# **Report as of FY2007 for 2006UT69B: "Irrigation Demand Forecasting for Management of Large Water Systems"**

# **Publications**

Project 2006UT69B has resulted in no reported publications as of FY2007.

# **Report Follows**

### **Irrigation Demand Forecasting for Management of Large Water Systems**

#### Problem

The relative scarcity of water in the western US is increasing due to population and economic growth, pollution, and diversification of the types of demands that are being placed on water use (e.g., traditional consumptive uses such as irrigation and municipal supply, as well as emerging uses for such concerns as water quality maintenance and endangered species protection). This increasing relative scarcity brings: (1) a greater need to more intensively manage the resource, and (2) a requirement for better characterizations of the current and potential future states of our water resources systems--including estimates of the uncertainty contained in these characterizations--so that management decisions can be better informed.

In spite of these increasing needs for better water resources management information, investments in traditional water resources data collection programs (e.g., point stream flows, snow pack, soil moisture, etc.) are declining at the federal and state levels. For example, USGS support for maintenance of several stream gages in Utah has been withdrawn in recent years due to a lack of state cost-sharing commitments. In contrast, investments on the part of other Federal agencies (that have not traditionally played a significant role in support of water resources management) in new data collection methods are increasing (e.g., satellite imagery of land cover, snow cover, ocean surface temperatures, etc.; radar estimation of precipitation; aircraft and satellite imagery for estimation of evapotranspiration). These new data streams will have to be used to back-fill the decline in availability of traditional data. Moreover, analytic methods will need to be developed to apply to these data in order to improve the quality of the information base available to managers of large water systems.

Today's managers have not been schooled in new ways of collecting data or in the analytic approaches required to understand the data. Before new methods of gaining information and making decisions can be practical, investments must be made to place the resulting capabilities into the hands of the water managers who need them. These must be practical and effective, and the water managers must themselves see the value of the information that results.

The operation of large irrigation systems is an important area in which gains in efficiency in the management of water resources can be made realized the development and use of timely and strategic information. This is especially the case in Utah, where there exist many large irrigation and canal systems that provide significant volumes of water for use in an arid or semi-arid setting, and for which there is substantial uncertainty at any given time in the current state of the system and in the irrigation water demands that will emerge in the relative short term. This project will focus on the development of practical approaches for forecasting short-term irrigation water demands on a canal system so that overall system operation can be made more efficient.

Research is needed to develop the data now becoming available from emerging remote sensing sources into useful information for all temporal and geographical scales of water resources management. This must be done in such a way as to maximize the total value of the information

coming from both these new, emerging data sources and from the traditional water resources monitoring approaches. Further, the products of such research must be of practical use to the water resources managers who (1) are now losing access to traditional data sources and (2) have not been trained in how to access and use the information flowing from new remote sensing capabilities. In addition, the research products must also be of use to a growing range of stakeholders who have heterogeneous technical backgrounds and skill levels.

#### **Research Objectives**

The purpose of this project is to develop a significantly enhanced capability within the state of Utah--that will also be appropriate for application in the arid West--to more efficiently manage the state's scarce water resources by exploiting emerging technologies in data collection and analysis. Specifically, the focal objective of this project is to develop and test methodologies from statistical learning theory for combining meteorological and hydrological data from traditional and new remote sensing sources to produce information valuable to managers of large water resources systems. These methodologies will be directed at supplying reliable predictions of irrigation water demands for periods of one to five days in advance of the time of delivery to irrigators. These forecasts are based on a methodology that utilizes data from on-ground soil moisture probes, coarse-scale satellite imagery, and, potentially, other immerging sources of remotely sensed data and/or meso-scale modeling forecasts.

#### Methodology

Evapotranspiration (ET) can be modeled using remotely sensed data. A number of models have been developed in this area and can be categorized into two classifications: (1) residual methods that calculate ET by subtracting sensible heat flux from net radiation (Moran et al., 1994), and (2) vegetation index-surface temperature (VI-Ts) methods that utilize scatter plots between the vegetation index and surface temperatures to approximate surface resistance (Nagler et al., 2005; Nishida et al., 2003; Nemani and Running, 1998; Yang et al., 1997). When using the VI-Ts method, however, derivation of surface resistance from a scatter plot requires a continuum of soil moisture (from dry bare soil to saturated bare soil) and vegetation status (from water-stressed full-cover vegetation to well-watered full-cover vegetation) to provide a range of surface conditions (Yang et al., 2006).

