Progress Report during June 15 – September 15, 2008

Developing Seasonal Predictive Capability for Drought Mitigation Decision Support System

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1. Introduction

This report presents the progress of the project during its first six months, June 15, 2008 – January 15, 2009. It is prepared by PI Ximing Cai, Co-PIs Xin-Zhong Liang and Jae Ryu with inputs from all other Co-PIs and supporting staff. The major tasks include a pilot downscaling experiment using the GMAO forecasts, drought information extraction for regional applications, preparation of DSS users' survey, and the development of an algorithm of using short-term forecast for irrigation scheduling decision.

2. Activities and Outputs

The activities during the first three months of the project (June-September 2008) have been described in the three-month report submitted in September 2008. The major work included the development of project management details, data processing, and communication with extension agencies including National Irrigation Association, and National Corn Growers Association. In the following the activities and outputs are presented by project tasks.

Task 1: Extended Literature Review

We conducted an extended literature review following what was presented in the proposal on drought studies particularly on drought damage, potential drought index, drought frequency and intensity change with climate change and variability and the use of drought forecast for decision making. This review ends with research challenges and future roadmap. A tentative draft of the literature report is included in the appendix.

Task 2: CWRF Downscaling of NASA GMAO Climate Prediction

The drought prediction group has acquired, from Dr. Siegfried Schubert, the NASA experimental climate forecasts using the GMAO (Global Modeling and Assimilation Office) coupled atmosphere-ocean general circulation model (GCM). The GMAO predicts, at a 10-month lead, global variations of surface and atmospheric circulation. Currently GMAO data are available on a 2.5° longitude by 2° latitude grid at a daily time interval. They provide the initial surface boundary conditions and the time-varying lateral boundary conditions for the CWRF (Climate-Weather Research and Forecasting model) to produce regional downscaling at 30-km grid spacing.

A pilot downscaling experiment has been completed using the GMAO forecasts for the period of May 1 to October 31, 2007. There are 21 GMAO realizations, each initialized by different surface and atmospheric states. Without any bias correction, the raw GMAO outputs, including both surface and atmospheric variables, are used to drive CWRF. The main purpose of this initial experiment is to identify key problems in downscaling for subsequent improvements.

Figure 1 illustrates summer (June-July-August) mean surface air (2 m) temperature, including the ensemble mean and deviation over the 21 realizations. The CWRF downscaling result is compared with those observed and simulated by the driving GMAO. Clearly, the GMAO contains substantial biases over the whole U.S., while the CWRF downscaling provides significant improvements with the ensemble mean distribution much closer to observations. On the other hand, there exist large spreads across different realizations, centered in the central U.S. and northwest U.S. These spreads, caused by internal or natural climate variability, offer a quantitative measure of prediction uncertainty.

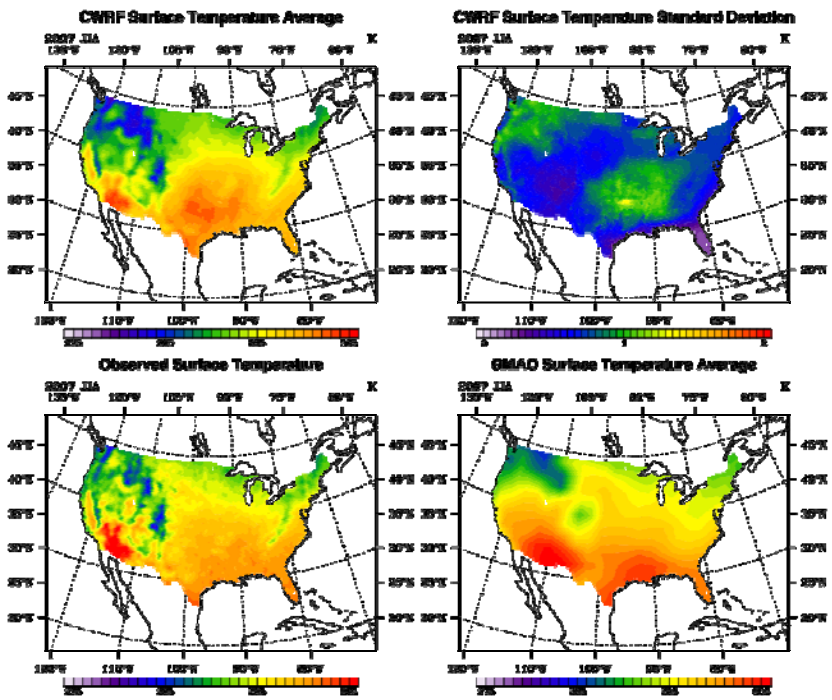

Fig. 1. JJA mean surface air (2 m) temperature, including the ensemble and deviation over the 21 realizations. The upper left, lower left and lower right are the average values for CWRF, observation and GMAO respectively, the upper right is the deviation values for the CWRF.

