

DEVELOPMENT OF A UNIFIED LAND MODEL WITH MULTI-CRITERIA
OBSERVATIONAL DATA FOR THE SIMULATION OF REGIONAL HYDROLOGY
AND LAND-ATMOSPHERE INTERACTION

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Abstract

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A unified land model (ULM) is described that combines the surface flux parameterizations in the Noah land surface model (used in most of NOAA's coupled weather and climate models) with the Sacramento soil moisture accounting model (Sac; used for hydrologic prediction within the National Weather Service). The major motivation was to develop a model that has a history of strong hydrologic performance, while having the ability to be used as the land surface parameterization in coupled land-atmosphere models. Initial comparisons were made with observed surface fluxes and soil moisture wherein ULM performed well compared with its parent models (Noah, Sac) with a notably improved representation of the soil drying cycle. Parameter tuning was ultimately needed to capture streamflow dynamics, leading to a parameter estimation framework that utilized multiple independent data sets over the continental United States. These included a satellite-based evapotranspiration (ET) product based on MODerate resolution Imaging Spectroradiometer (MODIS) and Geostationary Operation Environmental Satellites (GOES) imagery, an atmospheric-water balance based ET estimate that uses North American Regional Reanalysis (NARR) atmospheric fields, terrestrial water storage content (TWSC) data from the Gravity Recovery and Climate Experiment (GRACE), and streamflow (Q) primarily

from United States Geological Survey (USGS) stream gauges. At large scales ($\geq 10^5$ km²) calibrations using Q as an objective function resulted in the best overall multi-criteria performance. At small scales ($< 10^4$ km²), about one-third of the basins had their highest Q performance from multi-criteria calibrations (to Q and ET) suggesting that traditional calibration may benefit by supplementing remote sensing data. Finally, a scheme to transfer calibrated parameters was employed using Principal Components Analysis (PCA) to derive predictive relationships between model parameters and commonly used catchment attributes (meteorological, geomorphic, land-cover characteristics), several satellite remote sensing products, as well as the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II) database. Regional model performance was most improved when locally optimized parameters were first resampled based on their performance at neighboring basins, termed *zonalization*. For a large number of basins, the regionalized model performed comparably to the calibrated version, affirming this PCA methodology as a viable means for transferring geospatial parameter information.

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I. INTRODUCTION

The storage and transfer of water between the land, atmosphere, and water bodies comprise the hydrologic cycle. The interaction of these components with energy from the sun and disturbances in the lower atmosphere, contribute to processes of weather that affect human activities and water availability at the land surface. Models provide a means of representing these interactions and anticipating changes therein. Consequently, accurate simulation of the hydrologic cycle is important both for applied hydrological forecasting – e.g., of floods and droughts – and for representation of land-atmosphere energy exchanges in coupled land-atmosphere-ocean models used for numerical weather climate prediction. The field of land surface modeling has developed from highly simplified approximations of the Earth’s surface – such as the bucket model of Manabe (1969) – into a broad network of hydrologic, biological, and physical processes and outputs. A model that accurately simulates the terrestrial water balance can be a valuable tool to answer questions that relate land-use and climate variability to the hydrologic cycle, past, present, and future.

This dissertation focuses on the development and implementation of a land surface model (LSM), intended for use both in hydrological predictions and for representation of the land surface in coupled land-atmosphere-ocean models. The Unified Land Model (ULM) described herein is a merger of two operational models. The hydrology-focused model is the Sacramento Soil Moisture Accounting model (Sac; Burnash et al., 1973), which is the primary model used for river forecasting by the NWS River Forecast Centers (RFCs) across the United States. It has been shown to perform well in streamflow prediction comparisons with other models and observations (e.g. Schaake et al., 2001, Smith et al., 2003; Reed et al., 2004). The Noah LSM (Ek et al., 2003) serves as the land surface scheme in the numerical weather and climate prediction models of the National Centers for Environmental Prediction (NCEP) of the National Weather Service (NWS). Improving hydrological realism within the modeling framework has the potential to improve the representation of a wide range of land-atmosphere interactions. Hydrologic factors – especially soil moisture – play an important role in modulating climate (Wang and Kumar, 1998, Mahmood and Hubbard, 2003, Koster et al., 2004, Seneviratne et al., 2010). Furthermore, surface latent heat fluxes are largely controlled by the interaction of soil moisture with evapotranspiration (ET – Xiu and Pleim, 2001). Other meteorological

processes like cloud formation are also sensitive to soil moisture (Wetzel et al., 1996) and may result in either positive or negative feedbacks between the land and atmosphere (Ek and Holtlag, 2004, Taylor and Ellis, 2006).

Model development and validation was approached in three stages. The first stage involved merging model components from Noah and Sac. ULM takes the vegetation, snow model, frozen soil, and evapotranspiration schemes from Noah, and merges them with the soil moisture accounting scheme from Sac. Given the differences in model structure of ULM relative to the two parent models, comparisons were made of ULM predictions with observations of surface fluxes, soil moisture, and streamflow over a range of hydro-climatic conditions. ULM initially used a set of *a priori* parameters from Sac and Noah, however it was anticipated that changes to the ET formulation would require new estimates of certain model parameter values, which would be obtained via a calibration process.

The increasing availability and length of satellite records, as well as reductions in spatial resolution and computational processing constraints makes these data sources a promising tool for hydrologists. The second stage of model development made use of remote sensing data sets for terrestrial water budget components in addition to in situ (gauge-based) streamflow observations, within a parameter estimation framework. This multi-criteria approach was chosen because traditional validation of models using observations of a single variable (i.e., single criterion approach) can result in model predictions that are inherently biased towards that variable (McCabe et al., 2005). Moreover, multi-criteria analyses can aid in addressing the issue of equifinality (Beven and Freer, 2001). The evaluation of multiple model outputs (as opposed to single-output analysis, such as streamflow) has received increasing attention (e.g. Gupta et al., 1999, Crow et al., 2003, McCabe et al., 2005, Kampf and Burges, 2007, Khu et al., 2008, Kampf and Burges, 2010, Werth and Guntner, 2010, Milzow et al., 2011), which has been possible in part due to the growing availability of multivariate observations.

The investigation of multi-criteria parameter estimation came about because *a priori* Sac parameters in particular were not sufficiently representative of ULM's structure (i.e., explicit representation of vegetation; differing ET mechanisms). The explanatory variables in the multiple-objective parameter estimation included a satellite-based evapotranspiration (ET) product based on MODerate resolution Imaging Spectroradiometer

(MODIS) and Geostationary Operation Environmental Satellites (GOES) imagery, an atmospheric-water balance based ET estimate that utilizes North American Regional Reanalysis (NARR) atmospheric fields, terrestrial water storage content (TWSC) data from the Gravity Recovery and Climate Experiment (GRACE), and streamflow (Q) primarily from United States Geological Survey (USGS) stream gauges. The study domain was expanded to include ten large-scale ($\geq 10^5$ km²) river basins and 250 smaller-scale ($< 10^4$ km²) tributary basins, to provide an understanding of parameter sensitivity and interaction. At large-scales, calibration utilized numerous combinations of criteria, since all the criteria mentioned above are applicable at these scales (11 combinations of Q, TWSC, and two ET products as objective functions). At smaller scales, only three combinations of potential explanatory variables were considered (Q, QET, ET); however a much larger number of basins were available that at large-scale (250 versus 10). The expectation from this aspect of model development and implementation was that it would inform model simulations with the nearly ubiquitous coverage of the potential explanatory variables (especially remote sensing); so that the model ultimately can be applied in regions in which in-situ measurements are sparse.

An alternative means of estimating model parameters over data-poor regions is by using predictors for the parameters that are based on readily observable catchment attributes. The third stage of model development was therefore focused on regionalization and implementation using such variables. Past work in this area has used regression-based methods (e.g. Abdulla and Lettenmaier, 1997; Merz and Blöschl 2004, and others), or spatial averaging, hydrologic classification, and clustering (e.g. Gupta et al., 1999, Zhang et al., 2008, etc...). A Principal Components Analysis (PCA) framework was chosen here and several recently available data products were used as potential explanatory variables. These included two remote sensing products, as well as the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II) database (Falcone et al., 2010). The study domain was similar to the domain in chapter III, although there were fewer catchments as a consequence of limited availability of catchment attribute data for parts of the domain. In a series of regionalization experiments, the more conventional procedure of using locally optimized parameters was contrasted with an approach that uses *zonally* representative parameter values.

1.1 Science questions

This dissertation develops and implements a new modeling system based on the Unified Land Model, applied over a large portion of the continental United States for the prediction of surface heat fluxes, soil moisture, and streamflow. The science questions that motivated this model development and implementation effort were:

1. *Can the ULM, which takes structures from the Noah LSM and Sacramento model, produce more realistic simulations of surface hydrology and land-atmosphere interactions than either of the parent models?*
2. *How well can the ULM structure estimate the terrestrial water balance at both catchment and regional scales?*
3. *Can the use of ground-based and satellite observations provide a physically consistent framework from which to derive model parameters that result in realistic water balance estimates?*
4. *To what extent can parameter information from ULM simulations ($10^2 - 10^4 \text{ km}^2$) be transferred to other catchments through predictive relationships derived exclusively from directly observable catchment attributes?*

The following three chapters address these questions. Chapter II (published as Livneh et al., 2011) describes ULM model structures and includes testing with observations that address question 1 above. Questions 2 and 3 are addressed in Chapter III (Livneh and Lettenmaier, 2012) through the incorporation of remote sensing and observational data into a parameter search together with model comparisons pertaining to the major components of the terrestrial water budget. Question 4 is addressed in Chapter IV (Livneh and Lettenmaier, 2012) via a series of regionalization experiments that consider a large array of catchment attribute information into predictive equations.

II. DEVELOPMENT OF THE UNIFIED LAND MODEL

This chapter has been published in its current form in the *Journal of Hydrometeorology* (Livneh, et al., 2011).

2.1 Introduction

The principal role of land schemes in numerical weather and climate prediction models is to partition net radiation into turbulent surface and ground heat fluxes, which are required to characterize the atmospheric model's lower boundary. Although land surface models (LSM's) perform full land surface hydrologic calculations, they generally focus more on representation of land-atmosphere fluxes than on the processes, such as soil moisture dynamics, that control runoff generation (Koster et al., 2000, Bastidas et al., 2006). As a case in point, the Noah LSM (Ek et al., 2003) which serves as the land surface scheme in the numerical weather and climate prediction models of the National Centers for Environmental Prediction (NCEP) of the National Weather Service (NWS), has been shown to be less skillful in streamflow prediction compared with more hydrologically based models (Bohn et al., 2010). Nonetheless, hydrologic factors – especially soil moisture -- play an important role in modulating climate (Wang and Kumar, 1998, Mahmood and Hubbard, 2003, Koster et al., 2004, Seneviratne et al., 2010). Within an atmospheric model, surface latent heat fluxes are largely controlled by the interaction of soil moisture with evapotranspiration (ET – Xiu and Pleim, 2001). Other meteorological processes like cloud formation are also sensitive to soil moisture (Wetzel et al., 1996) and may result in either positive or negative feedbacks (Ek and Holtslag, 2004, Taylor and Ellis, 2006). Therefore, if an LSM's representation of these processes is poor, it will produce unrealistic evaporation rates regardless of the quality of the evaporation formulation (Koster et al., 2000). Another consideration is that the runoff that results from an LSM's soil moisture computation ultimately becomes an input to the oceans (from major river basins) constituting an important boundary condition for the modeling of oceanic circulation and climate. The impact of streamflow on salinity at the continental boundaries can affect both ocean convection and thermohaline circulation and therefore

influences sea surface temperature and sea ice, all of which exert a strong influence on climate (Verseghy, 1996, Arora, 2001).

Hydrologic models focus on accurately simulating components of the surface water budget, especially streamflow. The Sacramento Soil Moisture Accounting model (Sac; Burnash et al., 1973), which is the primary model used for river forecasting by the NWS River Forecast Centers (RFCs) across the United States, has been found to perform well in streamflow prediction compared with other models and observations (Reed et al., 2004). A number of recent studies have focused on techniques for Sac parameter estimation based on numerical optimization methods (Duan et al., 1994, Yapo et al., 1998, Gupta et al., 1998, Thiemann et al., 2001, Smith et al., 2003, Vrugt et al., 2006, Gan and Burges, 2006, Tang et al., 2007, van Werkhoven et al., 2008). Sac parameters are usually obtained via a calibration process since most model parameters are not directly measurable. An alternative approach is to estimate model parameters from measurable soil characteristics such as percentages of sand and clay, and soil field capacity (Koren et al., 2000, Koren et al., 2003, Anderson et al., 2006). Such approaches are attractive, because they provide a basis for parameter estimation in ungauged basins, as well as the ability to provide physical constraints on calibration in gauged basins.

Two major obstacles prevent the Sac model from being coupled with atmospheric models. The first is the absence of a surface energy budget, which (in the case of LSMs) includes surface heat fluxes and radiative partitioning. Surface heat fluxes define the near-surface air temperature, ground temperature (sensible heat fluxes), and humidity (latent heat flux). Their estimation is indirectly important for surface hydrology, since feedbacks between soil moisture and precipitation affect the models' runoff production (McCumber and Pielke, 1981, Betts et al., 1996).

The second major shortcoming of Sac is the absence of an explicit representation of vegetation. Vegetation can have a profound influence on climate through surface exchanges of heat, moisture and momentum (Bonan et al., 1992, Pan and Mahrt, 1987, Pielke et al., 1998). The presence of vegetation also alters the rate of moisture movement to and from the soil, via canopy interception and root-zone water uptake for transpiration. Sub canopy soils are frequently moister than intercanopy patches suggesting the possible existence of a positive feedback between vegetation and soil water content (D'Odorico,

2007). Additionally, ET rates have been shown to vary according to vegetation type, such as forest versus grassland (Zhang et al., 2001); hence there is a possible link between vegetation and streamflow production.

Another consideration that is central to nearly all aspects of LSM performance is the estimation of ET. On a global average, between 60-80% of precipitation reaching the land surface is returned to the atmosphere through ET, which is the largest component of the terrestrial hydrological cycle (Tateishi and Ahn, 1996). In both the Noah and Sac models, ET is a function of potential evapotranspiration (PET), and PET therefore strongly influences ET predictions. PET is a representation of the environmental demand for ET; it is controlled both by the energy available to evaporate water, and the ability of the atmosphere to transport the water vapor from the ground into the lower atmosphere. ET is said to equal PET when moisture is freely available at the surface. Both the Noah and Sac models compute actual ET as a fraction of PET that depends on resistances of each ET component (bare soil – both models, canopy evaporation and transpiration – Noah only). The main point of interest is that Noah computes PET dynamically, following a Penman Monteith approach (Mahrt and Ek, 1984), whereas Sac cannot do so (lacking incorporation of radiation and surface roughness). In most cases, Sac requires PET as an input, and it is often prescribed as a fixed value (but seasonally varying). This approach does not account for interannual variability, and perhaps more importantly invokes an implicit assumption of stationarity, which arguably no longer is defensible (Milly et al., 2008) due to anthropogenic changes in land cover and changes in the Earth's climate.

For cases where hydrologic model parameters are not readily observable (e.g. Sac), they can be estimated via calibration, in which a set (or sets) of model parameters are obtained that result in differences between observed and simulated states or fluxes (e.g. streamflow) being minimized. Given the complexity of the hydrologic system, parameter estimation generally requires automatic (versus manual trial-and-error) optimization procedures of multi-objective functions. For those parameters that most directly affect model predictions of surface fluxes, flux tower measurements can be used (Betts et al., 1996, Chen et al., 1997, Gupta et al., 1999, Sridhar et al., 2002, Rosero et al., 2011).

In this paper, we describe a unified land model (herein ULM), which is a merger of the Noah and Sac models. The motivation for this merger is to incorporate a hydrologically

realistic structure within a model construct that can be used in coupled land-atmosphere applications. Because Noah is used operationally at NCEP for offline hydrologic simulations (e.g., for drought characterization) and is coupled with a suite of atmospheric models, the implications of improving its soil moisture-runoff generation scheme would be widespread. Conversely, the Sac model is used operationally for flood forecasting at over 3000 forecast points across the U.S., and it would benefit from Noah's more physically based vegetation and ET algorithms. We follow with a brief description of the heritage and components of each model; the nature of the approach we used to merge key parameterizations from each, and an assessment of ULM performance.

2.2 Model Structure

2.2.1 Noah

The heritage of Noah dates to the early 1990s, when NCEP adopted the Oregon State University (OSU) LSM (Mahrt and Pan, 1984; Pan and Mahrt, 1987) for use in its numerical weather prediction model. Subsequently, the OSU model became NOAH, with many upgrades described by Ek et al. (2003). NOAH originally stood for the collaborators in the project which adopted the OSU model (NCEP, OSU, Air Force – both AFWA and AFRL, Hydrologic Research Lab at the NWS), however the model acronym has since been dropped and it is referred to simply as Noah.

Noah has been run at spatial resolutions ranging from several km to hundreds of km. Sridhar et al., (2002) found that Noah's surface heat fluxes compared favorably with observations, however other studies have shown Noah is less skillful than other land surface models in streamflow simulation (Reed et al., 2004, Bohn et al., 2010). Figure 2.1 shows the main elements of Noah. The model uses a bulk surface layer with a single (dominant) vegetation class and snowpack, overlying a (dominant) soil texture divided into 4 layers. The vegetation canopy is assumed to cover a fraction of the land surface that varies spatially and temporally by an input greenness fraction, G_{vf} , (Gutman and Ignatov, 1998), derived from the photosynthetically active portion of leaf area index (LAI), based on a monthly 5-year climatology of AVHRR satellite data. The remainder of the grid cell is

bare soil. Water can be intercepted by the vegetation canopy up to a prescribed maximum threshold.

