunity for participants to test their models on three different scales of basins, each having observed streamflow data at interior locations as seen in Figure 1. The smallest basin, Baron Fork at Eldon, Oklahoma (OK) has a drainage area of 795 sq. km. with an interior gage on Peachester Creek at Christie, OK. Next to the Baron Fork basin is the Illinois River above the gage at Watts, OK. This basin has a drainage area of 1,645 sq. km. and includes the interior gage on the Illinois River at Savoy, Arkansas. The Illinois River at Watts, OK. is nested within the largest basin, the Illinois River above Tahlequah, OK, having a drainage area of 2,484 sq. km. The Tahlequah
basin also includes an interior gage on Flint Creek at Kansas, OK. Thus, the Illinois River above Tahlequah, OK. contains three interior gage locations.

The Elk River basin above the gage in Tiff City, Missouri, and the Blue River basin above the gage in Blue, Oklahoma, have no interior gage locations. These two basins represent additional cases for testing and comparison of distributed hydrologic models.

Appendix B contains specific modeling instructions so that readers can follow the discussion of results by Reed et al., (this issue)

9. Participants

The following institutions and lead investigators participated in DMIP:

1. Massachusetts Institute of Technology, Dr. Raphael Bras
2. Hydrologic Research Center, Dr. Konstantine Georgakakos
3. Danish Hydraulic Institute, Dr. Michael Butts
4. University of Arizona, Dr. Hoshin Gupta
5. NCEP/EMC, Dr. Kenneth Mitchell, Dr. Dag Lohman, Dr. Christa Peters-Lidard
6. University of Oklahoma, Dr. Baxter Vieux
7. University of Waterloo, Ontario, Dr. Allyson Bingeman
8. University of Utah, Dr. David Tarboton and National Institute of Water Research, (NIWR), New Zealand, Dr. Ross Woods.
9. NWS Hydrology Lab
10. USDA ARS, Dr. Jeff Arnold and TAES Blackland Research Center, Dr. Mauro Di Luzio
10. Evaluation of Results

A multitude of statistical evaluations were performed on a run-period and event basis. Appendix A presents all of the formulas used in the analysis by Reed et al., (this issue).

11. Acknowledgements

We thank Dr. Dennis Lettenmaier of the University of Washington for contributing the large volume of meteorological data. Also, we acknowledge Dr. Ken Mitchell and Dr. Jin Huang of the NWS/NCEP for contributing the other set of meteorological data. The USGS is gratefully acknowledged for providing the observed streamflow values through its field offices. The endorsement of Dr. John Schaake and the GCIP GAPP project is appreciated.

Appendix A.

Statistics used in the analysis of DMIP results

1. Percent Bias, PB (%)

PB is a measure of total volume difference between two time series. It does not measure differences in timing.

\[
P.B. = \frac{\sum_{i=1}^{N} (S_i - O_i)}{\sum_{i=1}^{N} O_i} \times 100\%
\]
where \( S_i \) is the simulated discharge for each time step, and \( O_i \) is observed value. \( N \) is total number of values within the time period of analysis.

2. Simulated or Observed Mean

\[
\bar{Y} = \frac{\sum_{i=1}^{N} Y_i}{N}
\]

where \( Y \) is any type of data value.

3. Standard Deviation, \( \sigma \)

\[
\sigma_Y = \sqrt{\frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^2}{N - 1}}
\]

4. Correlation Coefficient, \( R \)

\[
R = \frac{N \sum_{i=1}^{N} S_i O_i - \sum_{i=1}^{N} S_i \sum_{i=1}^{N} O_i}{\sqrt{\left[ N \sum_{i=1}^{N} S_i^2 - \left( \sum_{i=1}^{N} S_i \right)^2 \right] \left[ N \sum_{i=1}^{N} O_i^2 - \left( \sum_{i=1}^{N} O_i \right)^2 \right]}}
\]

5. Nash-Sutcliffe Coefficient, \( N_r \)

\[
N_r = 1 - \frac{\sum_{i=1}^{N} (S_i - O_i)^2}{N \sigma_{obs}^2}
\]

6. Modified Correlation Coefficient, \( R_m \) (McCuen and Snyder, 1975)

\[
R_m = R \cdot \frac{\min\{\sigma_{sim}, \sigma_{obs}\}}{\max\{\sigma_{sim}, \sigma_{obs}\}}
\]
\[ R_m = R. \]

\[ \frac{\min \left\{ \left( \sum_{i=1}^{N} S_i^2 - \left( \sum_{i=1}^{N} S_i \right)^2 \right) \left( \sum_{i=1}^{N} O_i^2 - \left( \sum_{i=1}^{N} O_i \right)^2 \right) \right\}}{\max \left\{ \left( \sum_{i=1}^{N} S_i^2 - \left( \sum_{i=1}^{N} S_i \right)^2 \right) \left( \sum_{i=1}^{N} O_i^2 - \left( \sum_{i=1}^{N} O_i \right)^2 \right) \right\}} \]