Figure 2 depicts summer (June-July-August) mean precipitation, including the ensemble mean and deviation over the 21 realizations. As compared with observations, the CWRF downscaling generates more realistic (than the driving GMAO) precipitation over the North American monsoon region and the coastal areas along the Gulf of Mexico. Improvement is also seen over the Upper Mississippi basin. Overestimations, however, exist over most of the Missouri and Ohio basins as well as the eastern coast states. They can be traced back to the driving GMAO with even more excessive rainfall over these regions. This suggests that certain bias corrections or data assimilation are needed to improve precipitation prediction at regional-local scales. Like temperature, large precipitation spreads due to natural variability also exist in central U.S., requiring incorporation of uncertainty in the decision support system.

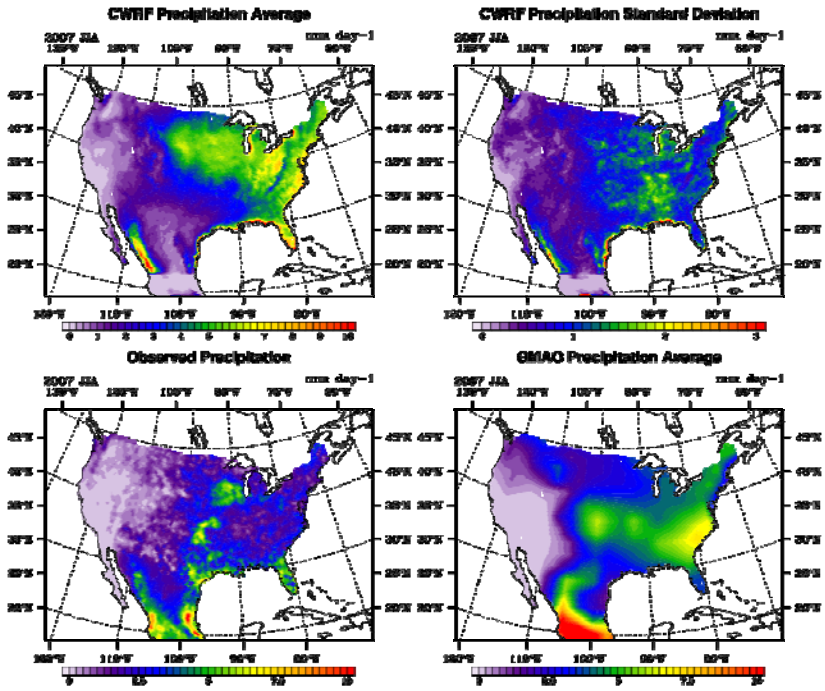

Fig. 2. The same as above, but for precipitation.

Figure 3 shows daily variations (during summer of 2007) of the ensemble mean and deviation for surface air temperature, precipitation, evaporation, and top-1m soil moisture content as averaged over the Midwest. The large spreads across 21 realizations are evident in all these variables, with the respective standard deviation of 2.1°C, 2.25 mm d^{-1}, 0.44 mm d^{-1}, and 12 mm, as averaged over the summer. They can be used to construct probability distribution functions for implementation into the region-specific hydrologic models (e.g. Republican river basin model) and the decision support system. Note that the soil moisture systematically declines during the integration, starting fast and gradually approaching an equilibrium around October. This results from the initial soil moisture based on the GMAO forecasts that seem too wet. A big problem is that we currently do not have high-quality observations to evaluate the accuracy of soil moisture. A preliminary comparison with the North American Regional Reanalysis (NARR) indicates that the modeled soil moisture is larger in the Midwest. This may partially explain that the CWRF downscaling reduction on GMAO excessive rainfall is not significant over the Midwest. We are planning to use the NARR as well as other bias corrections and data assimilation techniques to initialize the surface states, including soil temperature and moisture, and rerun the case to determine how a more realistic initialization will affect the precipitation result.