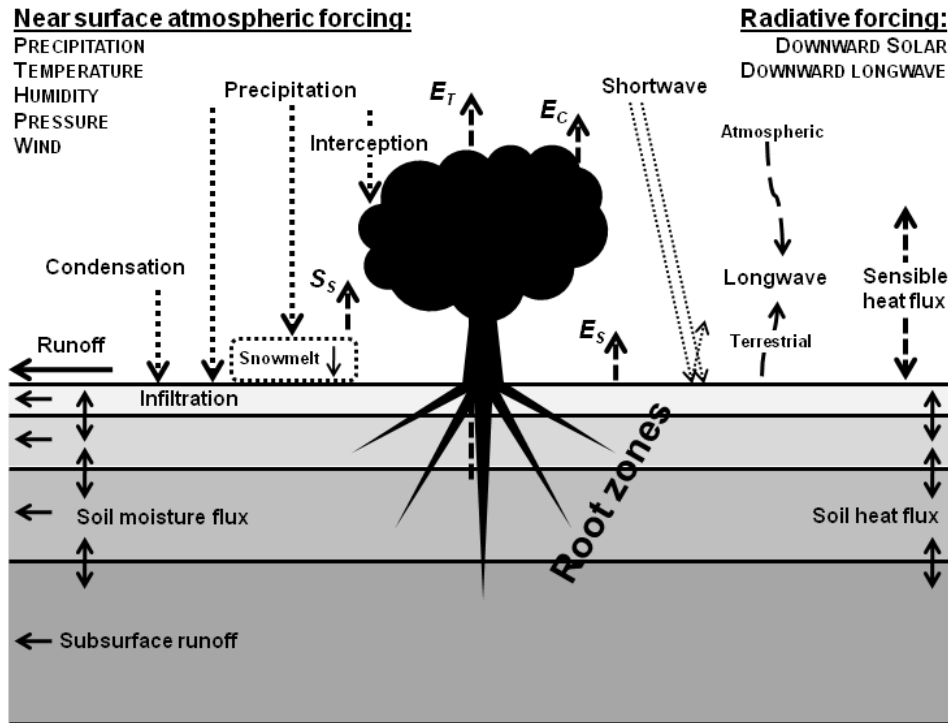


Figure 2.1: Schematic of the Noah LSM including required forcing variables, evaporative components of transpiration, E_T , canopy evaporation, E_C , soil evaporation, E_S , and snow sublimation, S_S . Precipitation is partitioned into evapotranspiration, runoff and infiltration.

A Richard's equation approach is used to solve for the movement of moisture through the four soil layers. The soil temperature profile is determined using nonlinear functions for the thermal conductivity of each soil layer (Johansen, 1977). Both of these computations require parameters such as porosity, wilting point, dry density, and quartz content that relate to soil texture. The model does not explicitly form a water table and capillary rise does not occur in the strict sense, but rather as the result of vertical dispersion via the solution to the Richards equation. Infiltration into the soil follows Schaake et al. (1996) as a nonlinear function of soil saturation, bounded above by precipitation and below by soil hydraulic conductivity. Sensible heat flux and ground heat flux are computed by the thermal diffusion equation (Chen et al., 1996), as differences between skin-and-air temperatures, and soil-and-skin temperatures, respectively, while latent heat flux is a function of the actual ET. In the absence of snow, ET occurs either by canopy evaporation,

bare soil evaporation, or transpiration through the root zones, described in greater detail in section 2.3.3. The Noah snow model prescribes a seasonally varying snow albedo decay function, and provides for liquid water retention within the snowpack and partial snow coverage. Frozen soil physics follow Koren et al. (1999) which provides for a reduction in moisture movement in response to increased soil ice content. Further details of the Noah snow model can be found in Livneh et al. (2010).

2.2.2 Sac

Sac is the operational flood forecasting model of the U.S. National Weather Service. It is also used for seasonal ensemble forecast applications at most of the 13 RFC's throughout the United States (Anderson et al., 2006). The model was developed by Burnash (1973) with the initial charge of being "A Generalized Streamflow Simulation System" that could be used to aid in water management decision making. The model was designed to be computationally efficient (run at a daily time step), run over an entire basin using a single set of model parameters (i.e. spatially lumped). Although there are many exceptions, the model has most often been used to generate river forecasts for rivers with response times of greater than 12 hours, and drainage areas ranging from 300 km² up to 5000 km² (Finnerty et al., 1997). Recent work by Koren et al. (2003) generalized the model for use in a spatially distributed context. Other recent enhancements include implementation of frozen soil physics representations which also have resulted in an ability to map the model's moisture storage contents (in five zones) to physical layers (Koren, 2006).

Absent an explicit representation of vegetation, the model's ET representation utilizes monthly ET factors that adjust a prescribed (monthly varying but otherwise constant) PET. Snow processes are represented in a separate snow model (SNOW-17; Anderson, 1973). Figure 2.2 shows the model conceptually. The five storage zones represent 'free' and 'tension' water reservoirs in an upper and lower zone. Free water is a representation of the quantity of water in excess of the soil's field capacity, for which gravity governs the moisture movement through the soil. The tension water zones represent the quantity of water between the soil's field capacity and soil's wilting point that is bound more closely to the soil and hence must be satisfied before any moisture can be extracted from the free water zones. Movement between upper and lower zones is controlled by a non-linear

percolation function, while subsurface flow is computed based on parameters derived from the hydraulic conductivity of each zone and other factors. Surface infiltration is a linear function of upper zone tension water saturation and direct runoff is controlled by an impervious fraction, which increases up to a prescribed threshold depending on the degree of the upper zone saturation.

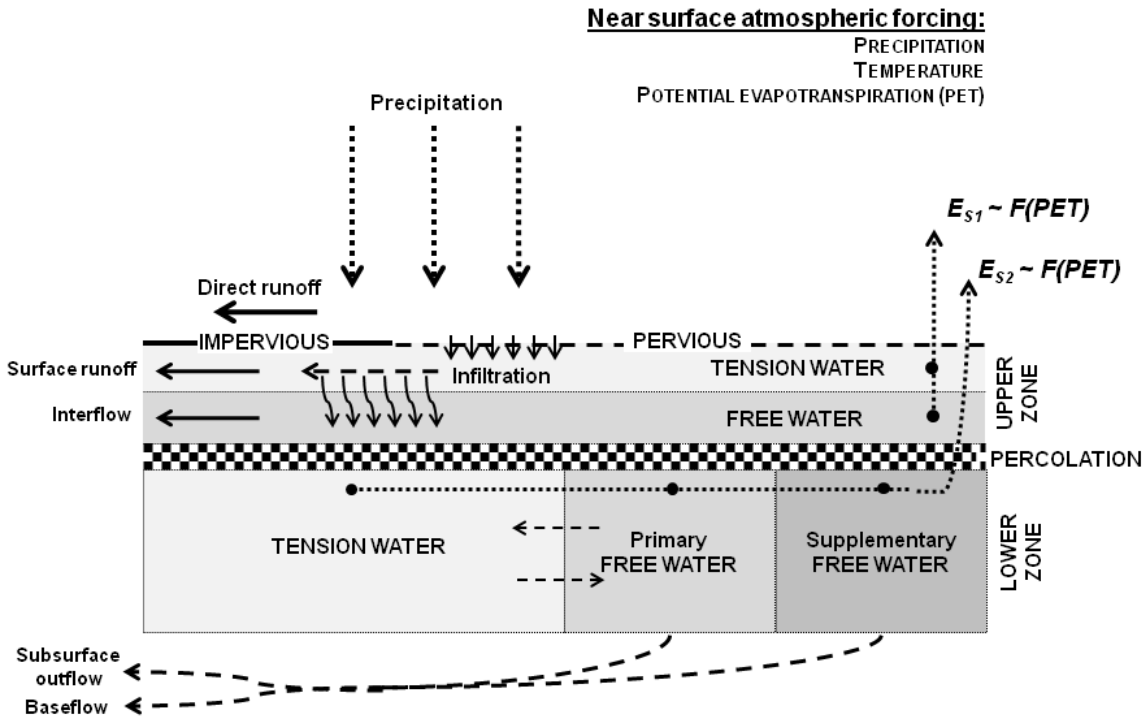


Figure 2.2: Schematic of the Sac model, including required forcing variables and evaporative components. The upper zone tension and free water contents (UZTWC and UZFWC, respectively) can vary from 0 to a maximum value (UZTWM and UZFWM, respectively). Similarly, lower zone tension water, primary and secondary free water contents (LZTWC, LZFPC, LZFSC respectively) can also vary from 0 to a maximum value (LZTWM, LZFPM, LZFSM respectively).

2.2.3 ULM

The Noah and Sac models have been widely used in operational settings to simulate soil moisture (both models), energy fluxes (Noah only), and streamflow (primarily Sac). Figure 2.3 illustrates the components that are preserved from each of the parent models in ULM. In general, we retained the land surface components from Noah (e.g., vegetation and ET), as well as the Noah snow model, and Noah's algorithms for computing surface heat and radiative fluxes. We also retained Noah's frozen soil algorithm. The soil moisture and runoff generation algorithms (including infiltration) were taken from Sac. A key element of the merger is conversion from Sac's conceptual soil moisture storage zones to physical

layers, which is achieved through an adaptation of the SAC-HT (heat transfer) mechanism, in which ‘tension’ and ‘free’ water storages are transferred to physical layers as moisture that exceeds the soil wilting point (Koren, 2006).

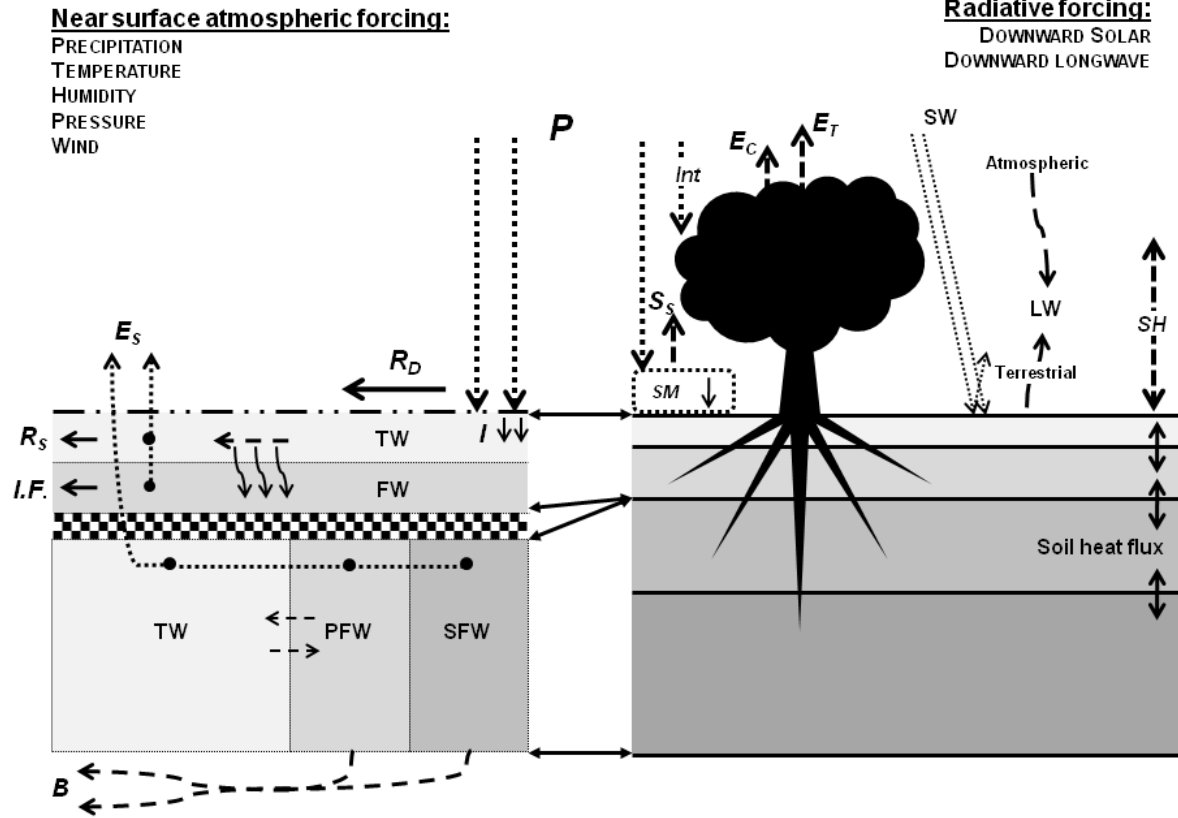


Figure 2.3: Schematic of ULM, including required forcing variables, moisture and energy components. Precipitation, P , and snowmelt, SM , are partitioned into direct runoff, R_D , infiltration, and evapotranspiration. Infiltration becomes either surface runoff, R_s , or interflow, $I.F.$, in the upper zone, the remains of which can then infiltrate further into the lower zone and become baseflow, B . The double arrows represent the transfer of model structure, wherein the soil schematic on the left is only considered for soil moisture computations, while the schematic on the right is used for all other model computations.

ET is an essential flux in hydrological models that defines the soil moisture balance, and hence storm runoff production, as well as the cycling of moisture to the atmosphere.

During snow free periods, ET in Noah (hence ULM) is based on a relationship with PET taken from Mahrt and Ek (1984):

$$PET = \left(\frac{R_o \Delta + AR_r}{\Delta + R_r} \right) \left(\frac{\rho c_p C_h U}{L_v} \right) \quad (2.1)$$

Where R_o is the radiation flux density, Δ is the slope of the saturation vapor pressure curve, A is a function of the specific humidity of the air with respect to saturation, R_r is a function

of surface air temperature, surface pressure, C_h , C_h are the surface exchange coefficients for heat and moisture, respectively, ρ is the air density, c_p is the specific heat capacity, U is wind speed, and L_v is the latent heat of vaporization.

Very generally, each ET component (soil, canopy, transpiration) is a fraction (≤ 1) of PET, scaled by its resistance to moisture transfer. Soil evaporation, E_S , only occurs over the non-green fraction of the grid-cell, over which PET is scaled accordingly. This demand is then applied to the Sac upper and lower zones as follows:

$$E_S = E_{SOIL-UPPER} + E_{SOIL-LOWER} \quad (2.2a)$$

$$E_{SOIL-UPPER} = PET(1 - G_{vf}) \left[\left(\frac{UZTWC}{UZTWM} \right) + \left(1 - \frac{UZTWC}{UZTWM} \right) \left(\frac{UZFWC}{UZFWM} \right) \right] \quad (2.2b)$$

$$E_{SOIL-LOWER} = \left(PET(1 - G_{vf}) - E_{SOIL-UPPER} \right) \left(\frac{LZTWC}{LZTWM} \right) \quad (2.2c)$$

The above logic keeps the Sac soil ET extraction scheme intact with the exceptions that (i) ET from riparian vegetation as represented by Sac (usually small) is neglected in favor of the more complete and explicit vegetation scheme from Noah, and (ii) soil evaporation from the Sac lower zone, $E_{SOIL-LOWER}$, which was intended to represent deeper soil moisture extraction via transpiration (e.g., by trees) is replaced by root water uptake from Noah's explicit vegetation scheme. Soil evaporation is a function of soil saturation, which is indexed to the relative storage in each zone. Hence, the zone capacities influence model moisture movement through the soil, and the quasi-equilibrium moisture state of ULM will differ from Sac because of the moisture demands from canopy evaporation and transpiration.

Canopy evaporation, E_C , in ULM is a Noah analogue, equal to PET over the 'green' area reduced by a nonlinear canopy factor, n , which is applied to the degree of canopy saturation such that:

$$E_C = PET \times G_{vf} \times \left(\frac{W_i}{W_{max}} \right)^n \quad (2.3)$$

Where W_i is the current canopy moisture content, always less than or equal to the vegetation-class defined maximum W_{max} .

The transpiration computation in ULM is similar to Noah's. It uses a Jarvis-type canopy resistance scheme (Jarvis, 1976), which is described in detail by Niyogi et al. (2008). Essentially transpiration, E_T , is a function of PET , reduced by the canopy resistance and scaled by saturation between zero and one, during wet and dry canopy conditions, respectively, such that canopy evaporation dominates in the former case. Therefore:

$$E_T = PET \times G_{vf} \times F_C \times \left[1 - \left(\frac{W_i}{W_{max}} \right)^n \right] \quad (2.4)$$

where F_C is the canopy resistance, which is derived empirically from four non-interacting environmental stress functions, each of which represents a statistical relationship between canopy resistance and: incident solar radiation, humidity, air temperature, and leaf water potential. The removal of transpiration water from the physical soil layer structure is weighted based on soil-class defined root-zone distributions.

2.3 Model testing and evaluation strategy

ULM was tested with respect both to its hydrologic prediction capabilities, and its ability to predict land-atmosphere moisture and energy fluxes. The evaluation strategy included comparisons of flux tower measurements of surface energy and moisture, point observations of soil moisture, as well as predicted and observed streamflows over catchments of varying size and hydroclimatic characteristics. To the extent possible, the study catchments and flux towers were collocated. The evaluation criteria included the ability to reproduce the observed diurnal cycle of turbulent heat and radiative fluxes, seasonal patterns of soil moisture, and timing and magnitude of streamflow variations. Our main objective in evaluation of ULM was to determine the ability of the model to produce plausible results with a set of *a priori* parameters from its parent models. The Noah parameters were obtained from the North American Land Data Assimilation System (NLDAS) which uses existing high-resolution vegetation and soil coverages derived from satellite and other remote sensing sources. The Sac parameters were derived by the method of Koren et al. (2003) which relates model parameters to soil texture characteristics. A secondary objective of this research was to develop strategies for geographic transfer of

ULM model parameters that account for differences in hydro-climatic conditions, and avoid the necessity for computationally intensive site-specific model calibration.

In an attempt to reduce the relatively large number of Sac parameters (13) that need to be estimated, we examined the quality of their *a priori* values within ULM (herein ULM_A) via individual parameter sensitivity tests at each study basin. These tests involve uniformly sampling each parameter over its plausible range of values, while holding all other parameters at their *a priori* value over the respective catchment. Comparing the resulting root mean squared error (RMSE) from these simulations with observed streamflow allows for a preliminary assessment of the quality of the *a priori* value and the sensitivity of the parameter to streamflow. The amplitude of RMSE variability associated with each parameter describes its sensitivity, while the quality of the *a priori* value itself is described by the proximity of its ensuing RMSE to the minimum RMSE over the sampled parameter space.

To further understand sensitivities and higher-order parameter interactions we employed a Monte Carlo search procedure with the ultimate aim of defining an improved set of parameters (herein ULM_M). Performance using these parameters was then compared with performance: (i) using strictly *a priori* parameters, (ii) by preserving adjusted values from a subset of only the 3 most sensitive model parameters while keeping the remaining parameters at their *a priori* value (herein ULM₃), and (iii) using the parent models (Noah and Sac). A Monte Carlo procedure was selected because other methods for parameter sampling, such as iterated fractional factorial design (IFFD), or Sobol's method (see Tang et al., 2007 for a complete discussion) require a prohibitively large number of samples (simulations) to adequately account for the effects of second order parameter interactions given the number of parameters (13) (e.g. $> 10^3$ simulations for IFFD, $> 8 \times 10^3$ simulations for Sobol's method). The Monte Carlo procedure varies all parameters simultaneously and randomly, thus having the potential to reveal higher order interactions with fewer simulations (in this case 250). We acknowledge that this approach is more approximate and less exhaustive than the systems mentioned above, but nevertheless it should capture the essence of each parameter's sensitivity given the random component. Finally, it should be noted that the emphasis here is not on extensive calibrations, but rather to show that ULM can produce plausible results with limited parameter tuning.

2.4 Study areas and data

Streamflow, soil moisture and flux tower sites were chosen to represent a range of elevation, climatic, soil, and vegetation conditions, subject to the availability of observation sites and the quality of data. To the extent possible, stream gauges and flux towers in close proximity to one another were selected to facilitate comparison of the streamflow and flux predictions. The selected study locations are shown in Figure 2.4.