7. Some overall statistics were generated for selected events:

   a. Event Bias, \( B_{avg}, \% \)

   \[ B_{avg} = \frac{\sum_{i=1}^{N} |B_i|}{NY_{avg}} \times 100 \]

   b. Peak Error, \( E_p, \% \)

   \[ E_p = \frac{\sum_{i=1}^{N} |Q_{pi} - Q_{psi}|}{NQ_{avg}} \times 100 \]

   c. Peak Time Error, \( B_{p,avg}, \text{hrs} \)

   \[ B_{p,avg} = \frac{\sum_{i=1}^{N} |T_{pi} - T_{psi}|}{N} \times 100 \]

Notation for event statistics:

- \( B_i \) is runoff bias per i-th flood event, mm,
- \( Y \) is a total observed runoff of all selected floods, mm,
- \( Y_{avg} \) is an average observed flood event runoff, mm,
- \( RMS_i \) is a root mean square error per i-th flood, cms
- \( Q_{avg} \) is an average observed flood event discharge, cms,
\( Q_{p,i} \) is an observed peak discharge of the i-th flood event, cms,
\( Q_{ps,i} \) is a simulated peak discharge of the i-th flood event, cms,
\( Q_{p,avg} \) is an average observed peak discharge, cms,
\( T_{p,i} \) is an observed time to the i-th peak, hrs,
\( T_{ps,i} \) is a simulated time to the i-th peak, hrs, and
\( N \) is a number of selected floods.

8. Statistics used to denote improvement of distributed versus lumped models:

a. Flood runoff improvement \( I_Y \), %

\[
I_Y = \frac{\sum_{i=1}^{N} |Y_{i} - Y_{s,i}| - |Y_{i} - Y_{z,i}|}{N \cdot Y_{avg}} \times 100
\]

b. Peak flow improvement \( I_P \), %

\[
I_P = \frac{\sum_{i=1}^{n} |Q_{p,i} - Q_{ps,i}| - |Q_{p,i} - Q_{pz,i}|}{N \cdot Q_{p,avg}} \times 100
\]

c. Peak time improvement

\[
I_T = \frac{\sum_{i=1}^{n} |T_{p,i} - T_{ps,i}| - |T_{p,i} - T_{pz,i}|}{N}
\]

\( Y_i \) = an observed runoff of the i-th flood, mm
\( Y_{s,i} \) = a simulated runoff of the i-th flood, mm
\( Y_{z,i} \) = a runoff of the i-th flood to compare with, mm
\( Y_{avg} \) = average observed flood event runoff, mm
\( Q_{p,i} \) = an observed peak discharge of the i-th flood event, \( m^3/s \)
\[ Q_{ps,i} = \text{a simulated peak discharge of the } i\text{-th flood, } m^3/s \]

\[ Q_{p, avg} = \text{an average observed peak discharge, } m^3/s \]

\[ T_{p,i} = \text{an observed time of the } i\text{-th peak, } hrs \]

\[ T_{ps,i} = \text{a simulated time to the } i\text{-th peak, } hrs \]

\[ T_{pz,i} = \text{a time to } i\text{-th peak to compare with, } hrs \]

\[ N = \text{number of selected events} \]

Appendix B.

Specific Modeling Instructions

B. Specific Instructions - Illinois River basins, Blue River basin, Elk River basin

B.1. Model Run Periods


2. Verification period: June 1, 1999 to July 31, 2000

B.2. Simulations should have an hourly time step or have an ordinate spacing that includes hourly values to facilitate comparison to the USGS observed hourly discharge data.

B.3. Illinois River Basin: Baron Fork with basin outlet at USGS gage 07197000 at Eldon, Oklahoma. Drainage area 307 square miles. USGS gage location: Lat. 35° 55’ 16” Lon. 94° 50’
18", on downstream left abutment of bridge on State Highway 51, 0.4 miles southeast of Eldon.

a. Generate 2 simulations at the basin outlet that span both the calibration and validation periods:

   1. with uncalibrated/initial parameters
   2. with calibrated parameters

b. While generating the 2 basin outlet simulations, compute interior simulations at:

   1. Peacheater Creek at USGS gage 07196973 at Christie, Ok. drainage area 25 square miles. Gage: Lat. 35° 57’ 17" Lon. 94° 41’ 46", 0.4 miles upstream of junction with Baron Fork. No calibration is allowed using observed streamflow data at this point. It is to be a "blind" simulation.