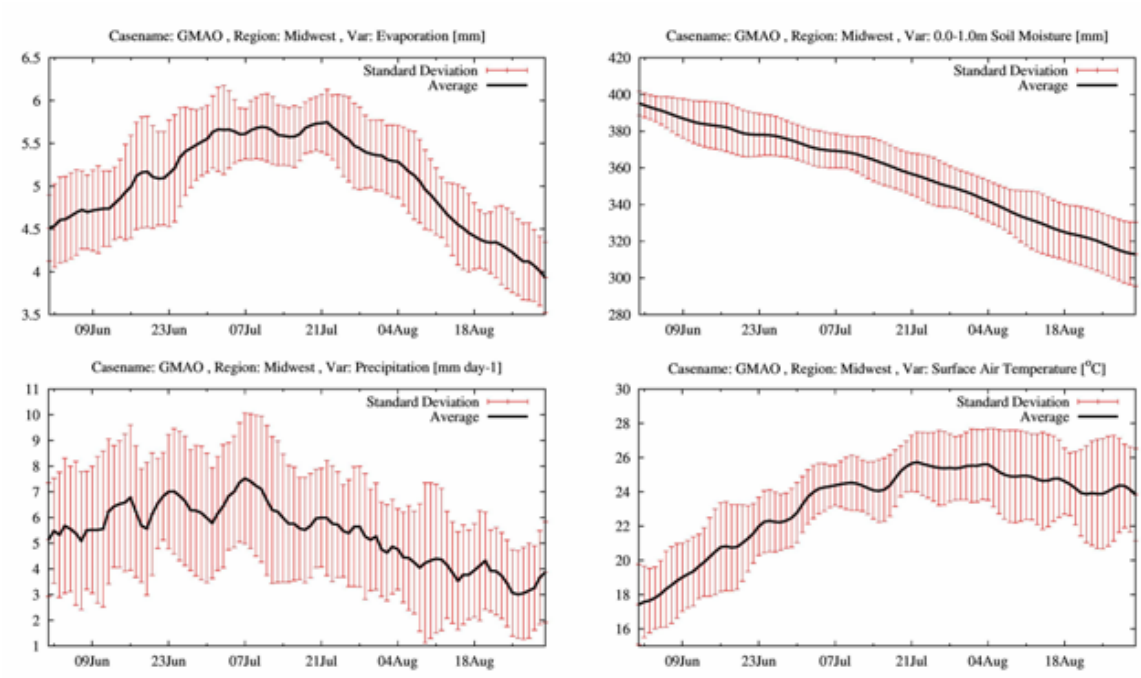

Fig. 3. Daily variations of the ensemble mean and deviation for evaporation, top-1m soil moisture content, precipitation and surface air temperature averaged over the Midwest during the summer of 2007.

Task 3: Drought information extraction for regional applications

To improve the predictability of climate forecast at local watershed scales in terms of meteorological anomalies associated with precipitation and temperature forecast products, a statistical correction and evaluation technique are needed. Thus, since the spatial resolutions of these products are still relatively coarse, it is necessary to apply adjustment procedures to all ensemble members to a specific regional watershed to minimize the error associated with a coarser grid. The systematic biases in the CWRF forecasts of precipitation and temperature are first examined with four distinct sub-tasks: 1) transformation, 2) statistical correction, 3) improvement of forecasts, and 4) skill test for regional streamflow forecasts. A statistical correction procedure can be conducted to minimize the spatial and temporal difference between two models (the CWRF and the hydrology model). This process is conducted in a probability framework using normal probability density functions (PDFs). Potential forecast improvements is then determined based on the correspondence between the observed conditional mean and the conditional forecasts. These measures classify the forecast/observation pairs into groups according to the value of the forecast variable and characterize the conditional distribution of the observations given the forecasts. Once forecast improvement processes along with bias correction have been completed, bias-corrected climatological variables (e.g. precipitation) from the CWRF's forecast products will be routed through a computational routine to derive the forecasted standard precipitation index, and those variables are also routed into the regional watershed model as forcing to generate streamflow, which is a component of forecasted hydrologic index. Figure 4 represents the statistical correction procedure for monthly

precipitation, which related to one CWRF grid point with one weather station in the Republican River Basin.