Models that are based on or that utilize remote sensing data have two central advantages over purely process-based models: (1) satellite remote sensing offers broad spatial coverage and regular temporal sampling, and (2) requirements for spatial and temporal parameterization of water-constraining variables are reduced or eliminated. Remote sensing models are thus theoretically capable of accurately predicting actual ET at regional to continental scales (Yang et al., 2006). In a recent application, Yang et al. (2006) investigated the use of support vector machines (SVMs) in modeling ET. The SVM model was trained on AmeriFlux data to produce a distributed ET product over the continental US. The output of this model will eventually become the MODIS (MOD16) product. Since the MOD16 product was not released at the time of this research, latent heat simulations from the Noah land-surface model (Ek et al., 2003) run offline at 1-km resolution through the Land Information System (LIS) (Kumar et al., 2006), the sister project of the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004), were used.

A downscaling/forecasting algorithm was developed that builds multiple relationships between inputs and outputs at different spatial scales. These relationships are then used to downscale and forecast the output at the finest scale. As a conservative assumption, this model assumes that the output image is available at the coarsest resolution. All inputs are upscaled to the coarsest output resolution. Upscaling is carried out using two-dimensional (2D) discrete wavelet decomposition with the basis functions suiting the property in physical terms. 2D wavelet decomposition for one level will result in one datum image (Low-Low pass filter image, or LL) and three detailed images (i.e., LH, HL, and HH). Once the inputs are available at the spatial resolution of the output, an SVM can be employed to learn the underlying physics between the inputs and the output using a random subset of pixels. The outcome of this SVM will be the LL image for this particular resolution. Since some inputs are available at higher spatial resolutions, these "leftover" inputs can still be upscaled to the output resolution and another SVM can be implemented to learn the relationship between these leftover inputs and the output. This SVM will be applied on three high-pass components of these leftover inputs. The result of this SVM will be inherently biased due to the convolution processes performed at the decomposition step. This bias is linear and it could be corrected. The linear bias corrector could be obtained at a coarser resolution where the three output detailed images are available. Once corrected for linear bias, the result of the SVM will be the three high-pass components, which can be used along with the datum image established in the first SVM to reconstruct the output at the next finer spatial resolution. The algorithm continues in this manner until all the inputs at higher spatial resolutions are consumed. Similar to the (downscaling only) explanation, the SVM can be trained against an output image ahead of time assuming all inputs are at time t and the output is at time t+n, where n is the number of time steps ahead. In the case of water management in the Sevier River Basin, time steps are in days. This provides the framework for the algorithm serving not only as a means for downscaling, but also for forecasting.

The algorithm will have three parameters per SVM machine. Figure 1 shows the scheme of this model. The triangles pointing up represent the 2D wavelet decomposition operations, while those pointing down represent 2D wavelet reconstruction operations. The dashed borders around the abbreviation SVM refer to "operational mode", while solid borders refer to training mode. Dotted images represent observed images. In this schema, there are two inputs and three different resolutions. One input is observed at fine resolution while the other is observed at a medium resolution. The output is observed at a coarse resolution.

#### **Principal Findings**

The above algorithm was applied to two case studies. Since ET MODIS (MOD16) is not released yet, the first case study was applied to downscale and forecast the photosynthesis (PSN) MODIS product MOD17A2 in the Sevier River Basin in Utah. A second case study, which is not reported here, successfully demonstrated the downscaling and forecasting LE model output in Bondville, Illinois. The results in this case study were validated with the AmeriFlux data over different snapshots in the irrigation season.



### The Sevier River Basin, Utah

The Sevier River Basin, a closed system in rural south-central Utah, is one of the state's major drainages, encompassing 12.5 percent of the state's total area. The Sevier River Basin, shown in Figure 2, has five subwatersheds and is divided into two major divisions, the upper and lower basins, for the purpose of administration of water rights.

Average annual precipitation ranges from 6.4 to 13.0 inches in the valleys, and the growing season ranges from 60 to 178 days (Utah Board of Water Resources, 2001; Berger et al., 2002). Most of the surface water runoff comes from snowmelt during the spring and early summer months. The primary use of water in the basin is for irrigation. The average annual amount of water diverted for cropland irrigation is 903,500 acre-feet. Of this amount, approximately 135,000 acre-feet are pumped from groundwater. The irrigation season in the basin generally extends from April to the end of October. About 40 percent of the diversions are return flows from upstream use (Berger et al., 2002). More detailed information about the basin and much of the real-time database utilized in this research is available at http://www.sevierriver.org (Khalil et al., 2005).



#### Application to the Sevier Basin

The algorithm was used to downscale the photosynthesis MODIS product (PNS- MOD17). The inputs used in this application are shown in Table 1. The Landsat TM multi-spectral image, available at 15m resolution, does not satisfy the relationship  $s \times 2^n = S$ , where *s* is the original spatial resolution (15 m), *S* is the upscaled spatial resolution (250 or 1000 m), and *n* is an integer. Therefore, the image had to be re-sampled at resolution s = 15.625 m, in which case, *n* will be 4 (for S = 250 m) or 6 (for S = 1000 m).