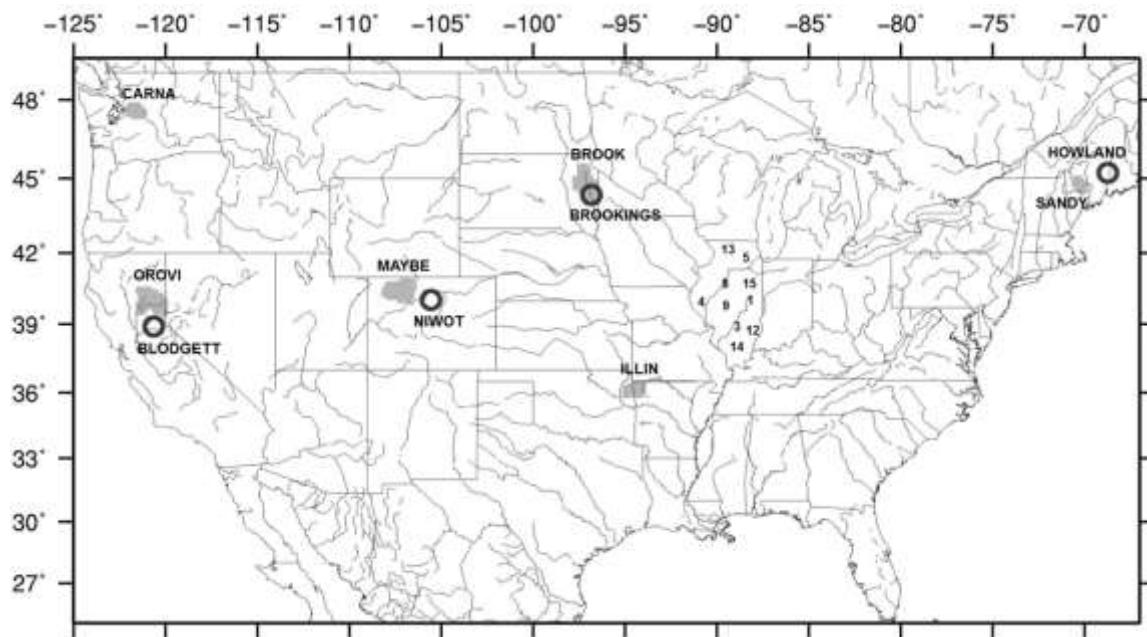


Figure 2.4: Location of study basins (shaded areas), flux tower sites (black circles), and ICN soil moisture stations (numbered).

2.4.1 Study basins

In addition to hydroclimatic and geographic diversity, selected stream gauge locations were either free of significant anthropogenic effects upstream (reservoir storage and/or diversions), or had naturalized flow data available (flows that would occur in the absence of upstream water management effects). In addition, two periods of at least 10 years were required for which quality assured streamflow data were available. The selected river basins are listed in Table 2.1, along with relevant information on the local environment and climate for each basin. Figure 2.5 summarizes mean monthly precipitation and streamflow for each basin.

Table 2.1: Description of river basins used in this study.

	Snoqualmie R. near Carnation	Illinois R. near Tahlequah	Yampa R. near Maybell	Big Sioux R. near Brookings	Sandy R. near Mercer	Feather R. near Oroville
Abbreviation	CARNA	ILLIN	MAYBE	BROOK	SANDY	OROVI
Location	Washington State (USA)	Oklahoma (USA)	Colorado (USA)	South Dakota (USA)	Maine (USA)	California (USA)
Latitude (°N)	47.56	35.92	40.43	44.18	45.01	39.98
Longitude (°W)	121.66	94.92	-107.27	96.74	70.78	120.78
Mean elevation (m.a.s.l.)	706	358	2385	540	378	1743
Basin area (km²)	1562	2484	8832	10354	1340	9390
Dominant vegetation type (UMD)	Evergreen Needleleaf Forest	Cropland	Grassland	Cropland	Wooded Grassland	Deciduous Needleleaf Forest
Climate	Maritime	Continental	Temperate Alpine	Continental	Humid Continental	Mediterranean
Seasonality of Precipitation	Peak in Winter	Peak in May; secondary peak in Autumn	Peak in March; secondary peak in Autumn	Peak in June	Nearly uniform, with peak in late autumn	Peak in Winter

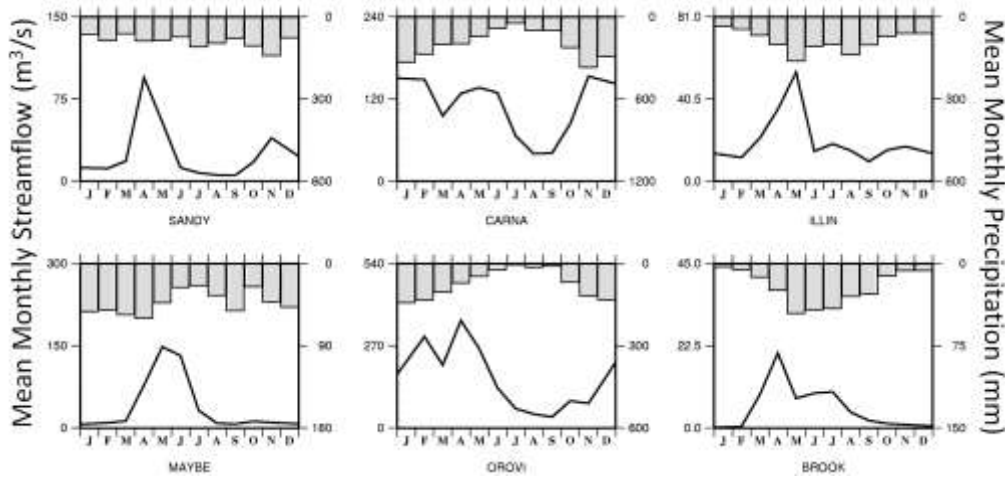


Figure 2.5: Mean monthly precipitation (right axis, bars) and streamflow (left axis, lines) for the 6 study basins.

For the three largest river basins, model forcing data were obtained from the Maurer et al. (2002) data set, which is a 1/8° latitude-longitude grid of the required model inputs derived from climatological station data (precipitation, daily maximum and minimum temperature). For smaller basins, such as CARNA, ILLIN, and SANDY (< 3000 km²), station data were

gridded to $1/16^\circ$ spatial resolution using the Maurer et al. (2002) approach to derive model forcings. For each basin, the model was run at the same resolution as the forcing data. For one of the stations (OROV) Bohn et al. (2010) conducted a rigorous statistical analysis of the naturalized streamflows (obtained from the California Department of Water Resources) and meteorological data, and found them to be in good agreement with respect to major storm and drought events. The other five basins are part of the Model Parameter Estimation Experiment (MOPEX – Schaake et al., 2006) for which naturalized (or minimally regulated) streamflow, mean areal precipitation, daily maximum and minimum temperatures had already been assembled. A major effort of MOPEX was to assemble a large number of high quality historical hydrometeorological and river basin characteristics data sets for a wide range of river basins ($500 - 10\,000\text{ km}^2$) for model development and understanding. The model forcings for the selected MOPEX basins were obtained as described above, however, we performed a post-processing adjustment to make the monthly average of the gridded temperature and precipitation values averaged over the basins match the mean-areal values produced by MOPEX. To assure consistency of daily and monthly values, the daily gridded values were adjusted by the ratio (precipitation) or difference (temperature) between the monthly means of the gridded data and the MOPEX mean areal values. Finally, to account for topographic effects, each model grid cell was subdivided into up to five elevation bands, depending on the elevation range within the grid cell. Within each band, the air temperature was lapsed to the band's average elevation using a lapse rate of 6.5° C/km and precipitation was redistributed to reflect the nonlinearity in precipitation with respect to topographic effects, as obtained from the PRISM data set (Daly et al., 1994).

2.4.2 Surface fluxes and soil moisture observations

Flux data were taken from the Ameriflux network, which consists of flux towers at approximately 50 sites (in the continental U.S.) that represent a range of hydroclimatic and ecological conditions. A central issue to flux measurement is energy balance closure. By construct, latent (λE) and sensible (H) heat fluxes must be balanced by net radiation (R_{net}), ground heat flux (G), heat storage change between the soil and the height of the flux measurement system (S), and other advected (source and sink) fluxes (A):

$$\lambda E + H = R_{net} + G + S + A \quad (2.5)$$

However, each of the terms is measured independently, so closure is not assured. Typically the advection term is small and can be neglected, leaving five main terms to be considered for energy balance closure. Latent and sensible heat fluxes are measured at the flux towers using the eddy covariance method, a direct, micrometeorological approach that relies on a simplification of the conservation equation (Baldocchi, 2003). Within the Ameriflux network, these fluxes are calculated at half hour intervals, as the time average covariance between the (essentially) instantaneous vertical wind speed fluctuations, w' , and the instantaneous scalar quantity, c' , (temperature, water vapor). Other quantities of interest measured at Ameriflux stations include: precipitation, net radiation and/or its components (downward and upward solar and longwave radiation), soil heat flux, soil moisture, and other micrometeorological variables. Specific details of Ameriflux measurement standards can be found at <http://public.ornl.gov/ameriflux/sop.shtml>.

Studies such as Baldocchi et al. (2000), Wilson et al. (2002), and Loescher et al. (2006) have examined potential error sources in eddy covariance measurements including those used in the Ameriflux network. These studies have reported energy imbalances on the order of 20% at stations across a wide range of vegetation and climate types.

The two criteria used in selecting flux tower sites were: (i) to use sites with a high degree of energy balance closure, and (ii) to select sites (where possible) in proximity to study basins described in section 2.4.1, that span a range of hydroclimatic conditions. Only sites with the maximum Ameriflux quality rating, LA , were selected. These data include quality-control flags and specify any gap filling algorithms that were applied to the final, processed data set (see e.g. Falge et al., 2001 for details). Table 2 summarizes the selected flux tower sites, including their respective principal investigators. An inspection of energy balance closure across these sites indicates < 20 % closure imbalance during the warm season at half hourly intervals (Figure 2.6), with the BLODGETT generally having greatest closure and HOWLAND having the least. Local observations of precipitation, air temperature, wind speed, and downward solar radiation were used to force model simulations at each flux tower site. Additional forcing variables not directly measured but required by the models were derived following the techniques described in section 2.4.1.

Table 2.2: Summary of characteristics of Ameriflux sites

	Blodgett Forest	Niwot Ridge	Brookings	Howland Forest
Location	California (USA)	Colorado (USA)	South Dakota (USA)	Maine (USA)
Latitude (°N)	38.89	40.03	44.35	45.20
Longitude (°W)	120.63	105.55	96.84	68.74
Elevation (m)	1315	3050	510	60
Vegetation type	Ponderosa Pine	Sub-alpine mixed coniferous	Temperate Grassland	Spruce-Hemlock mixture
Climate	Mediterranean	Temperate	Humid Continental	Temperate Continental
P.I.	Dr Allen Goldstein	Dr. Peter Blanken	Dr. Tilden Meyers	Dr. David Hollinger
Citation	Goldstein et al., 2000	Turnipseed et al., 2002	NA	Hollinger et al., 1999

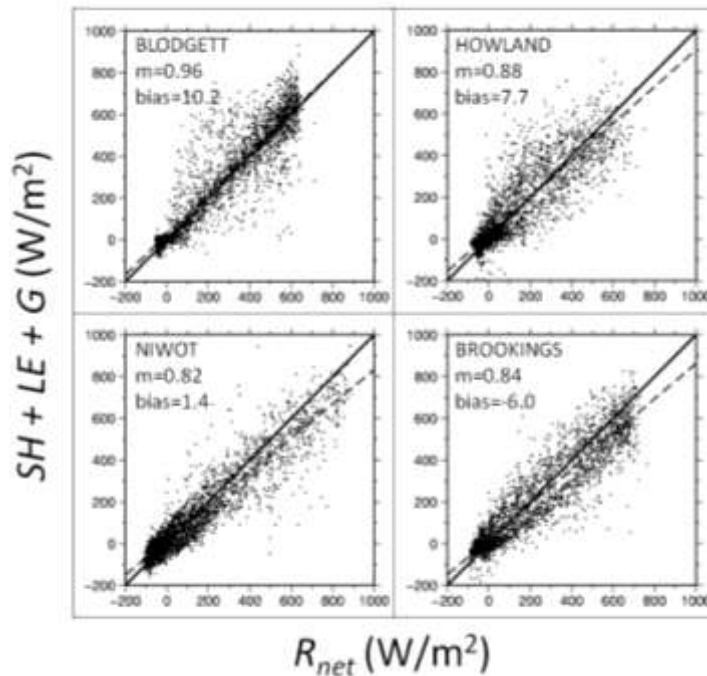


Figure 2.6: Scatter plots of observed energy balances (sensible (SH) plus latent (LE) plus ground heat flux (G) versus net radiation (R_{net}). Shown on each plot are the slope of the line of best fit (m) and the bias (W/m^2), where a slope of $m=1$, and bias = 0 would characterize zero energy balance closure error. A single summer is shown for each site, namely Blodgett Forest (2004), Niwot Ridge (2006), Brookings (2005), and Howland (2001).

Only two of the flux towers produced usable soil moisture data. For this reason, soil moisture simulations were compared with 10 stations from the Illinois Climate Network (ICN; Hollinger and Isard, 1994) that are summarized in Table 2.3. Previous studies have found these data to be of good quality for purposes of model evaluations, given the range of measurement depths and completeness of data record (e.g. Mishra et al., 2010, Maurer et al., 2002).

Table 2.3: Summary of characteristics of Illinois Climate Network stations.

Site Number	Name	Latitude (°N)	Longitude (°W)	Elevation(m)
1	Bondville	40.05	88.22	213
3	Brownstown	38.95	88.95	177
4	Orr Center	39.80	90.83	206
5	De Kalb	41.85	88.85	265
8	Peoria	40.70	89.52	207
9	Springfield	39.52	89.62	177
12	Olney	38.73	88.10	134
13	Freeport	42.28	89.67	265
14	Rend Lake	38.13	88.92	130
15	Stelle	40.95	88.17	213

2.5 Model validation and discussion

In this section, we compare ULM simulations with observations and with Noah and Sac simulations. The analysis begins with a comparison of the models' surface fluxes, followed by an evaluation of their soil moisture predictions. Finally, we compare the models' streamflow predictions, along with an analysis of parameter sensitivities.

2.5.1 Surface fluxes

Given Noah's history as the land scheme in coupled land-atmosphere models, the ability for ULM to, at minimum, match Noah skill in simulating surface energy fluxes is of key importance. Figure 2.7 summarizes the observed diurnal cycles of fluxes at the four flux towers BLODGETT, NIWOT, BROOKINGS, and HOWLAND that are in the vicinity of OROVI, MAYBE, BROOK, and SANDY basins, respectively. The net radiation cycle encompasses variations in surface albedo (fraction of reflected shortwave radiation), surface temperature (quantity of emitted longwave radiation) and emissivity. Sensible and latent heat fluxes describe how much of the available energy goes into heating the near-surface air and how much goes into changing the phase of near-surface water, both are also affected by the moisture state of the soil through its effect on soil temperature (sensible heat flux) and saturation which drives evaporative efficiency (latent heat flux). Ground heat flux is affected by soil moisture, through its effect on soil heat capacity and thermal conductivity. Recognizing the nature and potential magnitude of flux measurement errors,

we focus on major overall features, such as the timing and relative magnitude of the diurnal cycles, and less on accumulated values.

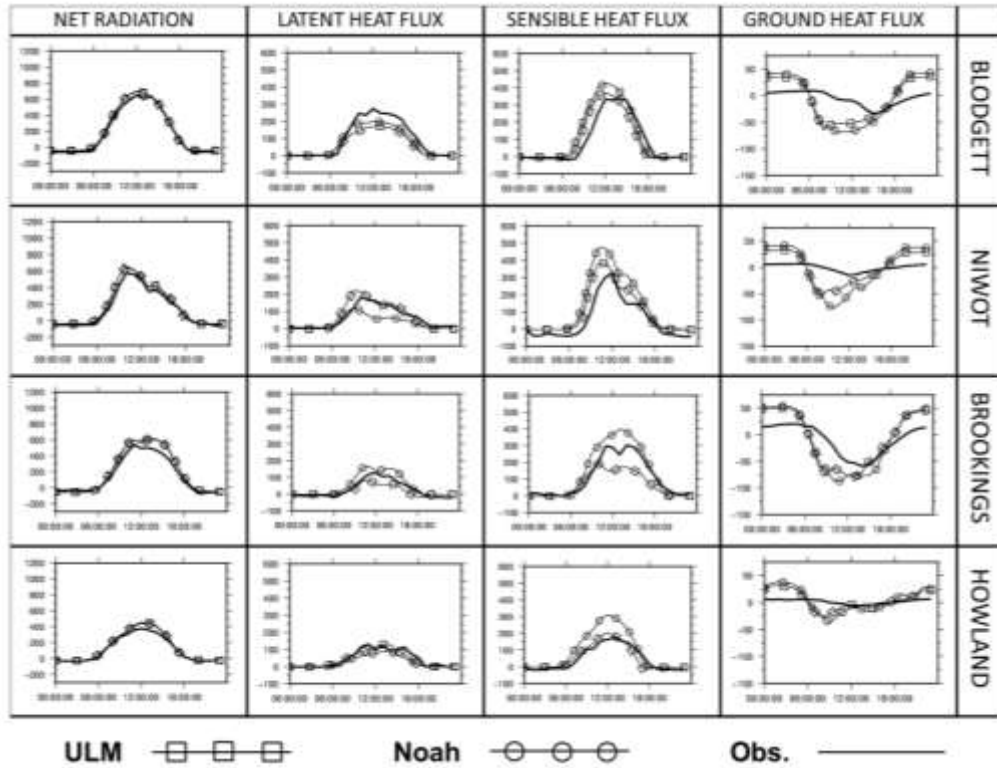


Figure 2.7: Mean diurnal fluxes (W/m^2) for ULM during summer for 4 Ameriflux sites shown at 30-minute intervals for the years with greatest energy balance closure at Blodgett Forest (2004), Niwot Ridge (2006), Brookings (2005), and Howland Forest (2001).

At all flux towers, both Noah and ULM capture the net radiation cycle well, with the main exception being BROOKINGS and HOWLAND where both models slightly over predict the peak magnitude. Latent and sensible heat fluxes were slightly more variable between the models. The timing of peak latent heat flux was generally predicted correctly, however its magnitude was under predicted at BLODGETT and HOWLAND by both models, while it was slightly over predicted by Noah and under predicted by ULM at BROOKINGS; the opposite was true at NIWOT. Sensible heat flux timing was better predicted at the lower elevation sites (BROOKINGS, HOWLAND); with a noticeable disparity in sensible heat magnitude for both models throughout the diurnal cycle at NIWOT, which was by far the windiest site. ULM matched sensible heat magnitudes equally or slightly better than Noah at each site. The ground heat flux simulations had the poorest match between simulations and observations across the four sites. This is the result of two features: (i) ground heat

flux measurements are notoriously prone to errors. Particularly at BLODGETT, NIWOT, and HOWLAND the magnitude of observed ground heat flux was extremely small compared to other fluxes, and (ii) regardless of measurement errors, peak timing of observed ground heat flux was lagged compared with other flux peaks, likely due to heat storage. Altogether, the model ground heat flux predictions were too large (small) during day (night) compared with observations.