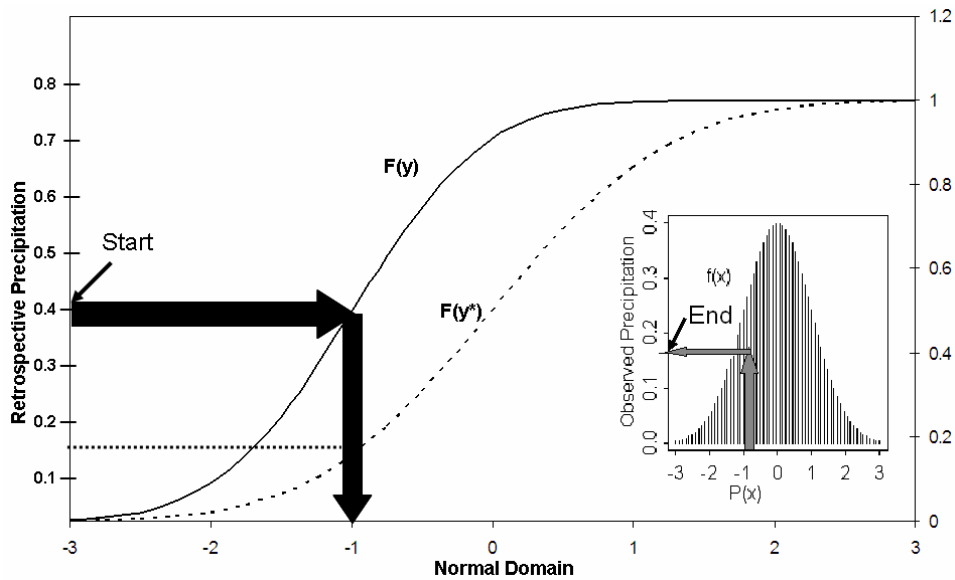

Fig 4. Bias-correction procedure of precipitation data (mm) for CWRF forecast (y) to one of observed data (x) in the Republican River Basin.

As shown in the Fig 4, the probability of the initial retrospective forecasts of ensemble mean precipitation from the CWRF for a given month is the probability, P(y) along the retrospective density function f(y). This P(y) relates to P(x), which produces a "bias-corrected" forecast, P(y*). The double sided direction of the arrow in the figure indicates the value of the bias-correction.

An algorithm of hydrologic drought index has been also developed in past three months. To generate hydrologic index, a simple algorithm has been developed. The procedure utilized in calculating the Log-Standardized Hydrologic Drought Index (LSHDI) is to de-sesonalize the logarithm of the monthly average streamflows by substracting the long-term mean of the monthly loarrithm and then dividing by the logarithm of the standard deviation for the given month to create a zero-mean process. The LSHDI is calculated as:

$$LSHDI_{t,i} = \frac{(Y_t - \bar{Y}_i)}{\sigma_i}$$

where

t = 1, 2, …, T is the monthly time step,

i = 1, 2, …, 12 is the month index,

Y_t = logarithm of the monthly average streamflows at time t,

$\bar{Y}_i$ = long-term mean of the logarithm of the average streamflow for month i,

σ_i = standard deviation of the logarithm of the average streamflow for month I,

$LSHDI_{t,i}$ = Hydrologic Drought Index at time t and month i.

Like other drought indices such as the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI), the LSHDI is standardized, which allows direct comparisons of diverse drought indices in the regional watershed. The LSHDI is a measure of the streamflow abnormality over a period of low flow, average flow, and peak flow. Thus, the lower the index, the more severe the hydrologic drought associated with low flow, while the higher the index, the more likely the occurrence of flooding due to subsequent peak flows. The range of the index can be analogous to PDSI values of -3 to -4 as a severe drought, -2 to -3 moderate drought, 2 to 3 moderately wet, 3 to 4 extremely wet, and so on.

Task 4: Users' survey development

During the past three months, the drought information assessment and dissemination group led by J. Ryu has met numerous times to discuss and develop an initial draft of an online survey questionnaire to be administered to members of the National Corn Growers Association (NCGA). The main purpose of this survey is to identify the perceptions of irrigating and non-irrigating corn growers across the country in regards to forecast data, the usefulness of forecasts to them, the optimal forecast timescale for decision making (15, 30, 90 day forecasts, etc.), and at what time of the year forecasts are most beneficial. Understanding the needs of end-users is essential for designing and disseminating appropriate forecast information, and was highlighted as an important activity at the 33rd Climate Diagnostics and Prediction Workshop (Oct 20-24, Lincoln, Nebraska) organized by NOAA and the NDMC.

An initial draft of survey questions were developed and selected by Co-PIs J. Ryu, C. Knutson, and M. Svoboda with inputs from other team members. The questions were generated and selected to match our intended project objectives and goals. The questionnaire commences with descriptive questions such as location, education, and farm ownership. It also employs a series of closed-ended questions such as categorical, numerical and ordinal questions to generate the quantitative data that we will utilize in meeting our objectives. A draft mock-up of the web-based survey is available at http://rainier.unl.edu/survey.