   2. Ungaged location on channel at Lat. 35°54’ 38", Lon. 94° 32’ 16", drainage area 58.4 square miles (Note: before 2/23/2002, the area estimate given on this site was 80.66 square miles. The 80.66 estimate was derived using a 400-m resolution DEM (See DMIP DEM data page.), but there is a big discrepancy between this area and the area derived from the 30-m DEM (58.4 square miles). We believe the area derived from the 30-m DEM is more accurate.)


   a. Generate 2 simulations at the basin outlet that span both the calibration and validation periods:
1. with uncalibrated/initial parameters
2. with calibrated parameters

b. While generating the 2 basin outlet simulations, compute interior simulations at:
   1. Illinois River at USGS gage 07194800 at Savoy, Arkansas. Drainage area 167 square miles. Gage: Lat. 36° 06' 11", Lon. 94° 20’ 39"
   2. Ungaged location on channel at Lat. 36° 2’ 53", Lon. 94° 19’16", drainage area 76.49 square miles.


   a. Generate 2 simulations at the basin outlet that span both the calibration and validation periods:
      1. with uncalibrated/initial parameters
      2. with calibrated parameters
   b. While generating the 2 basin outlet simulations, compute interior simulations at:
      1. Illinois River at USGS gage in Watts, OK
      2. Illinois River at USGS gage in Savoy, Arkansas.
      3. Flint Creek at USGS gage 07196000 in Kansas, OK. Drainage area 110 square miles.
         Gage location: Lat. 36° 11’ 11", Lon. 94° 42’ 24" upstream from bridge on U.S. Highway 412.
(Note: no specific calibration using observed streamflow at these points, even though calibration was performed for the Illinois River at Watts, OK for the runs in item B.4 above.)

B.6. Elk River with basin outlet at USGS gage 07189000 in Tiff City, Missouri. Drainage area 872 square miles. Gage location: Lat. 36° 37’ 53” Lon. 94° 35’ 12”, on bridge on State Highway 43, 3.0 miles southeast of Tiff City.

a. Generate 2 simulations at the basin outlet that span both the calibration and validation periods:

1. with uncalibrated/initial parameters

2. with calibrated parameters

b. While generating the 2 basin outlet simulations, compute interior simulations at ungaged location on channel at Lat. 36° 35’ 38”, Lon. 94° 9’ 17”, drainage area 122.93 square miles. (Note: there is no interior observed streamflow for this basin).

B.7. Blue River with designated basin outlet at USGS gage 07332500 in Blue, Oklahoma. Drainage area 476 square miles. Gage location: Lat. 33° 59’ 49” Lon. 96° 14’ 27”, on bridge on U.S. Highway 70, 1.0 mile west of Blue, Oklahoma.

a. Generate 2 simulations at the basin outlet that span both the calibration and validation periods:

1. with uncalibrated/initial parameters

2. with calibrated parameters

b. While generating the 2 basin outlet simulations, compute interior hydrographs at:
1  Ungaged location on main channel of the Blue River at Lat. 34° 30′ 24″, Lon. 96° 40′
30″, drainage area 59.15 square miles.

2  Ungaged location on main channel of the Blue River at Lat. 34° 26′ 39″, Lon. 96° 37′
30″, drainage area 116.87 square miles. (note: there is no interior observed streamflow for these
two points)

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Figure 1. Location of Basins and computational points in the DMIP project.
Figure 2. Baron Fork at the USGS gage located near Eldon, Oklahoma. The view is looking upstream from the highway bridge.
Figure 3. The Blue River looking upstream from highway bridge at USGS gage near Blue, Oklahoma.
Figure 4. Selected cross sections for the Blue River. Cross section 1 (CS1) is located at the USGS gage.
Table 1. DMIP Basin Data

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td></td>
<td>Full Name</td>
<td>USGS ID</td>
<td>Referred to As:</td>
<td>Area (km²)</td>
<td>Annual Rainfall (mm)</td>
<td>Annual Runoff (mm)</td>
<td>RC Ann. Rainfall (mm)</td>
<td>Ann. Runoff (mm)</td>
<td>RC Climate</td>
<td>Longest Path Length (km)</td>
<td>Longest Path Slope (m/m)</td>
<td>Major-minor axis ratio</td>
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Table 2. Schedule for Major DMIP Activities

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<th>Date</th>
<th>Task</th>
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<tr>
<td>January, 2000</td>
<td>Basic DMIP plan approved by NWS/HL</td>
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<tr>
<td>May 31, 2000</td>
<td>General Announcement of DMIP at Town Hall Meeting, AGU spring Meeting, Washington, DC</td>
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<tr>
<td>June 1, 2000</td>
<td>DMIP plan completed</td>
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<tr>
<td>December 2000</td>
<td>General Announcement to participate in DMIP DMIP web site officially opened.</td>
</tr>
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<td>1. All data in place for Illinois River Basins, Elk River Basin and Blue River Basin</td>
</tr>
<tr>
<td></td>
<td>2. Metadata and utilities in place</td>
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<tr>
<td>March 31, 2002</td>
<td>Participants send results to HL for analysis</td>
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<tr>
<td>August 22-23</td>
<td>DMIP workshop at NWS/HL</td>
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<tr>
<td>September 30, 2002</td>
<td>Participants verify that analyzed simulations are correct</td>
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</table>
Figure Captions

Figure 1. Location of Basins and computational points in the DMIP project.

Figure 2. Baron Fork at the USGS gage located near Eldon, Oklahoma. The view is looking upstream from the highway bridge.

Figure 3. The Blue River looking upstream from highway bridge at USGS gage near Blue, Oklahoma.

Figure 4. Selected cross sections for the Blue River. Cross section 1 (CS1) is located at the USGS gage.
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Table 2. Schedule for Major DMIP Activities