Our overall assessment of these comparisons is that ULM satisfies the minimum stated objective of performing comparably to Noah at the flux tower sites, although a few notable disparities persisted between simulated and observed values for both models. Taken over all the flux towers, ULM had slightly smaller average bias than Noah for each individual flux. For both models, the net radiation cycle was better captured at the alpine versus non-alpine sites, the timing of peaks in latent and sensible heat fluxes was generally better at the non-alpine sites, while ground heat flux had the poorest match with observations – although it is not clear whether the reason is model performance or observation errors, or both

2.5.2 Soil moisture

At 2 of the 4 flux towers, continuous soil moisture measurements overlapped the flux measurement periods which allowed comparisons of modeled and observed soil moisture. Figure 8 shows daily time series of soil moisture for BLODGETT and NIWOT over a 7 month period, illustrating the evolution of soil moisture throughout the warm season. The BLODGETT site, which experiences very dry summers, exhibits two successive periods of more or less monotonic decline in soil moisture beginning near the middle of June, without a significant increase until the last half of September. An important difference between Noah and ULM at this site is that ULM captures the two separate periods of decreasing soil moisture, particularly in the near-surface layers, whereas Noah predicts a longer single period of declining soil moisture throughout the summer. ULM's soil moisture evolution is dominated by direct soil evaporation in the early part of summer, which proceeds until the upper zone soil moisture becomes stressed, after which transpiration is dominant. During this second period, the rate at which soil moisture is extracted is reduced because the soil is under greater stress (i.e. near wilting) and thus soil moisture remains nearly constant. On

the other hand, Noah combines direct soil evaporation and transpiration (from all layers) into its solution for Richard's equation and both of these soil moisture processes proceed together. At greater depth, ULM soil moisture is greater than observed, due likely to an excessively large soil moisture reservoir and perhaps inadequate representation of the root-density which affects soil moisture removal via transpiration at this depth.

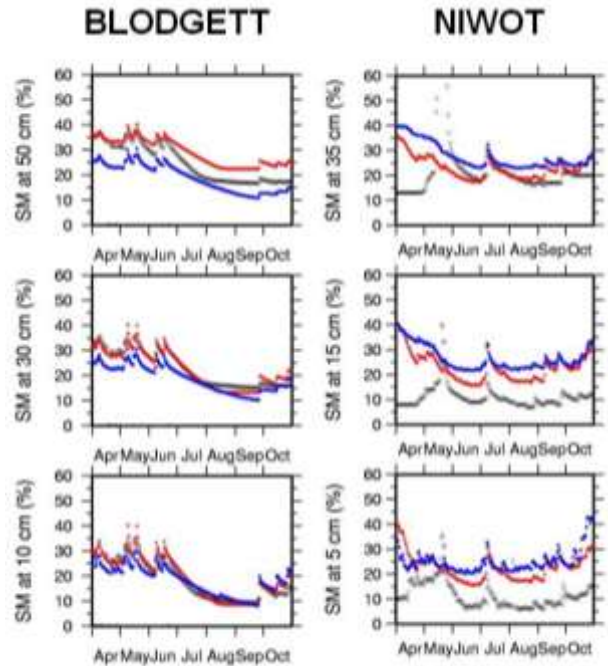


Figure 2.8: Observed (black circle) volumetric soil moisture, compared with ULM_A (red circle) and Noah (blue circle) during the warm season at Blodgett forest (2004) and Niwot Ridge (2006).

The NIWOT site has a less uniform progression of soil moisture as compared with the BLODGETT warm season, since frequent precipitation events and even lingering snowmelt supply the soil column with new moisture during spring and summer. The late May spike in soil moisture from a snowmelt event was missed in the snow model that is common to Noah and ULM. On the other hand, both models capture a large precipitation event in early July relatively well, in addition to several smaller events in August and September. However, the magnitudes of both Noah and ULM near surface soil moisture are too high. This may be due in part to problems with the soil texture data, such as porosity and inferred wilting point. Furthermore, the sensor appears to be in error during

most of April, during which anomalously low and nearly constant soil moisture readings were produced.

The mean soil moisture from 10 ICN stations is plotted in Figure 2.9. Because these data were available at approximately weekly intervals, a monthly analysis was performed, consistent with other studies that have used these data (see section 2.4.2). Overall, ULM has smaller bias than Noah across the 10 stations. Evaluation of the total column (~ 2.0 m) soil moisture and its monthly change allows for a comparison with the Sac’s conceptual storages. The change in monthly soil moisture provides a representation of how much water is available for plants and runoff versus the amount going to storage. With respect to the observed seasonal cycle, Noah (ULM) slightly over- (under) predict the total range of variability, while Sac significantly lacks seasonal variability. Overall, ULM performs best over the ICN stations with roughly equal performance to Noah in terms of the models’ representation of seasonal variations. ULM, however, had the least overall bias.

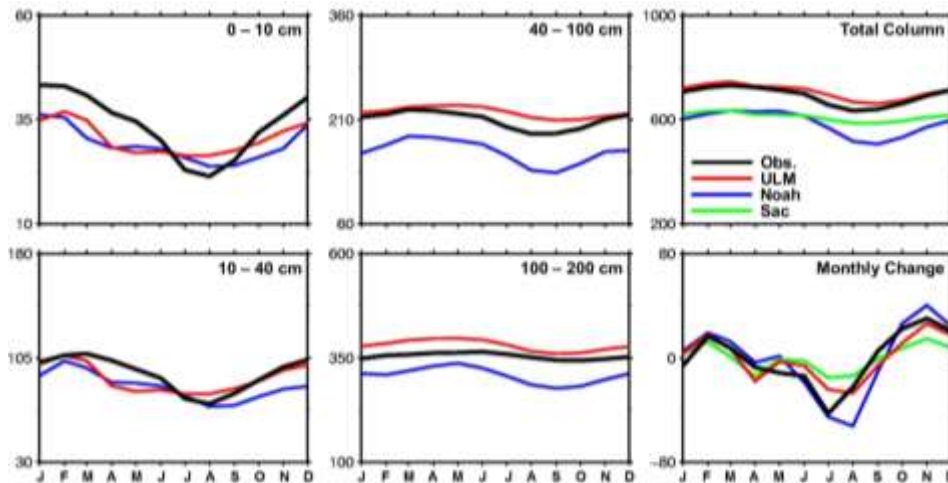


Figure 2.9: Illinois Climate Network (ICN) soil moisture data in units of millimeters of water equivalent (observations shown in black); where the leftmost 4 plots show the mean monthly soil moisture for the 4 model soil layers of ULM (red), Noah (blue), while the upper right plot shows the entire soil column, including Sac (green), and the lower right plot shows the change in monthly soil moisture for the entire soil column.

2.5.3 Streamflow and parameter sensitivities

Streamflow represents an integrated basin response to precipitation and evaporative demand. Given the model forcings, variability in simulated streamflow can result from a multidimensional space of soil parameter combinations. To address this problem, Sac, which is an operational model, typically is calibrated in practice. Although ULM uses Sac

soil parameters, the ULM model structure calls into question the extent to which Sac parameters are transferrable. Here we attempt to reduce the relatively large number of Sac soil parameters (13 – defined in Table 2.4) to a smaller set that control the bulk of simulated streamflow performance. Figure 2.10 shows the most sensitive soil parameters in each basin in terms of local RMSE, in the context of the corresponding *a priori* parameter values. Common among all basins except CARNA was sensitivity to the parameter UZTWM which plays a major role in controlling runoff and ET, as it represents the non-gravity-driven water content within the upper soil zone. In both ULM and Sac, UZTWM capacity must be filled before runoff and infiltration can occur, while its relative saturation linearly controls the rate of evaporation from the upper soil zone. Notable sensitivities were also exhibited to the parameters that control subsurface flow among the upper and lower zones (UZK, LZPK, LZSK). The results of the comparisons suggest that the *a priori* parameters for OROVI, SANDY, ILLIN, and BROOK are close to the values associated with minimum RMSE, whereas the *a priori* values for CARNA and MAYBE, are farther from minimum RMSE.

Table 2.4: List of Sac soil parameters and their plausible ranges

Parameters	Unit	Description	Plausible Range
UZTWM	mm	Upper zone tension water maximum storage	1.0 - 300
UZFWM	mm	Upper zone free water maximum storage	1.0 - 300
UZK	day ⁻¹	Upper zone free water lateral depletion rate	0.05 – 0.75
ZPERC		Maximum percolation rate	1.0 - 350
REXP		Exponent of the percolation curve equation	0.0 – 5.0
LZTWM	mm	Lower zone tension water maximum storage	1.0 - 500
LZFSM	mm	Lower zone free water supplemental maximum storage	1.0 – 1000
LZFPM	mm	Lower zone free water primary maximum storage	1.0 – 1000
LZSK	day ⁻¹	Depletion rate of the lower zone supplemental free water storage	0.01 – 0.8
LZPK	day ⁻¹	Depletion rate of the lower zone primary free water storage	0.0001 – 0.025
PFREE		Percolation fraction going directly from upper zone to lower zone free water storages	0.0 – 0.8
PCTIM		Impervious fraction of the ground surface	0.0 – 0.1
ADIMP		Maximum fraction of additional impervious area caused by saturation	0.0 – 0.45

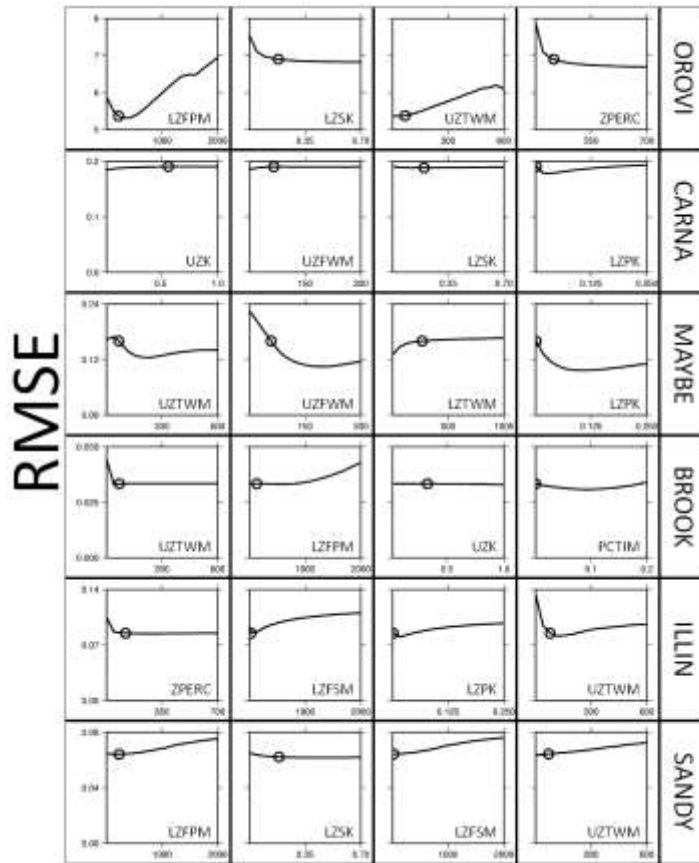


Figure 2.10: RMSE between simulated and observed streamflow (1960 – 1969) based on 15 parameter values varying uniformly within their plausible range (Table 2.3) plus an additional simulation using the *a priori* value for that parameter (black circle). Shown are only the most sensitive parameters for each basin based on this method.

Despite the model performance inferred from individual RMSE minimizations, the hydrographs produced by ULM_A (Figure 2.11) do not adequately match observations, with the exceptions of OROVI and SANDY. This warrants further analysis of parameter sensitivities to identify the effects of higher-order parameter interactions on simulated streamflow. Following a Monte Carlo approach, wherein all 13 soil parameters were allowed to vary simultaneously within their plausible ranges over 250 simulations per basin, a clearer maximum envelope of model efficiency evolved. Model performance as measured by Nash-Sutcliffe efficiency (NSE – Nash and Sutcliffe, 1970) which effectively is the MSE normalized by the variance, was selected for this extended analysis since it facilitates inter-basin performance comparisons. Figure 2.11 shows that an improved set of ULM simulations results from use of the parameter set obtained by the Monte Carlo search procedure (ULM_M), which shows notable improvements over ULM_A . Next, the 3

parameters to which NSE was most sensitive were identified for each basin (Figure 2.12); these parameters (ULM_3) are responsible for most of the increase in NSE for ULM_M relative to ULM_A .

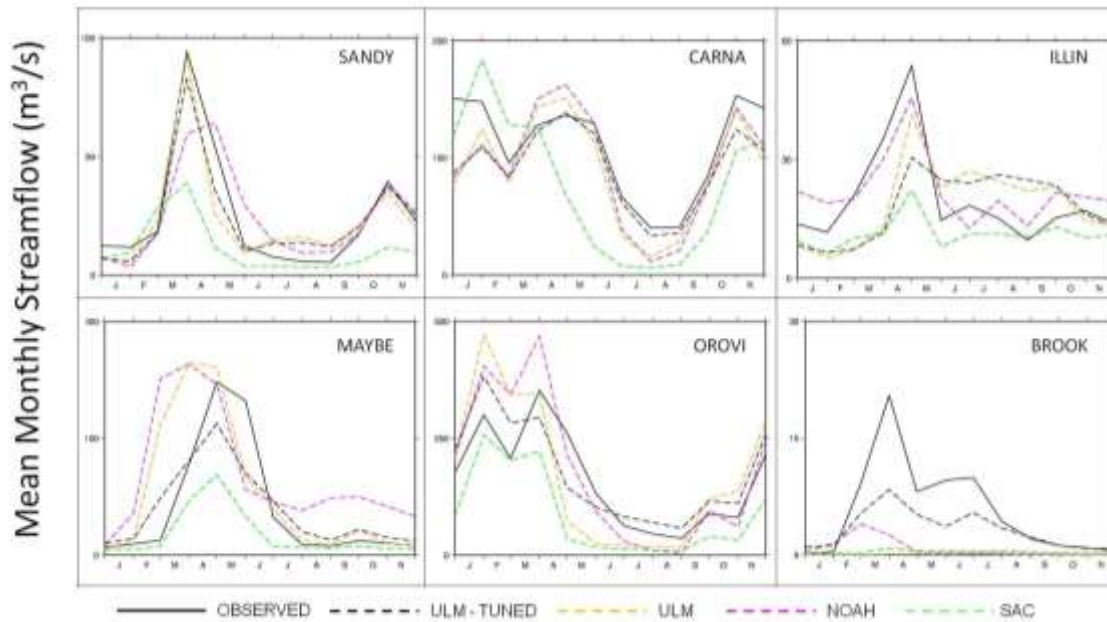


Figure 2.11: Mean monthly streamflows (1960 – 1969) for ULM using *a priori* parameters (ULM_A), ULM with parameters tuned towards maximized model efficiency (ULM_M), Noah, Sac, and observations.

Model Efficiency x -1

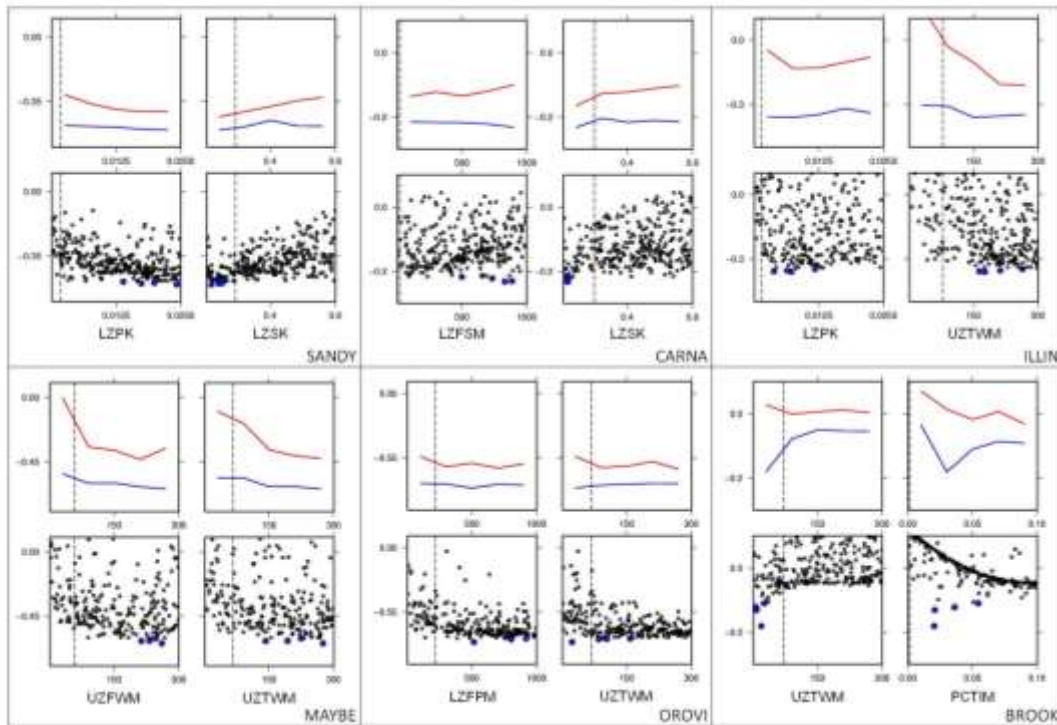


Figure 2.12: NSE values (multiplied by -1 for consistency with RMSE minimizations) corresponding to simulated versus observed streamflow for variation of individual parameter values following a Monte Carlo approach. For each basin, the scatter-plots of the two most sensitive parameters are shown (lower plots) with the best 4 simulations circled in blue for ease of viewing. The upper plots show trends in the data grouped into 50-simulation-bins, with bin minima in blue showing an envelope of parameter sensitivity and bin means in red. The ADIMP parameter (not shown) was found to be highly sensitive for all basins with an approximate minimum value of 0.225.

The mean monthly hydrographs presented thus far illustrate the general relationship between modeled and observed flows, however, for the two basins with particularly sporadic, peaked streamflow (ILLIN and BROOK); an examination of daily streamflows (Figure 2.13) over a single water year provides additional insights. ILLIN was part of the DMIP study (Smith et al., 2004; Reed et al., 2004) wherein a number of well-known models (including Noah and Sac) had relatively poor average NSE of approximately 40%, and required calibration to achieve average efficiencies of approximately 65%. This was due in part to the challenging hydroclimatology, from a hydrologic-modeling perspective, which consists of extended dry periods followed by high intensity rainfall. These peaked conditions are apparent in the daily hydrograph (Figure 2.13a). Noah underestimates high flows with overly-broad peaks and overestimates low-flows, whereas Sac and ULM_A simulate peaks better, but generally underestimate low flows. ULM_M shows modest improvements in both peak and low-flow response relative to ULM_A. A major part of the

improvement in ULM_M performance resulted from an increase in UZTWM, which dampens the rapid storm runoff response, and increases low-flows slightly as well.