The initial version of survey questions was sent to the board members of the National Corn Grower Association (NCGA) during the first week of December, 2008. The board members wanted to gain a better understanding of the type of survey they would be disseminating to their members. We are still collecting all of their input, although the initial comments were favorable.

Over the next three months, the DM-DSS research team at UNL will focus on two major tasks. First, the survey questionnaire will be refined and finalized. The research team is investigating potential research questions to ensure their appropriateness in meeting the project research objectives, and contributing to the basic science of forecast use and development. The project team is also investigating new software that could be utilized in developing an enhanced online survey. Once completed, the survey materials will be submitted to the UNL Institutional Review Board for final approval. Once the survey is approved, it will be disseminated to members of the NCGA who have internet access. The research team will follow a protocol based on the Dillman Total Design Survey Method (1986), which includes the use of multiple contacts with stakeholders to facilitate higher response rates. Once initiated, the survey is expected to take

up to a month to complete. We expect that we will have a reasonable response rate based on communications with NCGA.

As required by the University of Nebraska-Lincoln, members of the research team have also received the appropriate certification to conduct research that involves the use of human subjects. Members took the online training to meet the UNL Institutional Review Board's requirements to ensure high ethical and research standards. Co-PIs, J. Ryu and C. Knutson, Nicole Wall (Outreach and Research Specialist), and Jane Okalebo (Graduate Student Research Assistant) have taken these classes to comply with UNL's Federal-Wide Assurance requirement.

In addition to our project activities, we have had one project personnel change. Meghan Sittler has accepted a new position at the Lower Platter River Corridor Alliance (http://www.lowerplatte.org) and is no longer at NDMC. We have a new staff member, Nicole Wall who will take the role of Public Participation Specialist. Nicole will work closely with the Principal and co-Principal Investigators. Her experience and expertise are a close fit to the project requirements and her contribution will be valuable.

Task 5: Couple Decision Analysis Models for Case Studies

The decision modeling group has completed the formulation and validation of the methodology framework of an irrigation decision support system (DSS), which incorporates NOAA's one-week probability-based weather forecast into the decision process. The core of the DSS is a soil-water-atmosphere-plant (SWAP) simulation model. Taking advantage of previous work, this model has already been calibrated and versified for the case study site. This methodology test will address two questions: 1) how can we consider the uncertainty of the weekly forecast for real-time irrigation scheduling? 2) What is the economic value of the forecast for irrigation farmers? The preliminary results apply to one of the two case study sites identified for this project, the Havana Lowlands region, Illinois.

The objective of the DSS optimization framework is to maximize farmers' benefits (expected value) over an entire irrigation season by repeatedly answering two questions: should we irrigate? And if we decide to irrigate, how much should we irrigate? The DSS framework simulates the farmers' decisions at the daily temporal scale and maintains the mass balance of soil moisture and accumulating evaportranspiration as farmers' decisions progress through the irrigation season. The DSS provides a real-time stochastic optimization with short-term stochastic weather forecast. As depicted in Figure 5, decisions are made on daily basis in a moving window fashion, where today's irrigation decision of how much to irrigate is optimized based on existing conditions (today) and forecasted climatic conditions (future) over a maximum of one week.

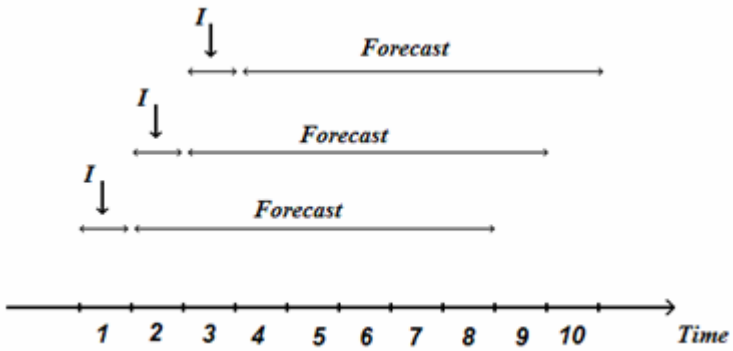

Fig. 5. Schematic of the moving-window stochastic optimization framework of irrigation in real-time.

The probabilities associated with each of the future 7 days is computed based on historical 7-day probabilistic forecast by NOAA in Mason County, IL during the years of 2002 to 2006. The historical forecasts of rainfall data during the growing seasons of the five years were compiled into 11 categories as described in Table 1. Preliminary results showed that the reliability of forecasts substantially change with the change in forecast horizon. For example, the probability of correctly predicting a rainfall event on day t+1 is much more pronounced than the same probability on day t+7.