PNS was forecasted 8 days ahead using all inputs at, or upscaled to, a resolution of 1000 m. Then it was downscaled from 1000 m to 250 m using the inputs available at or upscaled to 250 m. Finally, it was downscaled to 15.625 m using the inputs available at a 15.625 m resolution. Figure 3 shows the results of the model at the three benchmark spatial resolutions. Pending the release of the ET product of MODIS MOD16, the algorithm could be applied to forecast ET in the Sevier River Basin.

Spatial Resolution (m)	Product Description	Source	Product Code
1000	LAI/ FPAR	MODIS	MOD15A2
	Albedo	MODIS	MOD43B1
	Temperature/ Emissivity	MODIS	MOD11A1
250	Surface Reflectance	MODIS	MOD09Q1
	Vegetation Indexes	MODIS	MOD13Q1
15	Multi-Spectral	Landsat TM	

Table 1: Inputs used in the Sevier River Basin Case Study

#### Benefits

The Sevier River Basin, managed by the Sevier River Water Users Association (SRWUA) in Utah served as a case study and experimental site for the project. It was chosen because of its significant size, its importance in the agricultural sector of the state, its highly developed on-line, real-time database, and the willingness of local water resources managers to cooperate with the research and make use of the outputs of the project. The project focused on development of approaches to reduce the uncertainty that accompanies significant water management decisions through the implementation of real-time forecasting of irrigation requirements for periods of one to five days in advance. This capability will be useful in the Sevier River Basin for managing real-time reservoir release and canal diversion decisions. The output of these models will be utilized for development and deployment of decision-support systems that will be made available to managers of reservoir releases and canal diversions.



resolution, t+8days; and (c) PNS at 15.625 m resolution, t+8days.

#### References

- Berger, B., R. Hansen, and A. Hilton (2002). Using the world-wide-web as a support system to enhance water management. The 18th ICID Congress and 53rd IEC Meeting, Montréal, Canada.
- Ek, M.B., K.E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, G. Gayno, and J.D. Tarpley (2003). Implementation of Noah land surface model advances in the National Center for Environmental Prediction operational mesoscale Eta model. J. Geophys. Res., 108(D22):8851, doi:10.1029/2002JD003296.
- Khalil, A., M. McKee, M. Kemblowski, and T. Asefa (2005), Sparse Bayesian learning machine for real-time management of reservoir releases, *Water Resour. Res.*, 41, W11401, doi:10.1029/2004WR003891.
- Kumar, S.V., C.D. Peters-Lidard, Y. Tian, P.R. Houser, J. Geiger, S. Olden, L. Lighty, J.L. Eastman, B. Doty, P. Dirmeyer, J. Adams, K. Mitchell, E.F. Wood, and J. Sheffield (2006). Land Information System An interoperable framework for high resolution land surface modeling, Environ. *Modeling and Software*, 21:1402-14-15.
- Moran, M., T. Clarke, U. Inoue, and A. Vidal (1994). Estimating crop water deficit using the relation between surface air temperature and spectral vegetation index. *Remote Sens. Environ.*, 49(3):246–263.
- Nagler, P.L., R.L. Scott, C. Westenburg, J.R. Cleverly, E.P. Glenn, and A.R. Huete (2005). Evapotranspiration on western U.S. rivers estimated using the enhanced vegetation index from MODIS and data from eddy covariance and Bowen ratio flux towers. *Remote Sens. Environ.*, 97(3):337–351.
- Nemani, R.R. and S.W. Running (1998). Estimation of regional surface resistance to evapotranspiration from NDVI and thermal-IR AVHRR data. J. Appl. Meteorol., 28(4):276–284.
- Nishida K., R.R. Nemani, J.M. Glassy, and S.W. Running (2003). Development of an evapotranspiration index from Aqua/MODIS for monitoring surface moisture status. *IEEE Trans. Geosci. Remote Sens.*, 41(2):493–501.
- Rodell, M., P.R. Houser, U. Jambor, J. Gottschalk, K. Mitchell, C.-J. Meng, K. Arsenault, B. Consgrove, J. Radakovich, M. Bosilovich, J.K. Entin, J.P. Walker, D. Lohmann, and D. Toll (2004). The Global Land Data Assimilation System. *Bull. Amer. Meteor. Soc.*, 85(3):381-394.
- Utah Board of Water Resources (2001). Utah's water resources planning for the future. Division of Water Resources Publication, Salt lake City, UT.

- Yang, F., M. White, A. Michaelis, K. Ichii, H. Hashimoto, P. Votava, A.X. Zhu, and R.R. Nemani (2006). Prediction of continental scale evapotranspiration by combining MODIS and AmeriFlux data through Support Vector Machine. *IEEE Transactions on Geoscience* and Remote Sensing, 44(11):3452-3461.
- Yang, X., Q. Zhou, and M. Melville (1997). Estimating local sugarcane evapotranspiration using Landsat TM image and a VITT concept. *Int. J. Remote Sens.*, 18(2):453–459.