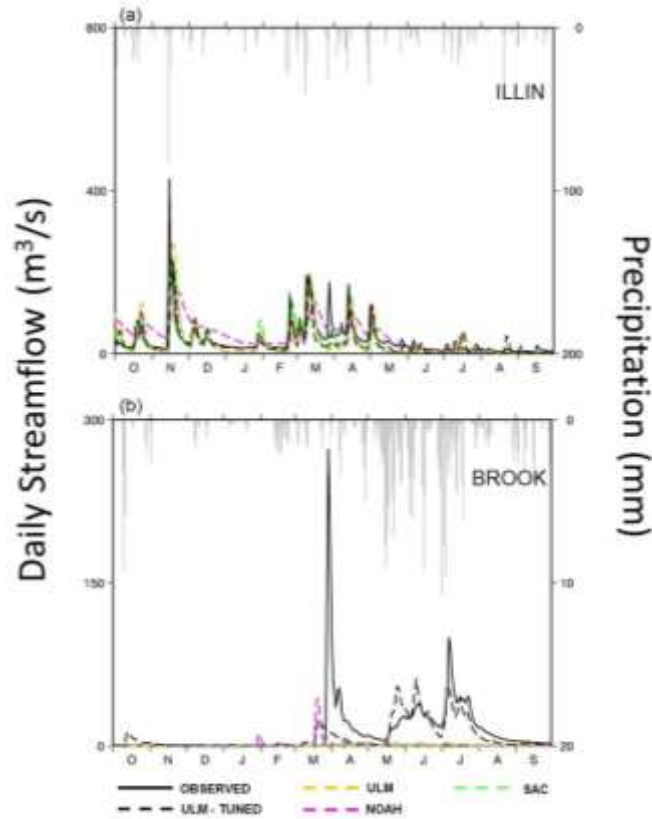


Figure 2.13: Daily streamflows and precipitation over the 1964 water year for the ILLIN (a) and BROOK (b) basins. Observed flow (solid black), ULM_M (dashed black line), ULM_A (dashed orange line), Noah (dashed pink line), and Sac (dashed green line) are included. These two basins provided the greatest challenge in modeling with relatively sporadic precipitation, and sharp streamflow peaks (BROOK: end of March snowmelt and soil thaw streamflow spike was poorly captured by the snow model and frozen soil physics).

BROOK is also characterized by low streamflow for most of the year, followed by large surges in late spring and early summer, complicated by the effects of snowmelt and frozen soil thawing which are not present (or negligible) at ILLIN. It has the lowest annual precipitation of all study basins, and in part for this reason, all models struggle to capture the peak flow response (Figure 2.13b) that is somewhat masked in the multi-year average, as year-to-year differences in timing appear as a broad peak (see Figure 2.11). Most notably, a substantial decrease in UZTWM is needed to increase model peak-response as confirmed in both the parametric scatter plot in Figure 2.12, and the daily hydrograph (Figure 2.13b).

The impact of snowmelt is more visible in the hydrographs of the other four basins. MAYBE has the lowest annual precipitation of these four and thus the soil response to snowmelt is of great importance (since much of the winter precipitation is released in spring as snowmelt). Noah and ULM_A have flashy response to the large spring snowmelt, while an increase in the upper-zone storage in ULM_M, buffers the runoff rate to more closely match observations. Sac, which uses a different snow model than Noah and ULM, has similar streamflow timing to both ULM_M and observations, however it has higher ET rates (not shown), which ultimately result in an overall reduced hydrograph. Both the OROVI and CARNA basins receive most of their precipitation between November and March, of which a majority is stored as snow that ultimately runs off in the warm season. The large surplus of water during melt season for these basins makes the larger lower zone storages of increased consequence for accurately simulating baseflow, runoff, and ET rates into the warm season. The wettest basin (CARNA) shows a marked improvement in streamflow simulations when the lower zone hydraulic conductivity LZSK is reduced to attenuate baseflow. Similarly, an increase in the lower zone storage LZFFM for the OROVI basin provides for more realistic spring and early summer streamflow. Precipitation over the SANDY basin is distributed nearly evenly throughout the year with a slight peak in autumn. However, the storage and release of winter precipitation as snowmelt in the spring is the dominant seasonal streamflow feature. It follows that a reduction in LZSK attenuates the snowmelt response to yield a modest improvement in streamflow in ULM_M. Sac gets the peak timing correct, however with flows that are generally too low, while the Noah peaks are too broad and low flows are overestimated. One way to organize the importance of model parameters by basin is through classification by an aridity index (*AI*); a metric first proposed by Budyko (1974):

$$AI = R_{net,ann}/LP_{ann} \quad (2.6)$$

Where $R_{net-ann}$ is the annual average net radiation, L is the latent heat of vaporization, and P_{ann} is the mean annual precipitation, such that LP_{ann} is the amount of energy needed to evaporate the available precipitation, P_{ann} . As *AI* exceeds 1, a basin becomes increasingly arid (or water limited), whereas for *AI* less than 1 radiation becomes limiting (increasingly moist), while the potential evaporation is theoretically reached at $AI = 1$. Comparing the respective *AI* values for each basin and its most sensitive parameters in Table 2.5 highlights

the importance of upper zone parameters for more arid basins, and lower-zone parameters for wetter basins. For water-limited basins, UZTWM plays a critical role in partitioning infiltration and runoff, as well as controlling direct soil evaporation, while for all basins, an increase of the allowable area that becomes impermeable during soil saturation (ADIMP) was beneficial in capturing streamflow timing related to large moisture input events, such as storms and snowmelt. Wetter basins benefited from an adjustment in the rate of baseflow response from the larger lower-zone reservoir, where LZSK was lowered from its *a priori* value and LZPK was increased.

Table 2.5: Aridity indices (AI) for each study basin and the key parameters for improved streamflow, where a decreasing parameter is given in parentheses. Supplemental to the parameters listed, the ADIMP parameter was increased to 0.225 for all basins.

Basin	Annual AI	Seasonal AI				Key Parameters
		DJF	MAM	JJA	SON	
CARNA	0.3	-0.2	1.7	8.1	0.6	(LZSK), LZFSM
SANDY	0.7	-0.9	3.3	5.5	1.4	(LZSK), LZPK
ILLIN	1.0	2.2	4.5	6.5	2.8	UZTWM, LZPK
OROVI	1.4	0.1	7.2	64.8	5.0	UZTWM, LZFP
MAYBE	1.6	-0.7	6.3	21.4	5.0	UZTWM, UZFWM
BROOK	3.0	-2.0	15.6	13.9	7.8	(UZTWM), PCTIM

Table 2.6 lists the NSE for ULM_A, ULM_M, ULM₃, Noah and Sac, computed for the six study basins for both training and evaluation periods (i.e. 12 cases). Beginning with the simulations using only *a priori* parameters (ULM_A, Noah, Sac), ULM_A scored highest 4 times, the median 6 times and the lowest 2 times. The latter cases were for the same basin (BROOK – the most arid basin) for which none of the *a priori* simulations performed distinctively better than climatology, so this was somewhat of an outlier. Considering the entire set of simulations in Table 2.6, ULM_M was the best model 9 times, ULM₃ was best twice, and Sac was best once. ULM₃ was capable of realizing much of the performance gains from ULM_M for most basins, including 3 exceptions where it outperformed ULM_M. We attribute these exceptions to the random component in the ULM_M parameter set (inherent in the Monte Carlo procedure), whereas ULM₃ used *a priori* values for less-sensitive parameters that performed better in these cases. Sac outperformed all models during the validation period in the snowmelt-dominated MAYBE basin, for which Sac’s snow model was particularly well suited.

Table 2.6: Summary statistics: Nash-Sutcliffe model efficiencies (in %) for training (1960 – 1969) and validation periods (1990 – 1999) for the Noah, Sac, and ULM models with a priori parameters (ULM_A), with a maximization of efficiency through a Monte Carlo experiment (ULM_M), and through adjusting only three parameters from their a priori values (ULM₃) based on sensitivity and climate. Daily statistics are non-parenthesized and monthly statistics in parentheses. Cases where ULM₃ scored higher than ULM_M for the respective period are bolded and any model scoring higher than ULM_M was underlined.

Basin	Training period					Validation period				
	ULM _A	ULM _M	ULM ₃	Noah	Sac	ULM _A	ULM _M	ULM ₃	Noah	Sac
SANDY	37.2 (81.2)	51.2 (83.2)	49.3 (81.7)	32.3 (74.4)	13.1 (22.1)	27.7 (71.7)	38.7 (70.8)	40.5 <u>(75.0)</u>	25.3 (52.9)	20.0 (38.9)
CARNA	0.5 (3.5)	23.2 (50.1)	21.0 (49.6)	-5.8 (-6.5)	-13.3 (12.4)	1.8 (54.5)	22.2 (57.5)	20.8 (54.3)	-5.5 (48.1)	-4.8 (36.9)
ILLIN	15.1 (67.0)	36.9 (69.3)	31.9 (52.8)	11.7 (23.1)	26.7 (54.8)	14.5 (64.3)	48.2 (76.8)	42.1 (64.3)	22.0 (69.2)	34.7 (66.3)
MAYBE	-12.8 (-4.7)	64.3 (74.3)	67.8 <u>(76.9)</u>	-32.1 (-22.6)	45.6 (26.1)	-40.6 (-6.2)	43.3 (57.3)	42.0 <u>(62.3)</u>	-98.0 (-28.7)	<u>47.1</u> (38.4)
OROVI	(46.9)	(81.4)	(59.3)	(57.7)	(38.7)	(64.5)	(80.0)	(71.7)	(46.7)	(70.0)
BROOK	-11.0 (-22.1)	18.2 (46.6)	5.4 (2.8)	2.2 (-10.1)	-8.0 (-24.9)	-29.1 (-47.1)	5.7 (-5.9)	-15.3 (-34.5)	-27.1 (-43.9)	-34.7 (-56.5)

In summary, ULM_A performed comparably or slightly better than Noah and Sac for the wetter basins, whereas it was generally on par or slightly poorer for the drier basins. With several, or all parameters estimated (ULM₃ and ULM_M, respectively) significant improvements were realized for all basins with the largest occurring for the drier basins. The parameter adjustments of ULM_M and ULM₃ are underscored because unlike Noah and Sac, ULM does not yet have an established set of default (or *a priori*) parameters. Such a parameter set depends in large part on the dynamic equilibrium of model soil moisture, which itself is dependent on the ET scheme, which come from Sac and Noah, respectively. Therefore, the potential advantage of the model structure change was offset by the lack of customized ULM-specific parameters for the ULM_A comparisons.

An experiment was conducted in which the parameter adjustments from ULM₃ and ULM_M were transferred to corresponding flux tower parameter sets, to attempt to improve model results for both surface fluxes and soil moisture (where applicable). However, the resulting simulations were not conclusively improved by this experiment, calling into question the merit of the parameter transfer strategy. In addition, comparing the seasonal (JJA) and annual AI values from basin to point, there were notable discrepancies

(BLODGETT/OROVI: AI_{JJA} = 65.7/64.8, AI_{annual} = 0.8/1.4; NIWOT/MAYBE: AI_{JJA} =

9.1/21.4, $AI_{\text{annual}} = 1.5/1.6$; HOWLAND/SANDY: $AI_{\text{JJA}} = 4.7/5.5$, $AI_{\text{annual}} = 0.7/0.9$; BROOKINGS/BROOK: $AI_{\text{JJA}} = 8.7/13.9$, $AI_{\text{annual}} = 1.5/3.0$). The apparent lack of transferability for Sac parameters is consistent with the findings of Gan and Burges (2006) and also follows the findings for other models (e.g. Heuvelmans et al., 2004, Abdulla and Lettenmaier, 1997). Alternate approaches likely will be required for effective parameter transferability and regionalization of ULM.

2.6 Conclusions

The objective of this work was to assess the potential of ULM to improve upon the weaknesses of its parent models, Noah and Sac, while taking advantage of their respective strengths. Model performance was examined in ways relevant to the typical uses of these models, including prediction of land-atmosphere moisture and energy fluxes and streamflow. We established a default set of soil parameters for ULM which we expected would perform differently from the Noah and Sac *a priori* values given an alternate equilibrium state within the new model structure. Finally, we evaluated a simple approach for transferring parameters estimated on the basis of basin streamflow prediction performance for energy and moisture flux predictions.

Our key findings are:

- (i) On the basis of observed flux data from 4 Ameriflux sites, the alternate soil moisture states of ULM result in diurnal variations of surface fluxes that are on par or modestly superior to Noah (Sac does not predict moisture or energy fluxes other than evapotranspiration and runoff).
- (ii) The nonlinearity of observed soil drying was better captured by ULM (as compared with Noah), whereas soil moisture response during wetter periods was more comparable between models. ULM had the smallest bias in a 10 site, multi-year soil moisture comparison. ULM and Noah comparably matched the observed seasonal cycle, with Sac's seasonality notably too small.
- (iii) ULM_A generally out-performed the Noah and Sac models over wetter basins, however performance was more variable for drier basins, for which parameter adjustments were required to achieve competitive performance.

- (iv) Much of the streamflow accuracy improvements achievable by calibration (ULM_M) can be realized by adjusting only 3 parameters (ULM₃), while leaving the remaining parameters at the *a priori* values of the parent models (Noah and Sac).
- (v) For drier basins, simulated streamflow was generally most sensitive to upper soil zone parameters, while the opposite was generally true for wetter basins.

Overall, ULM performance was encouraging. Parameter adjustments were ultimately needed to improve simulations comprehensively relative to the parent models. However, this has to be tempered by the fact that a suitable set of default (*a priori*) parameters has not yet been established for ULM, and the *a priori* parameters of its parent models may not be fully representative of the alternative quasi-equilibrium state within the new model structure. Work remains to find a reliable set of *a priori* parameters for ULM to further improve simulations of both moisture fluxes (streamflow and soil moisture) and energy fluxes without compromising one for the other. In its present form, ULM could be applied for any simulations for which Noah and Sac are currently used, with essentially the same capabilities for data assimilation and coupling as Noah. Additional testing will be required to evaluate the impact of ULM on atmospheric feedbacks and lateral moisture redistribution. Finally, further examination of parameter transfer strategies across gradients of vegetation, topography, soils, and climate is in order that will make ULM more applicable over large areas without the need for site-specific parameter estimation.

III. MULTI-CRITERIA PARAMETER ESTIMATION FOR THE UNIFIED LAND MODEL

This chapter has been published as a discussion paper in *Hydrology and Earth System Sciences* (Livneh and Lettenmaier, 2012).

3.1 Introduction

The evolution of land surface models (LSMs) towards increasingly complex representations of hydrologic and biophysical processes requires special attention to the fidelity of the models in partitioning water and energy budget components. The traditional validation of models using observations of a single prognostic variable can result in model predictions that are inherently biased towards that variable (McCabe et al., 2005). The evaluation of multiple model outputs (as opposed to single-output analysis, such as streamflow) has received increasing attention (e.g. Gupta et al., 1999, Crow et al., 2003, McCabe et al., 2005, Khu et al., 2008, Werth and Guntner, 2010, Milzow et al., 2011). Among the variables other than streamflow that have been used for LSM evaluation are evapotranspiration (Nandagiri, 2007), surface heat fluxes (Gupta et al., 1999; McCabe et al., 2005), hydrochemical and isotope tracers (Son and Sivapalan, 2007; Lischeid, 2008; Birkel et al., 2010), land surface temperature (Crow et al., 2003; McCabe et al., 2005), snow water equivalent (MacLean et al., 2010), terrestrial water storage (Werth and Gunter, 2010; Milzow et al., 2010), and water table level (Khu et al., 2008). The more frequent use of multivariate observations is attributable in part to their growing availability. Some satellite-based observations now have periods of record exceeding a decade for single sensors, and multiple decades for some multi-sensor merged records.

In the context of parameter estimation, multi-criteria analyses can aid in addressing the issue of equifinality (Beven and Freer, 2001). The equifinality problem arises when different parameter sets result in similar model performance. One approach to reducing equifinality issues and quantifying uncertainties in model calibration is the Generalized Likelihood Uncertainty Estimation (GLUE) framework of Beven and Binley (1992), which can aid in selection of model calibration parameters through estimating the likelihood that each parameter set is the true predictor of the system. A distribution of likelihoods among many parameter values is then generated and used to define uncertainties and select

parameters. Herein we consider an alternative calibration methodology (detailed in section 3.4) that selects parameters via ancillary objective functions. After identifying several top-performing sets of model parameters, the addition of observational sources is used to constrain parameter values – i.e. multivariate performance analyses. This reduces the number of similar feasible parameter sets to allow selection of a single best parameter set and hence produce robust parameter estimates. Robust model parameters are especially important when models are used to predict outcomes for model forcings outside the range observed in the model parameter estimation (calibration) period. Interannual variability of streamflow regime is one such example, which provides a basis for the investigation of potential future changes in river discharge that might result from climate or land-use change (Kingston et al., 2011). Robust model parameters are also essential for examining the importance of spatial and temporal scale on land surface response. Spatial scale can, for instance, determine the nature of environmental impact assessments (João, 2002), and the categorization of droughts (Shukla et al., 2011), but also determine how localized hydrologic events propagate through a larger system (for instance, flash flooding from tributary catchments as it affects the hydrologic response of a much larger region). The accurate modeling of scale effects ultimately aids in decision making and issuing timely warnings.

3.2 Modeling context

The Unified Land Model (ULM – Livneh et al., 2011) is the LSM used in this study. ULM is essentially a merger of two widely used models: the Noah LSM (Ek et al., 2003; used in most of NOAA’s coupled weather and climate models), and the Sacramento soil moisture accounting model (Burnash et al., 1973; used for hydrologic prediction within the National Weather Service). The parameter estimation experiments reported here can also be viewed as a means to evaluate ULM rigorously in ways that extend the work of Livneh et al. (2011). Additionally, given the ULM’s heritage and widespread use of Noah and Sac, the implications of the results should be broadly relevant to the modeling community. The objective of this work is to examine the benefits and potential tradeoffs of incorporating multiple observations (multiple-criteria) into model calibration across a range of hydroclimatic conditions and spatial scale. This will involve computing simultaneous

skill-scores between the model and each observed criteria. Using this information, the nature of error accumulations and interannual variability in resulting model predictions can also be examined.