Table 1. List of categories from NOAA's weekly rainfall forecasts in Mason County, IL

Category	Description
1	No rain
2	Chance of rain is between 20 and 40%
3	Chance of rain is between 40 and 60%
4	Chance of rain is between 60 and 80%
5	Chance of rain is between 80 and 100%
6	Chance of showers and thunderstorms is between 20% and 40%
7	Chance of showers and thunderstorms is between 40% and 60%
8	Chance of showers and thunderstorms is between 60% and 80%
9	Chance of showers and thunderstorms is between 80% and 100%
10	Showers and thunderstorms likely
11	Some thunderstorms may contain heavy rainfall

For each category and for each day, the probabilities of rain and no rain are computed based on historical data (see Figure 6). For each category, four scenarios are described along with their corresponding probabilities ($P_{No\ Rain} + P_{Rain} = P_{No\ Rain} + P_{Little\ Rain} + P_{Moderate\ Rain} + P_{Heavy\ Rain} = 1$) and rainfall depth values. The rainfall depth values are simply the historical mean values. The probabilities and their associated rainfall depth values differ for the various days of the forecasting horizon. So a 50% chance of rain tomorrow will carry a different a set of probabilities of rain and no-rain, than the same probability of rain on the 7th day of the forecasting horizon. Thus, to compute the maximum benefit, an expected value over all possible combinations of forecasting scenarios is necessary. For the preliminary results we have reduced

the number of rainfall forecasting scenarios to two (rain or no-rain) to reduce the computational requirements.

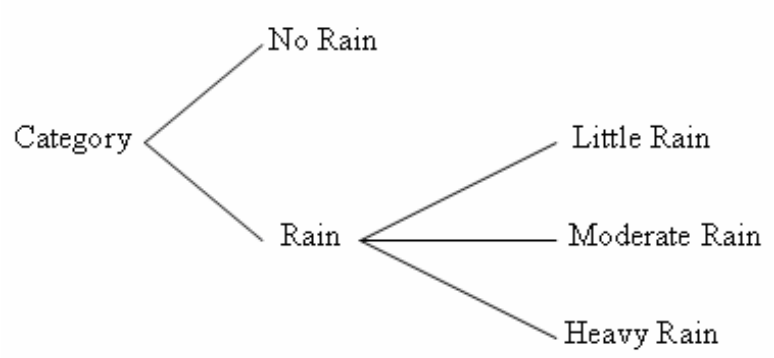

Fig. 6. Rainfall probabilistic scenarios to be determined from historical data.

Figure 7 compares the results between a rule-based simulation and the DSS optimization framework without incorporating any future rainfall forecasts. The rule-based algorithm is based on the conditions of soil moisture in the soil column or more specifically the ratio of cumulative actual evapotranspiration over cumulative potential evapotranspiration (cETa/cETp) and further details about the rule-based algorithm are available in Dingbao and Cai (2009). The results show a substantially higher cETa/cETp values from optimization over simulation especially during dry years. The results translate to a 50.5% improvement on average in total profit from optimization over the rule-based approach.