We first apply a multivariate model calibration procedure over some of the major river basins of the continental United States (CONUS), and follow with similar calibrations for selected interior tributary catchments. Single and multi-criteria objective functions were used to assess the added value of including information such as remotely sensed ET and TWSC in the calibration procedure. Estimated parameters were then used to analyze simulated streamflow variability, seasonality, and autocorrelation; examining both model skill and error propagation across different spatial scales and hydroclimatic regions.

3.3 Data and Methods

In this section we describe the experimental design, including the study domain, the model, and model forcing and evaluation data. We follow with a description of the model calibration strategy and the trend and error analyses.

3.3.1 Basin selection, streamflow, and meteorological data

The study domain is comprised of river basins of different sizes within the CONUS, selected to provide a broad cross section of hydroclimatic conditions and basin areas that are representative of typical land surface modeling applications. The largest river basins (hereafter major basins) are shown in Figure 3.1 and their characteristics are summarized in Table 3.1. For several major basins, particularly in the western U.S., naturalized streamflow data were obtained that have been adjusted for anthropogenic impacts, including upstream (reservoir) regulation, water withdrawals and evaporation from upstream reservoirs (see Table 3.1). In addition to the 10 major basins a set of 250 smaller catchments (herein tributaries) were selected, most of which are tributaries to the major basins (Figure 3.2). The tributaries are a subset of the MOPEX (Schaake et al., 2006) data set, which have been screened to assure that they have an adequate density of precipitation gauges and are minimally affected by upstream anthropogenic activities such as irrigation diversion and reservoir operations. Hence streamflow observations for the tributaries were obtained directly from United States Geologic Survey (USGS) archives. All basins were

further screened here to have a minimum of 20 years of data with 100 % record completeness within the period 1990-2009 to facilitate the use of remote sensing data sets in multi-criteria parameter estimation.

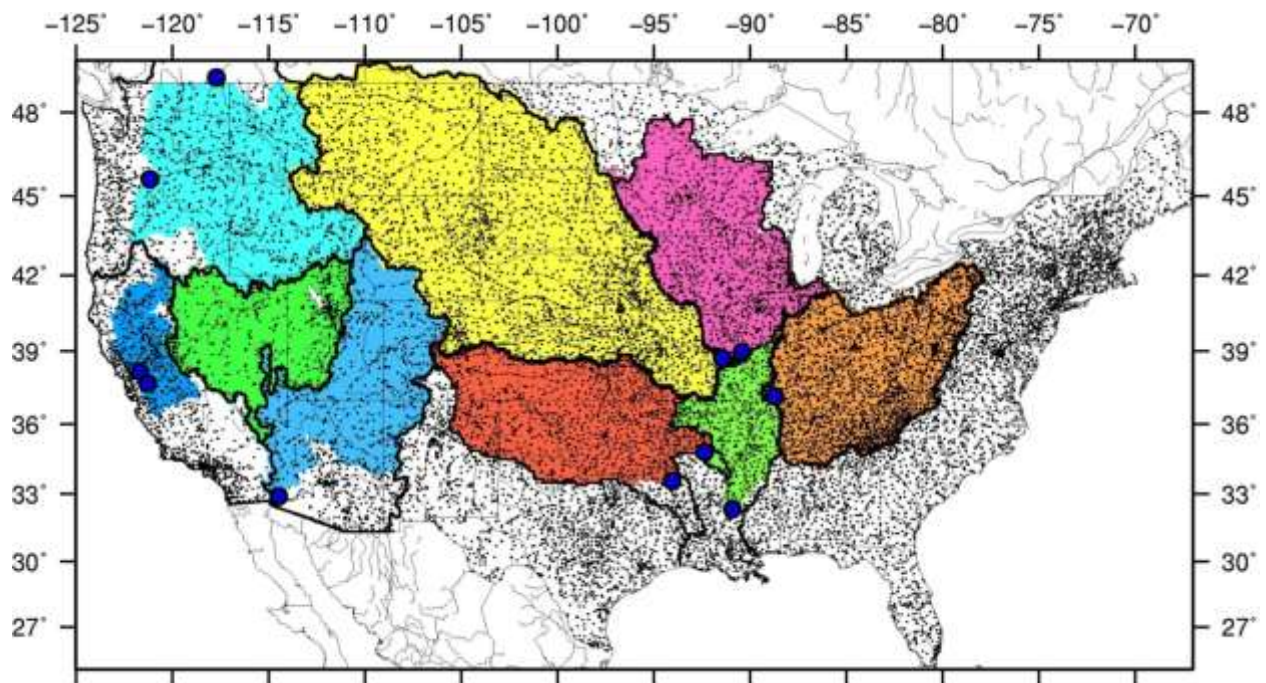


Figure 3.1: Large-scale study domain, including precipitation gauges (black dots), as well as major hydrologic regions (shaded) that are defined through their drainage at stream gauges (blue circles). The un-shaded areas within these regions are either downstream of the stream gauge, or consist of many smaller river basins which drain directly into the Atlantic or Pacific Oceans or the Gulf of Mexico.

Table 3.1: Major hydrologic regions considered in this study including streamflow gauges and drainage areas.

Hydrologic Region	Abbreviation	Applicable criteria	Streamflow gauge location	USGS ID	Area (km ²)
Arkansas-Red	ARK	Q*,ET,TWSC	Arkansas R. near Little Rock, AR	07263450	409296
	RED	Q*,ET,TWSC	Red R. at Index, AR	07337000	124397
California	CALI	Q*,ET,TWSC	Sacramento R. near Rio Vista, CA	11455420	69300
			San Joaquin R. near Vernalis, CA	11303500	35058
			Eastside streams and central valley floor	**	4655
Colorado	COLO	Q*,ET,TWSC	Colorado R. above Imperial Dam, AZ	09429490	488213
Columbia	CRB	Q*,ET,TWSC	Columbia R. at Dalles, OR	14105700	613827
			Columbia R. at Birchbank, BC	12323000	88101
Great Basin	GBAS	ET,TWSC	N/A	N/A	367602
Lower Mississippi	LOW	ET,TWSC	N/A	N/A	221966
Upper Mississippi	UP	Q,ET,TWSC	Upper Mississippi R. at Grafton, IL	05587450	443665
Missouri	MO	Q*,ET,TWSC	Missouri R. at Hermann, MO	06934500	1353269
Ohio	OHIO	Q,ET,TWSC	Ohio R. at Metropolis, IL	03611500	525768

* indicates that naturalized flows were obtained

** unimpaired flow data for the Sacramento-San Joaquin River Delta were estimated by the California Department of Water Resources, which receives a small contribution from eastside streams and flows from the central valley floor.

N/A – indicates that stream flow was not applicable; GB does not have an outlet at the basin boundary, LM represents the confluence of multiple inflows and reliable flow data was not obtainable.

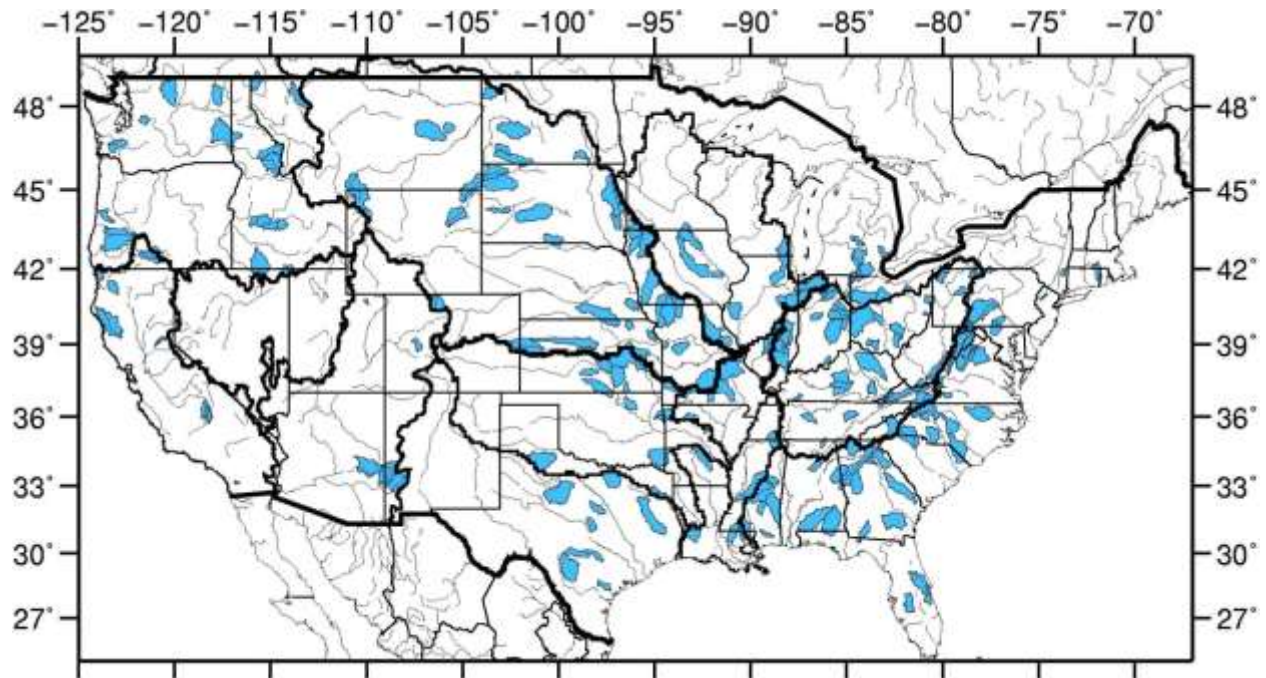


Figure 3.2: Small-scale study domain comprised of 250 tributary catchments using USGS stream gauges that were screened to be minimally affected by diversions, with at least 20 years of data in the past 3 decades to facilitate multicriteria comparisons.

The meteorological data used in this study were derived by Livneh et al. (2012) and are available at a $1/16^\circ$ resolution over the CONUS domain for the period 1915 – 2010. Precipitation and daily minimum and maximum temperatures were obtained for the National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer (Co-op) stations shown in Figure 3.1. Wind data were linearly interpolated from a larger (1.9° latitude-longitude) NCEP–NCAR reanalysis grid (Kalnay et al. 1996) that was used to produce daily wind climatology for years prior to 1948. For complete details of model forcing data, see Livneh et al. (2012).

3.3.2 Auxiliary model evaluation data

In addition to streamflow observations, we made use of two independent estimates of ET, which, like streamflow, are predicted by ULM. The first arises from an atmospheric water balance over the major basins, whereas the second, derived from remote sensing, is available on a spatially distributed basis, but for a relatively short (compared with most of the streamflow records) period of roughly one decade.

3.3.2.1 Atmospheric water balance ET (ET_{AWB})

Computing an atmospheric water balance has been a long-standing means for studying atmospheric exchanges of moisture over large areas. For a given atmospheric domain, with vertical extent to the 100 millibar height

$$\nabla \cdot \frac{1}{g} \int_{100}^{p_s} \overline{qV} dp + \frac{\partial}{\partial t} \left(\frac{1}{g} \int_{100}^{p_s} \overline{q} dp \right) = P - ET \quad (3.1)$$

Where the first term is the convergence of liquid into, or out of the column, the second term is the change in moisture (or precipitable water) from the column over time, q is the specific humidity, V is the mean horizontal wind velocity, p is pressure at elevation, g is the gravitational constant, and P is precipitation. Historically, the terms on the left-hand side of equation 3.1 were obtained using a “picket fence” approach based on radiosonde observations (e.g. Starr et al., 1965, Rasmussen, 1967, Rosen and Omolayo, 1981, Ropelewski and Yarosh, 1998). Areal moisture fluxes could then be estimated by integrating the divergence spatially over the domain, following Green’s Theorem. More recent studies (Oki et al., 1995, Yeh et al., 1998, Syed et al., 2005, Yeh and Famiglietti, 2008) have used this approach, where the spatial fields come from atmospheric reanalyses, which assimilate radiosonde data, as well as other satellite sources of information about the vertical profile of moisture and temperature. Yeh et al. (1998) examined the lower limit of spatial scale for applicability of the atmospheric water balance approach and found that despite early estimates requiring areas $>2 \times 10^6 \text{ km}^2$ (Rasmussen, 1968), accurate estimation of the climatology of regional evaporation is possible at scales as small as 10^5 km^2 . At spatial smaller scales smaller than about 10^5 km^2 , the accuracy of the estimates degrades rapidly.

We use the North American Regional Reanalysis (NARR; Mesinger et al., 2006) as the source of the two terms on the left-hand side of eq. 3.1, both of which are standard NARR archived fields. The NARR output reflects the assimilation of radiosonde and satellite data that are routinely used in numerical weather prediction, but performed with a “frozen” version of the weather prediction model and data assimilation systems. The right-hand side of equation 1 is based on the gridded precipitation fields derived from a network of approximately 20,000 precipitation gauges across the continental U.S. by Livneh et al. (2012). Figure 3 illustrates the atmospheric water balance as used in this study.

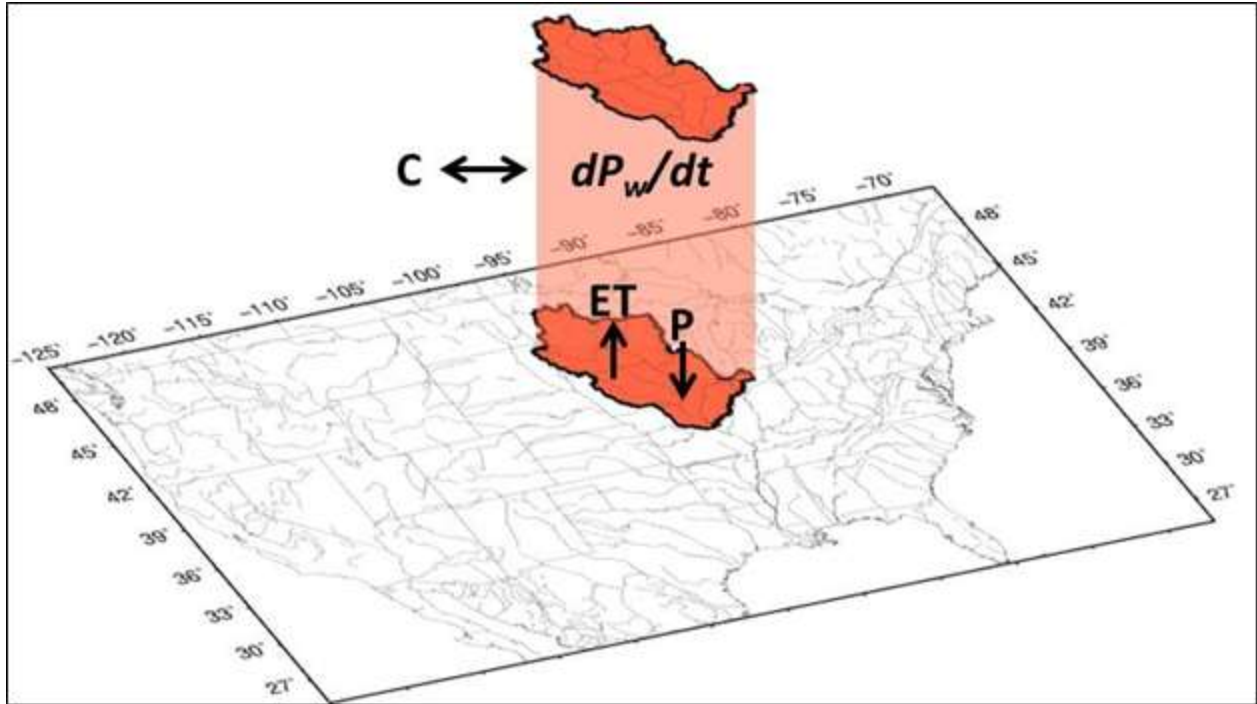


Figure 3.3: Example schematic of the Upper Mississippi river basin components needed to perform an atmospheric water balance to estimate ET (equation 3.1), including atmospheric moisture convergence, C , change in precipitable water, dP_w/dt , and precipitation, P .

3.3.2.2 Satellite-based ET (ET_{SAT})

Satellite remote sensing provides a promising alternative to direct observations for hydrologic prediction, although this is a source that has not been widely used to date – most likely because satellite-based data record lengths are only now approaching a decade. We used a MODIS-based ET data product produced by Tang et al. (2009). This product is based on the VI-Ts method described by Nishida et al. (2003) which uses only satellite-based (no surface data) products. Specifically, downward solar radiation is from the SRB data set of Pinker and

Laszlo (1992), based on Geostationary Operational Environmental Satellites (GOES) and vegetation index (VI) and surface temperature (Ts) data are from MODIS. Two key assumptions of the algorithm are a) that the evaporative fraction is constant over the diurnal cycle, and is well estimated by values from the daytime satellite overpass (of EOS/Terra in this case), and b) there is a substantial variation in VI-Ts pairs over a local region, such that an upper envelope of VI and Ts can be defined. The reader is referred to Tang et al. (2009) and Nishida et al. (2003) for details of the algorithm. The algorithm was applied at 0.05°

spatial resolution, where each pixel represents the average of an area with 0.25° radius, to address assumption (b) above.

Comparing this approach with ground observations, Tang et al. (2009) computed instantaneous and daily mean ET differences of less than 10% and 15% on average, respectively. $VI-T_s$ derived ET agreed favorably with estimates from a much higher resolution Landsat-based method over irrigated areas of the Klamath River Basin in the western U.S. Nishida et al. (2003) found correlations of $R^2 > 0.85$ at 13 flux tower sites over CONUS. Kalma et al. (2008) surveyed a number of satellite-based ET methods (including the Nishida et al. VI-Ts method) and noted they can provide good estimates of the catchment's average evaporation on a daily basis subject to cloud cover. However, they found that an important uncertainty in the ET estimates resulted from land surface temperature errors from the satellite estimates that could be as great as 3-5K due to atmospheric effects. Ferguson et al. (2010) analyzed a similar satellite-based ET product and argued that a significant issue with satellite-based ET products is that they are not constrained by soil/surface water availability. They found that in some cases the high ET-demand during the warm season results in satellite-based ET estimates that are unrealistically large.

3.3.2.3 Terrestrial Water Storage Change (TWSC)

The terrestrial water balance can be written as the difference between precipitation, P , and streamflow, Q , and ET :

$$TWSC = P - Q - ET \quad (3.2)$$

Storage plays a key role in the Earth's climate system and the supply of freshwater for human use, via interaction with groundwater, soil moisture, plant water, snow, and land-ice. The Gravity Recovery and Climate Experiment (GRACE) provides a basis for estimating monthly variations of TWSC over areas order of 10^5 km^2 based on the effect of TWSC on changes in the Earth's gravitational field measured by a pair of satellites.