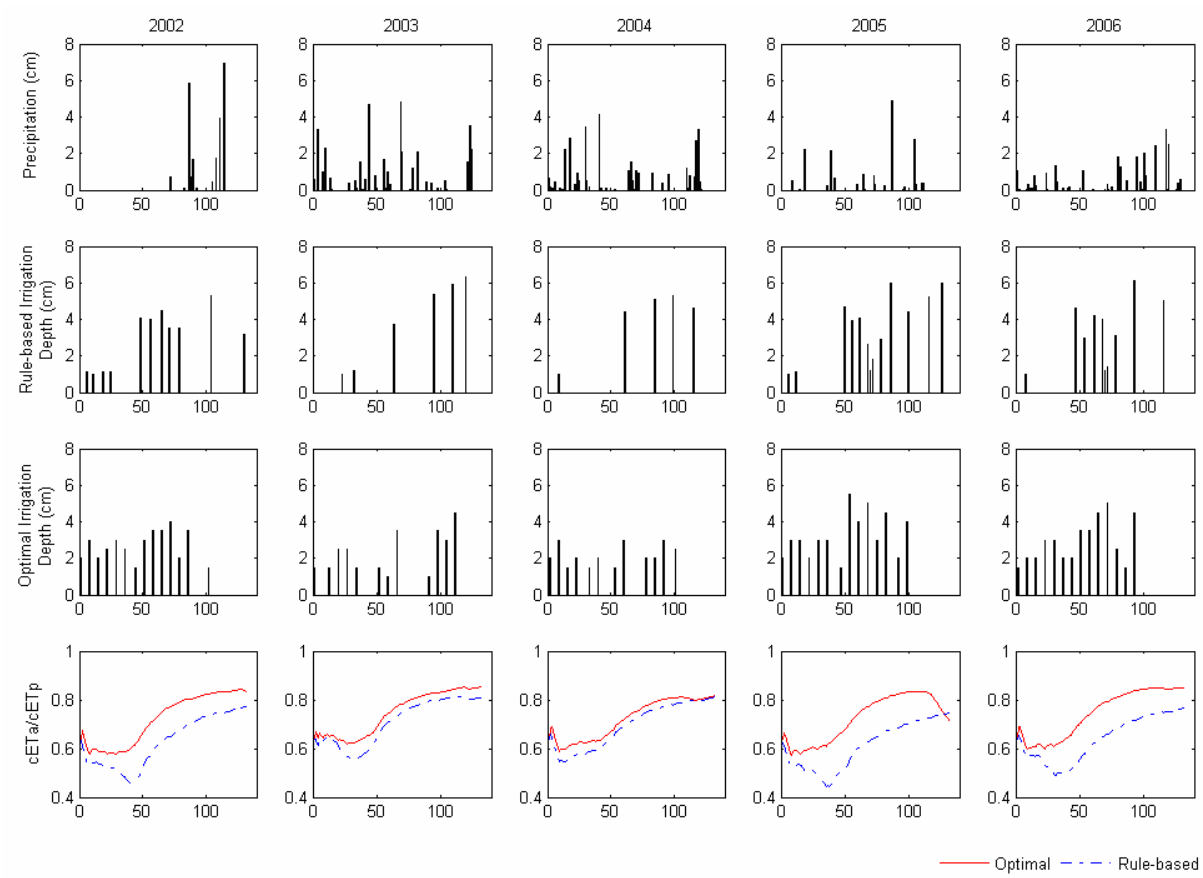

Fig. 7. comparing the result from the DSS optimization framework to a rule-based simulation approach; both scenarios assume no rainfall forecast.

Unlike Figure 7, Figure 8 compares the results between the rule-based simulation and the DSS optimization framework with incorporating 7-day uncertain forecasts of future rainfall. Again the results show a substantially higher cETa/cETp values from optimization over simulation especially during dry years. The results translate to a 36.8% improvement on average in total profit from optimization over the rule-based approach.

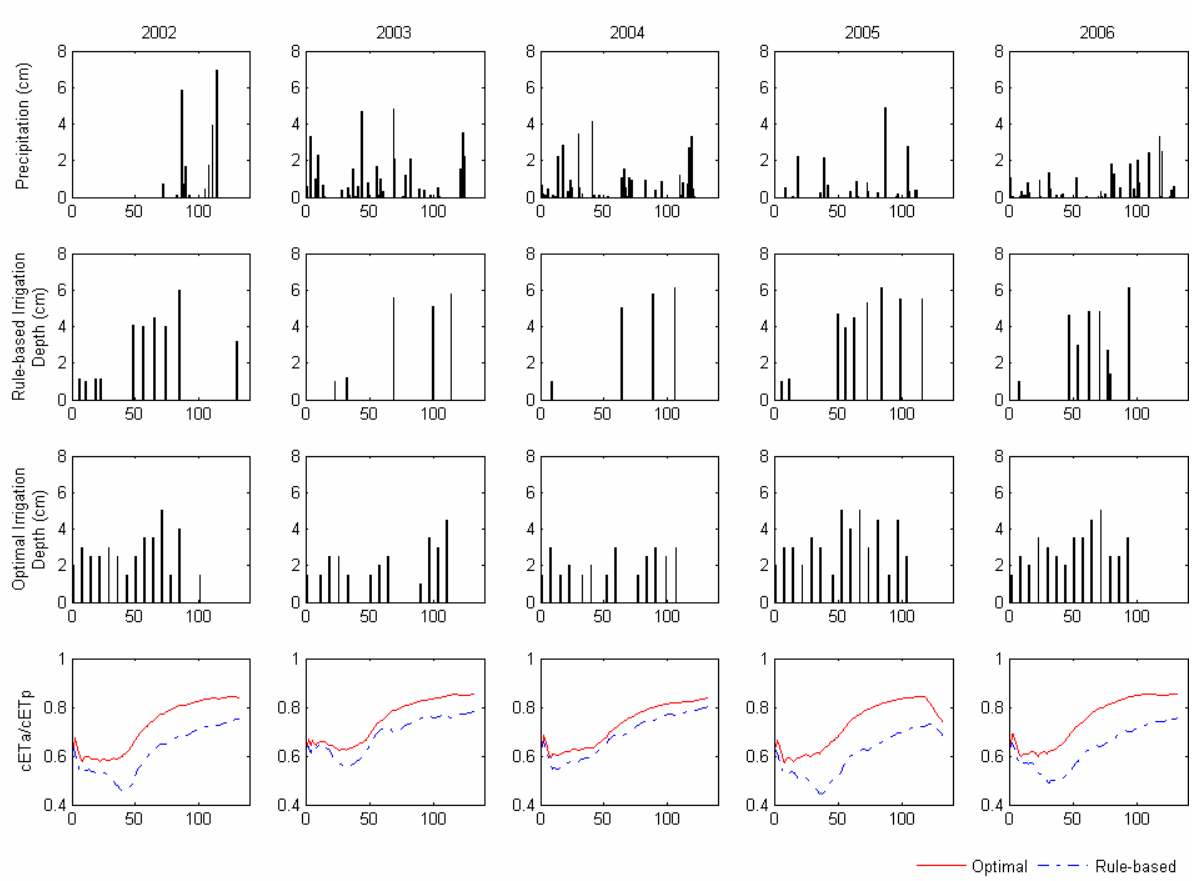

Fig. 8. Comparing the result from the DSS optimization framework to a rule-based simulation approach; both scenarios assume a 7-day uncertain rainfall forecast.

The current DSS framework will allow us to address questions such as:

- What is the advantage of optimization over the conventional rule-based approach?
- What is the gain from short-term weather forecasts (e.g., 1-day, 2-day, …, 7-day)?
- How reliable are current forecasts to aid farmers' decisions?

Task 6: Research Extension: Communication with users' representatives

We have been working with National Corn Growers Association (NCGA) for users' survey. We have been also working with Irrigation Association (IA) for the demonstration of the use of short-term forecast for irrigation scheduling. A site visit of IA and presentation are scheduled for April 2009. The contact person of NCGA is Richard Glass Vice president of NCGA; the contact person of IA is Erin D. Field, Agriculture Affairs Director, Irrigation Association. Both NCGA and IA will provide their existing mechanisms for conducting users' surveys and demonstrating decision making tools.

3. Work Plan for Next Three Months

Forecast: Climate Forecast Initialization: The initialization for the CWRF downscaling system will be improved. This will involve the interface development for CWRF to integrate the NARR

and/or GMAO reanalysis to initialize the surface states, including soil temperature and moisture. We will rerun the pilot case to determine how a more realistic initialization will affect the CWRF downscaling results.

Surveys: Web-based survey and result analysis will be conducted. This survey will collect users' expectation on the DM-DSS improvement, information requests for decision making, and evaluation on the research plans. Also, this survey will inform the users the possible update of the DM-DSS following this research project, which will also be used for benchmark.

Drought Information: A systematic framework of forecast drought indices will be established in a computer server. Algorithms to compute drought indices as a function of forecast outputs (e.g. precipitation, temperature, soil moisture, streamflow) from the research team at UIUC and ISWS will be developed, which will be associated with extensive literature review, taking advantage of the methods employed within the scientific community on drought prediction.

Real-time Decision Support: Future work will address two remaining questions:
How to incorporate medium-range climate forecasts (1-month to 3-months & to be provided by the drought prediction group) into the DSS framework? How to incorporate the drought indicators/triggers (to be provided by the drought information assessment and dissemination group) into the DSS framework? We will start to use the results from the pilot forecast study to test the method that incorporates medium-range climate forecast for real-time decision making.

Literature review: We will finish the literature with the involvement of other team members. The review will be improved by addressing the state-of-art of drought prediction, drought indices and triggers and decision making using drought information. We will pay particular attention on NASA funded projects on drought management. Our target is a white paper for discussion in drought research communication.

4. References

Hoddinott, S., M. Bass, (1986) "The Dillman Total Design Survey Method", *Can. Fam. Physician*, 32:2366-2368.

Wang, Dingbao, Ximing Cai, (accepted) "Irrigation scheduling – The role of weather forecasting and farmers' behavior", *Journal of Water Resources Planning and Management*.

5. Appendices

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