Temporal gravity variations at these spatial and temporal scales are mainly caused by mass redistribution in the atmosphere and oceans, tides, postglacial rebound, and terrestrial water cycling (Klees et al., 2008). Monthly gravity field solutions are computed at the University of Texas at Austin Center for Space Research (CSR), the GeoForschungsZentrum Potsdam (GFZ) and the Jet Propulsion Laboratory (JPL), which use different processing

strategies and hence yield slightly different results. Similar to Werth and Gutner (2010), we used an average of GRACE gravity fields from these three processing centers (differences among the data sets can be considered a measure of data uncertainty). Lo et al. (2010), Werth and Guntner (2010), and Milzow et al. (2011) have shown the potential for using GRACE-derived TWSC data in the calibration of LSMs. However, the GRACE record length is relatively short (from 2002), and the coarse spatial resolution complicates comparisons with model predictions for other than very large river basins.

3.3.3 Land surface model

Livneh et al. (2011) provide a complete description of ULM as used in this study. In general, the land surface components are from the Noah LSM – e.g., vegetation, ET computation, snow model, and algorithms for computing frozen soil, surface heat and radiative fluxes – whereas the subsurface elements (soil moisture and runoff generation algorithms, as well as infiltration) are from Sac. The snow model is described by Livneh et al. (2010). It essentially is the standard Noah snow model augmented to include time-varying albedo, partial snow cover, and retention of liquid water within the snowpack. Livneh et al. (2011) tested ULM at a small number of catchments and evaluated performance with respect to observed river discharge, flux towers measurements of surface heat fluxes, and soil moisture. Table 3.2 summarizes plausible physical ranges of the model soil parameters that constrained the parameter estimation here.

Table 3.2: List of ULM soil parameters from Sac and their plausible ranges.

Parameters	Unit	Description	Plausible Range
UZTWM	mm	Upper zone tension water maximum storage	1.0 - 300
UZFWM	mm	Upper zone free water maximum storage	1.0 - 300
UZK	day ⁻¹	Upper zone free water lateral depletion rate	0.05 – 0.75
ZPERC	-	Maximum percolation rate	1.0 - 350
REXP	-	Exponent of the percolation curve equation	0.0 – 5.0
LZTWM	mm	Lower zone tension water maximum storage	1.0 - 500
LZFSM	mm	Lower zone free water supplemental maximum storage	1.0 – 1000
LZFPM	mm	Lower zone free water primary maximum storage	1.0 – 1000
LZSK	day ⁻¹	Depletion rate of the lower zone supplemental free water storage	0.01 – 0.8
LZPK	day ⁻¹	Depletion rate of the lower zone primary free water storage	0.0001 – 0.025
PFREE	-	Percolation fraction going directly from upper zone to lower zone free water storages	0.0 – 0.8
PCTIM	-	Impervious fraction of the ground surface	0.0 – 0.1
ADIMP	-	Maximum fraction of additional impervious area caused by saturation	0.0 – 0.45

3.3.4 Calibration procedure and error analysis

By far the most common method for hydrologic model calibration is through minimization of differences between modeled and observed streamflow. The goal here was to extend this approach to include auxiliary observational data sources to evaluate and constrain model performance within a multi-criteria framework. The Nash-Sutcliffe efficiency (*NSE* – Nash and Sutcliffe, 1970) was chosen to quantify model performance. *NSE* is given as:

$$NSE = 1 - \frac{\sum_{t=1}^n (x_{s,t} - x_{o,t})^2}{\sum_{t=1}^n (x_{o,t} - \mu_o)^2} = 1 - \frac{MSE}{\sigma_o^2} \quad (3.3)$$

Where $x_{o,t}$ and $x_{s,t}$ are the observed and simulated values at each time-step, μ_o is the observed mean and n is the total number of time-steps. *NSE* is useful in comparing inter-basin performance, since it normalizes the mean squared error, *MSE*, by the observed variance, σ_o^2 , of each basin, where an *NSE* value of 1 corresponds to a perfect model, while any value less than 0 describes a model that performs worse than simply using μ_o as the predictor. As described by Gupta et al., 2009, the *NSE* may be decomposed to represent the correlation between model and observed calibration variables (e.g. streamflow), difference of means, and difference of standard deviations between simulations and observations. They argue that calibrating a model within a multi-objective perspective

towards these three components is preferred as it enables better hydrological interpretation of the solutions.

We performed optimizations using the MOCOM-UA algorithm, first developed by Yapo et al. (1998), as a means of maximizing NSE (minimizing model errors) and its components within a multiple objective framework. MOCOM-UA is a Pareto-based approach that yields an optimal front (or surface) in an N -dimensional space, where N is the number of objective-functions. The resulting set of parameters from the Pareto solution defines parameter uncertainty attributable to model structural errors (Vrugt et al., 2003), in which optimizing one objective function, has the trade-off of reducing the performance of another. In our implementation, the calibrations were first performed on the individual criteria specifically Q , both ET products, and TWSC to obtain an optimal set of model parameters by minimizing errors in the components of NSE. Next, the same procedure was applied to combinations of these criteria, maximizing their individual NSE, to determine the trade-offs between single and multi-criteria analyses. The relative impact of calibrations on model performance with respect to different criteria was further quantified through changes in the relative root mean square error (rRMSE). This metric provides an additional means for inter-basin comparison, because it is a normalized measure that is (nearly) independent of basin or process scale.

For each basin, the performance of the calibrated model was assessed relative to model performance with default parameters (described in greater detail by Livneh et al., 2011) herein CONTROL. The default parameters are comprised of the Noah LSM land surface characteristics from the National Land Data Assimilation System (NLDAS – Mitchell et al., 2004) and Sac parameters based solely on soil texture (Koren et al., 2003). For the major basins (section 3.2.1) we also evaluated the utility of incorporating ET (atmospheric balance and remote sensing) and TWSC as described in sections 3.2.2.1-3.2.2.3. The tributary catchments are an order of magnitude too small for use of either atmospheric balance ET or GRACE-based TWSC, and hence calibrations for these catchments used Q and ET_{SAT} .

To further evaluate model performance, an analysis of the variability of hydrologic response in both major basin and tributary streamflows was conducted, followed by an examination of model errors at two selected basins. Three components of model response

were examined: the lag-1 autocorrelation (persistence), coefficient of variation (variability), and runoff efficiency (precipitation partitioning). The model's ability to reproduce these observed components, quantifies its representation of seasonality, and its applicability for flood forecasting under different climate scenarios.

In the final part of the analysis, a subset of the domain was selected to further detail model errors. Examining hydrographs of selected major basins and their tributaries provides an additional means to understand the nature of differences between simulated and observed flows and if it is possible to predict how these errors may propagate within a given region. Lastly, overall uncertainties in the model and observational data are discussed including the manner in which they may affect this study's conclusions.

3.4 Results and Discussion

We present single-criterion calibration results from the major basins first, followed by the tributary single-criteria calibrations. We then present and discuss multi-criteria calibration results for both major and tributary basins. Finally, two regions are selected for a general examination of model errors.

3.4.1 Single criterion calibrations

We first calibrated ULM using a single criterion approach based on streamflow simulation errors with the objective functions of the NSE components. Figure 3.4 shows the results of model calibration to streamflow over major basins. Nearly all basins show calibrated streamflows that track observations, notwithstanding that some do not meet the threshold specified by James and Burges (1982). Notable improvements in modeled streamflow over those using a priori values were realized over COLO, despite the quantitatively poorer performance compared with other basins (performance statistics presented in the next section). COLO was among several basins in the western U.S. that used estimated "naturalized" streamflows to account for reservoir operations and irrigation (See Table 3.1 for the complete list). Streamflow simulation errors were noted by other investigators over COLO using the Noah LSM (Xia et al., 2011, Vano et al., 2011) which is relevant to the ULM simulations given its heritage from Noah. Errors were attributed to the significant changes that were made to the Noah canopy parameterizations in its latest official NCEP

version (v2.8 – noted by Wei et al., 2012) such as stomatal resistance, seasonal leaf-area index (LAI), and root distribution, all of which affect ET and runoff generation. These changes generally improved performance, however the Colorado basin was an exception that was compensated for here by ULM calibrations that allow for greater soil moisture capacity to store and release large snow melt volumes. For other regions, such as CALI and OHIO, control simulations were fairly skillful at capturing dynamics of seasonal low flows, such that only small improvements were obtained from calibrations. For the remaining regions runoff ratios were generally too high in the CONTROL simulation, requiring in most cases slight reduction in hydraulic conductivity and increases in moisture holding capacity and permeability parameters.

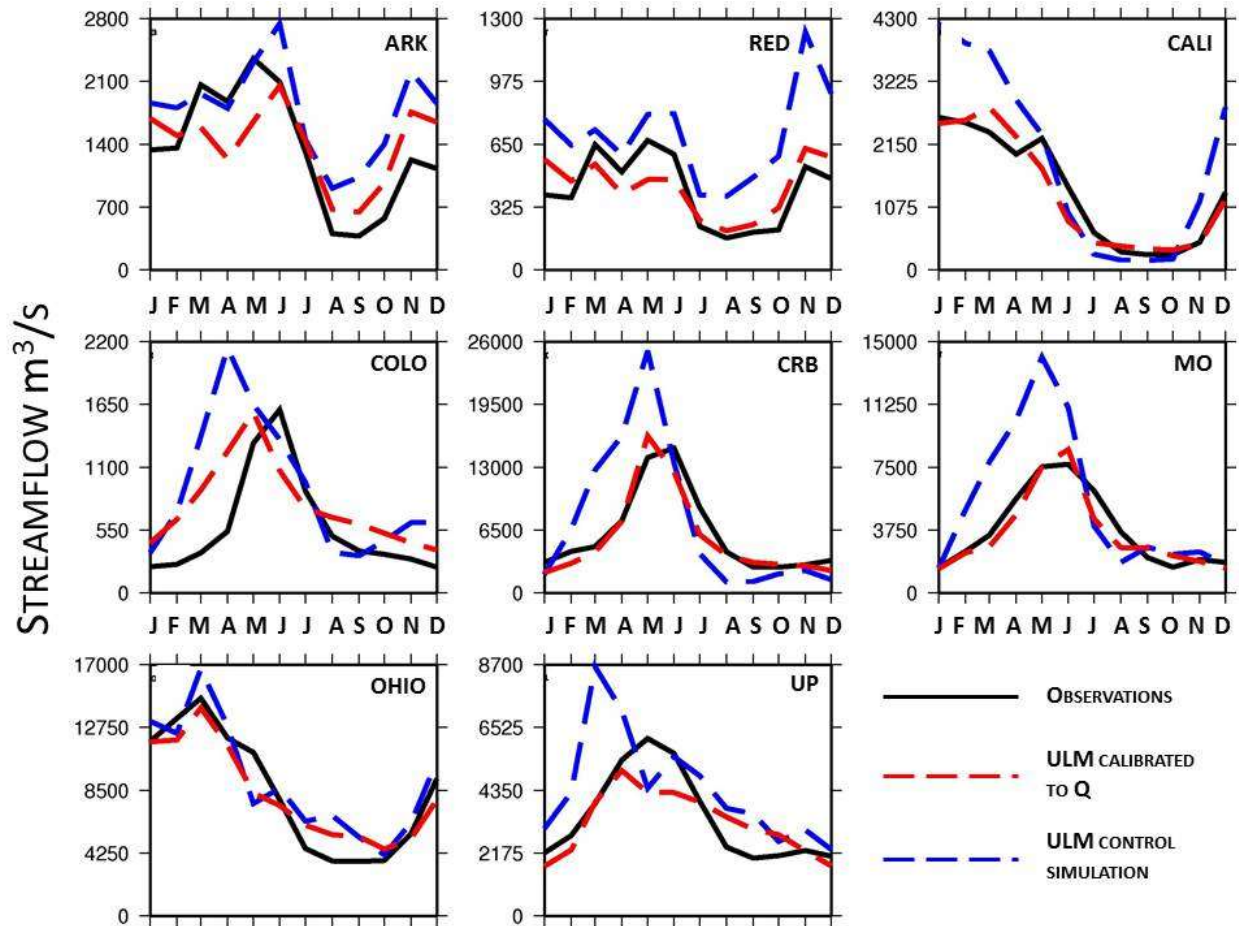


Figure 3.4: Mean monthly hydrographs in m^3/s for the major basins for a 20 year period, the beginning of which varies by basin, depending on data availability.

To quantify the relative uncertainty of the two remote sensing ET products, Figure 3.5 compares them with the long-term difference (P-Q) between observed precipitation, P, and streamflow, Q. The underlying assumption in this comparison is that over a sufficiently long time, the net change in soil moisture storage will become small and the ratio of ET to the difference P-Q, will approach unity. It should be noted that the ET_{AWB} and ET_{SAT} products are for different periods (1979-2010, and 2001-2010, respectively) and are plotted together to facilitate an initial approximation. In nearly all cases (except RED) ET_{AWB} is larger than P-Q, corresponding to either a negative change in TWS, or measurement uncertainty. ET_{SAT} is available for both major and tributary basins, where CALI is the only case with $ET_{SAT} > P-Q$ for a major basin as well as the mean of all of its tributaries. This consistent bias, if not an artifact of estimation error, implies a long term (2001-2010) loss of terrestrial water storage. Tang et al. (2009) tested this algorithm over northern California and found a slight high bias in ET compared with ground-based Bowen ratio stations, suggesting that the positive bias seen here could be due in part to the algorithm itself. ET_{SAT} for all other major basins was slightly less than unity, where the mean of the respective tributaries were also less than unity. The general form of the scatter in Figure 3.5 shows increasing ET_{SAT} negative bias with increasing P-Q, characterized by a pseudo-linear slope of slightly less than one. The mean relative biases on the order of 10 – 20% are due either to the ET_{SAT} algorithm, TWS, observational uncertainty in P and Q, or some combination of these.

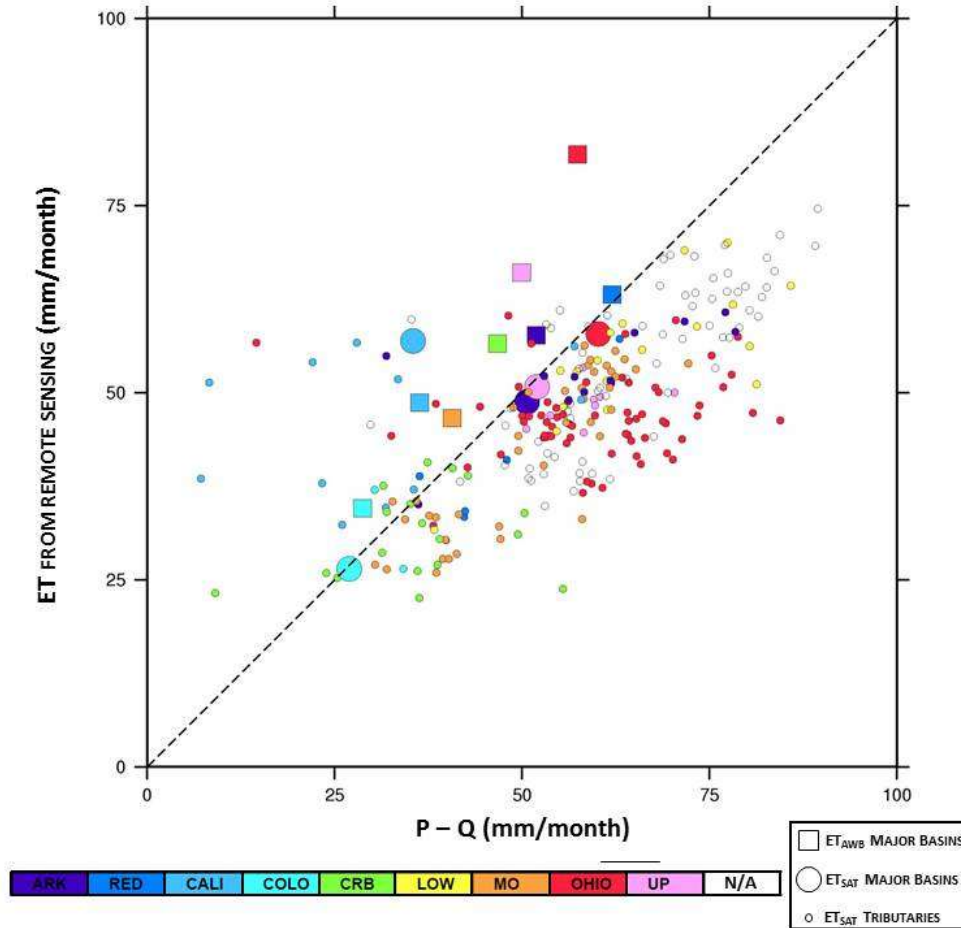


Figure 3.5: Estimates of mean monthly evapotranspiration by an atmospheric water balance (ET_{AWB} – section 2.2.1) in squares, and through satellite data (ET_{SAT} – section 2.2.2) in circles compared with the residual of precipitation, P , minus streamflow, Q , for the major basins and smaller tributaries (smaller circles). Shaded areas denote the domain within which ET was estimated, such that un-shaded circles represent ET from tributaries outside the major basins.

The requirement of variation of VI-Ts in the ET_{SAT} derivation method is examined in Figure 3.6 through a comparison of the long-term residual term, $P-Q-ET_{SAT}$, and the VI and Ts diversity of each basin. Basin-wide ET_{SAT} monthly averages are shown, which were computed from 0.05° pixels (described in section 3.3.2.1). With the exception of CALI, the large basins have a consistently small residual term and a larger VI-Ts diversity as compared with their tributaries. The bias in Figure 3.6 appears to be irrespective of the VI-Ts diversity, or at minimum does not imply decreasing water balance residual with increasing VI-Ts diversity. Mean NDVI ranges by basin vary from approximately 0.05-0.58, while skin temperature ranges vary from 46-72K throughout the simulation period. For example, the tributaries of MO possess among the smallest VI-Ts product range, while

their water balance residuals are near zero, while basins from CALI have larger VI-Ts diversity products with comparatively larger water balance residual. The implications of Figure 3.6 for this analysis are that these basins possess adequate VI-Ts diversity for the ET_{SAT} algorithm. Alternatively stated, the relative VI-Ts diversity alone cannot be used as a means to qualify or disqualify the ET_{SAT} data used here for model calibration.

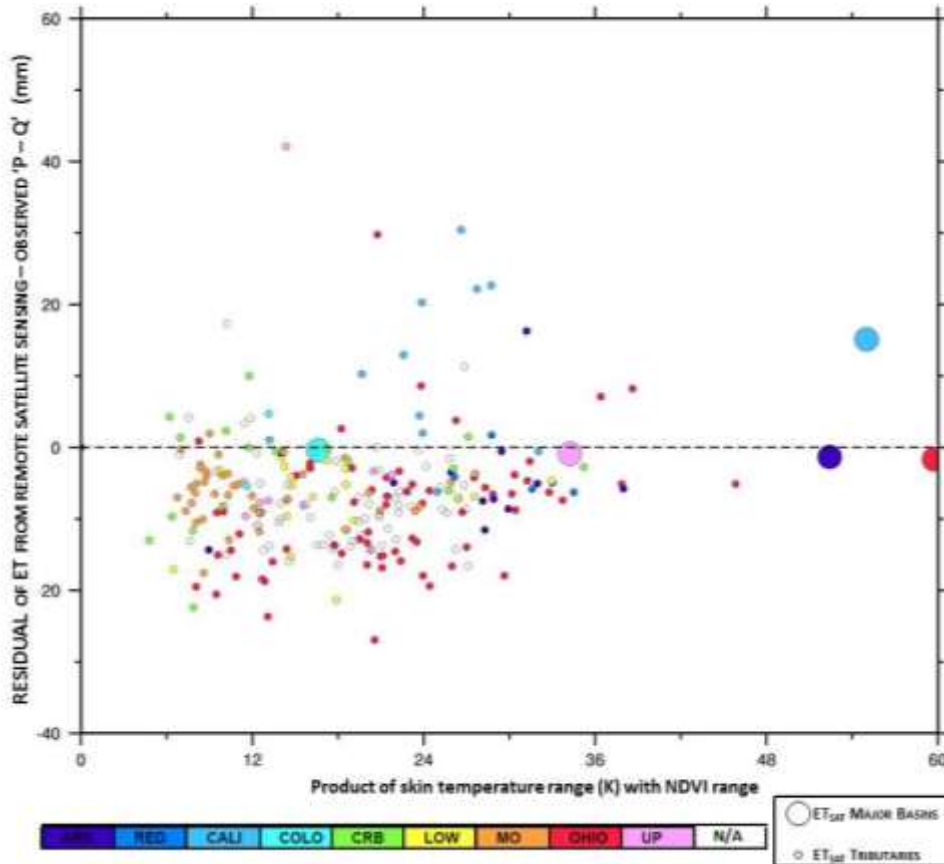


Figure 3.6: Comparisons of the residual of evapotranspiration from satellite data (ET_{SAT} –section 3.2.2.2) with precipitation, P, minus streamflow, Q, for the major river basins (larger circles) and smaller tributaries (smaller circles) 2001 – 2010, as a function of VI-Ts diversity, expressed as a product of the ranges of NDVI and skin temperature for each basin. Departures from the dashed line denote either an uncertainty in ET estimates, or significant long-term TWS, or other observational errors.

The two remote sensing ET sources show notable seasonal differences in Figure 3.7. For all basins, the ET_{AWB} peaks earlier in the year on average relative to ET_{SAT} , with greater peak magnitude in all cases except CALI. The calibrations were most effective in improving the seasonality and timing of peak ET, whereas calibration improved total ET (monthly) magnitude only for cases where the CONTROL ET was already larger than the respective remote sensing ET product. For cases where either ET_{SAT} or ET_{AWB} were

appreciably larger than simulated control ET (most frequently for ET_{AWB}), the calibrated ET remained less than the respective ET product. This difference in ET magnitude was greatest for the western-most basins, which generally exhibit warm-dry summers with large ET demand. This discrepancy comes about in part because of the constraint imposed by ULM's water balance, something that the remote sensing products don't reflect, and often plays a role when ET demand is high. In these cases, the remote sensing product approaches PET and exceeds the available moisture for actual ET. Over the cold-season (DJF), calibrated-ULM frequently matched ET_{SAT} , whereas the larger cold-season ET_{AWB} exceeded the calibrated model estimates at all but ARK and LOW, which have comparatively mild cold-seasons. Notwithstanding the western-most basins, the differences between the calibrated model and the respective ET (calibration objective-function) in Figure 3.7 are notably less than the difference between the two remote sensing data sets, which can be considered a measure of observational uncertainty.

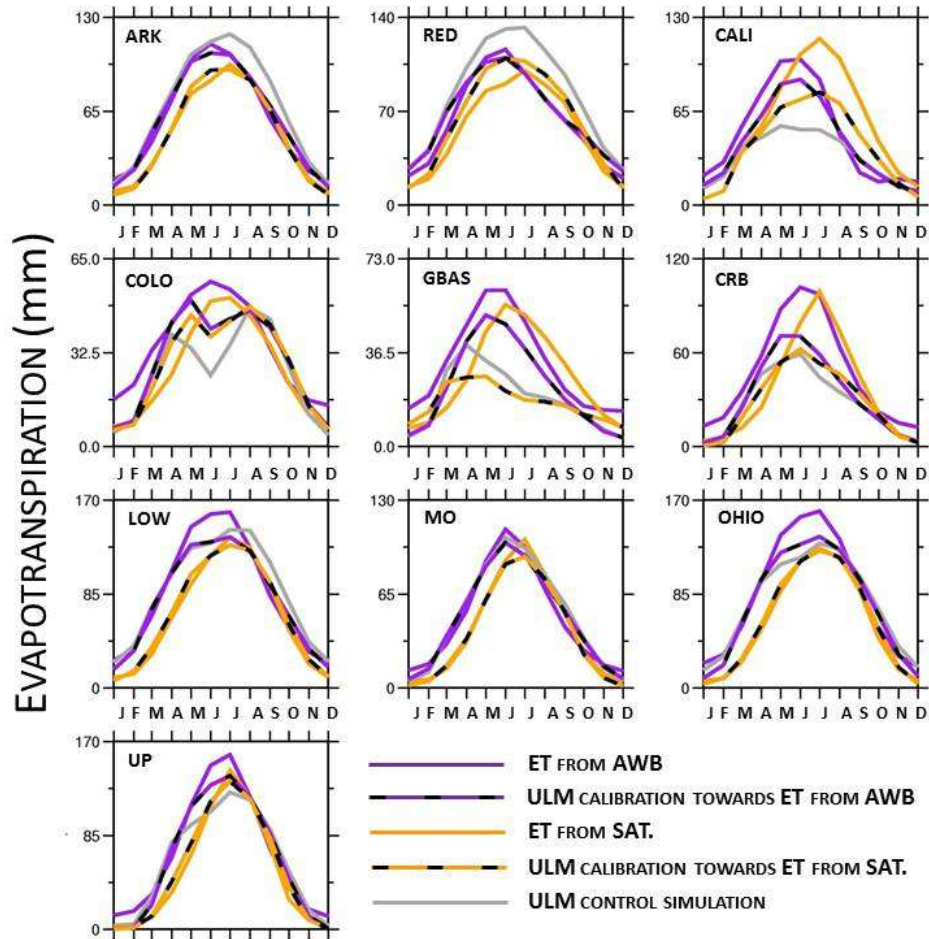


Figure 3.7: Mean monthly ET (mm) for the major river basins for the period 2001 – 2010 that include two sets of calibrations, satellite-based (SAT) or atmospheric water balance-based (AWB) observational products as well as the control simulation.

The seasonal cycle of modeled TWSC has similar amplitude to the GRACE product for most of the basins, as shown in Figure 3.8. In nearly all cases, calibration brings the mean simulated TWSC within the envelope of observational uncertainty for mean TWSC (denoted by the dark-gray shading). In relative terms, the CALI region has the largest seasonal cycle for both the observed and simulated signals, while regions such as ARK, GBAS, and MO, have much smaller amplitudes that are well replicated by ULM. Modest TWSC discrepancies can be expected since we are comparing the model – which is constrained by a relatively shallow (~ 2m) water balance – to the unconstrained estimate of TWSC made by GRACE, which may include contributions from deep groundwater movement and has a coarser native spatial resolution.

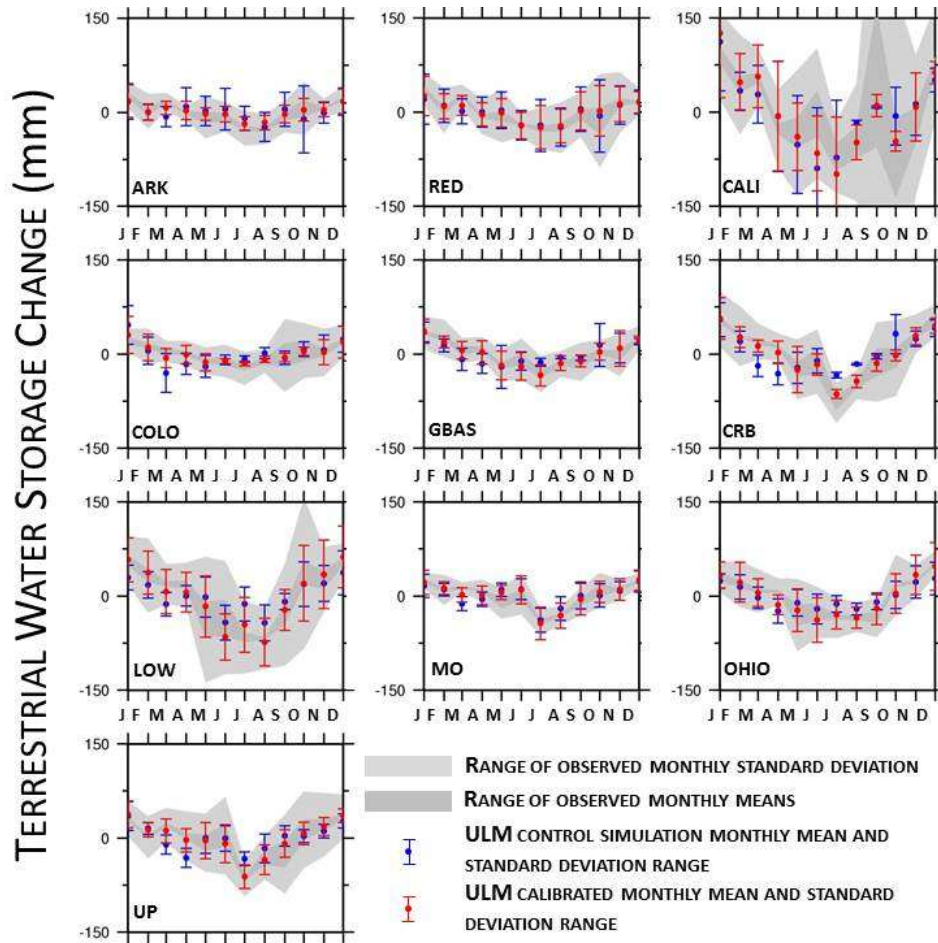


Figure 3.8: Mean monthly TWSC (mm) for the major river basins for the period 2002-2010 including the control and calibrated model simulations; the range of variability for each case is shown accordingly.

The single-criteria calibrations for the tributaries were organized by classifying each catchment by its aridity index, AI; a metric first proposed by Budyko (1974):

$$AI = R_{net,ann}/LP_{ann} \quad (3.4)$$

In which $R_{net,ann}$ is the annual average net radiation, L is the latent heat of vaporization, and P_{ann} is the mean annual precipitation, such that LP_{ann} is the amount of energy needed to evaporate the available precipitation, P_{ann} . AI values exceeding 1 denote increasingly arid (or water limited) conditions, whereas values less than unity denote moist (or radiation limited) conditions. Figure 3.9 shows the resulting daily calibrated NSE values for the tributaries. Daily NSE values are expected to be smaller than for monthly flows, due to the increased variability in observed flows at the finer temporal scale, which is indeed the case in Figure 3.9. It follows that these NSE values do not meet the performance threshold

proposed by James and Burges (1982), which appear to be somewhat optimistic in some cases. A large number of the total tributaries have AI between 0.6 and 1.2. With the exception of two tributaries of RED, the model performance appears to decrease with increasing AI, beginning at $AI \approx 0.6$. Figure 3.10 shows a similar plot but for ET calibrations. Given the seasonality of ET and its strong dependence on atmospheric forcing – i.e. downwelling radiation – many of the tributaries have NSE values above 0.6, with higher NSE values than for the corresponding Q calibrations. However, for a small number of cases (6), ET calibration could not raise model NSE above zero – e.g. less skill than climatology. These disagreements result from cases in the southern part of the domain where ET_{SAT} values are not constrained by water availability (arid basins) and peak ET_{SAT} values are in some cases greater than twice the peak modeled values. These are examples of cases where the remote sensing ET products approach PET. Notwithstanding specific NSE values for the aforementioned single-criteria calibrations, the degree of improvement resulting from calibration relative to the CONTROL case is presented in greater detail in the following section.

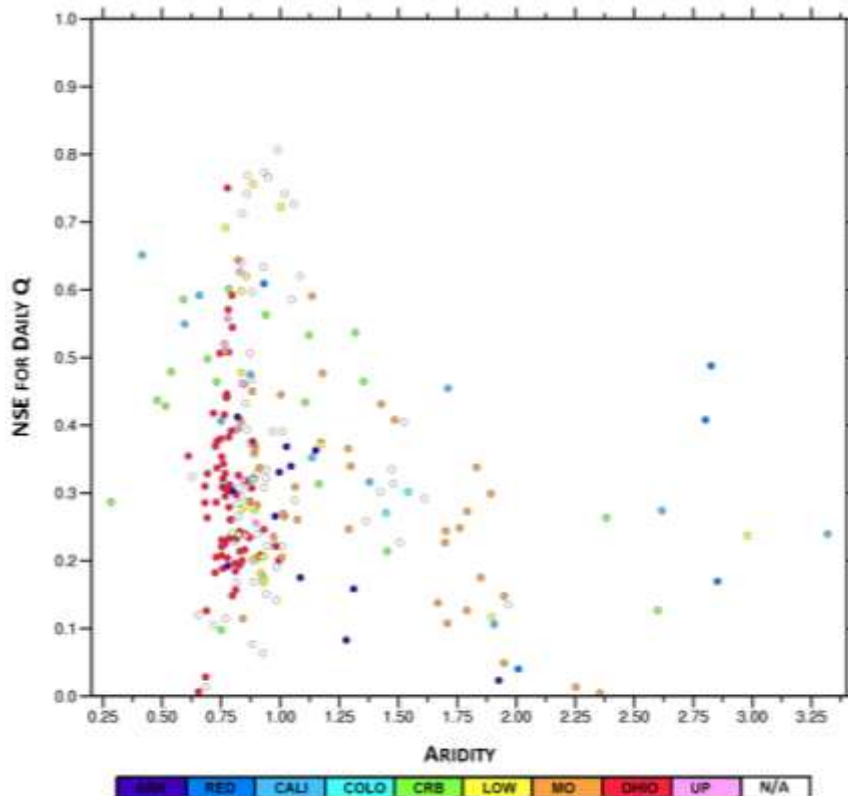


Figure 3.9: NSE values for ULM calibrations to streamflow at a daily time step as a function of AI for the period 1991-2010. Shading of individual points denotes the major region for each tributary.

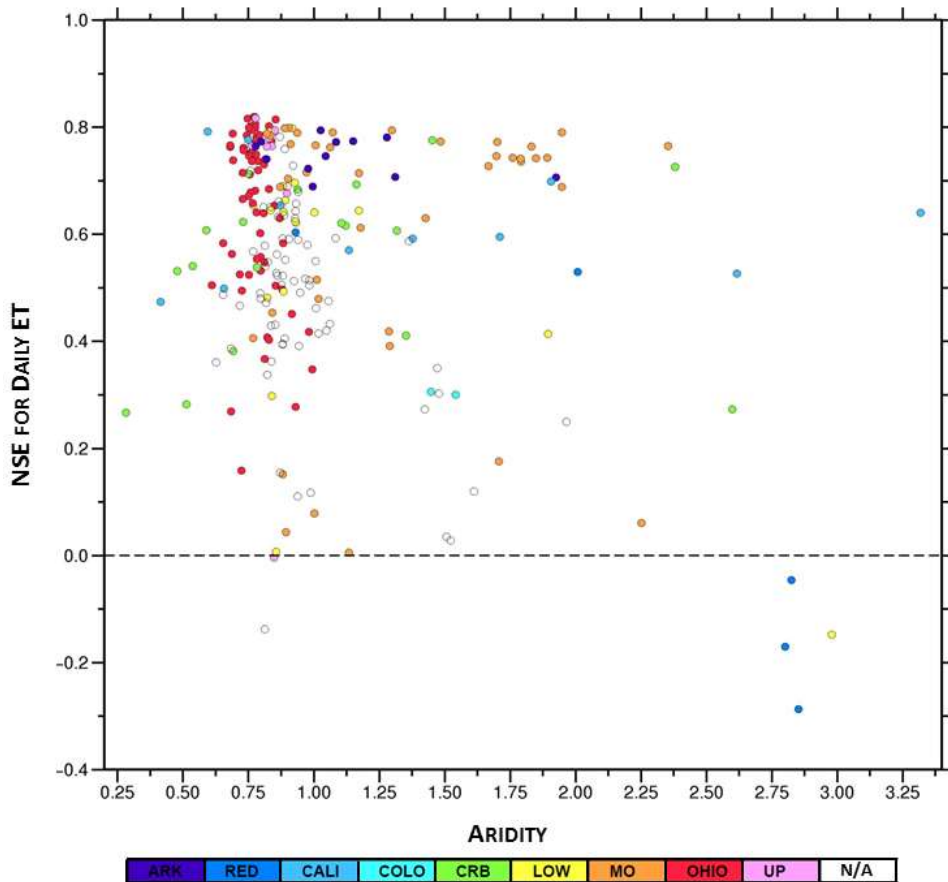


Figure 3.10: NSE values for ULM calibrations towards ET_{SAT} at a daily time step as a function of AI for the period 2001-2010. Shading of individual points denotes the major region for each tributary.

3.4.2 Multi-criteria calibrations

A central objective of this study was to examine the extent to which calibration towards multiple criteria could improve model simulations relative to each of the criteria. A visual representation of the multi-criteria calibration for the major basins is shown in Figure 3.11, while the entire set of results is tabulated in Table 3.3 and Table 3.4. The three axes in Figure 11a represent objective functions (NSE) geared towards minimizing modeled errors in, Q, ET, and TWSC, respectively. Within each calibration set, a single optimal solution was selected that represents a tradeoff between optimizing its respective objective functions, giving equal weight to each. As stated in section 3.3.4, multi-criteria calibrations considered objective functions of the NSE of each criterion, whereas single-criterion calibrations considered objective functions to be the components of the NSE. Consider the

example of the calibration labeled Q,ET_{AWB} that produced a set of simulations that minimized the objective functions for each of these quantities (Q and ET_{AWB}), creating an envelope of similarly scoring simulations (a Pareto front). In order to select the optimal calibration from among these, the simulations which best minimized errors in the auxiliary criterion – in this case TWSC – was chosen. From Figure 3.11a it is clear that single-criterion calibrations often lead to poor performance in the other criteria. The exceptions to this pattern are the single criterion Q-calibrations, which have the largest number of simulations closest to the ideal point (1.0,1.0,1.0). Double and triple-criteria calibrations that include Q, were generally the next closest to ideal, with those containing TWSC generally more successful. Conversely, calibrations that did not include Q more frequently performed poorly in one or more criteria, as this lack the implicit overall water balance associated with high fidelity Q simulations – i.e. the timing and partitioning of surface runoff, which encompasses water availabilities for both ET and TWSC. It is assumed here that the observational uncertainty associated with the ET_{SAT}, ET_{AWB}, and TWSC objective functions are larger than for Q observations.

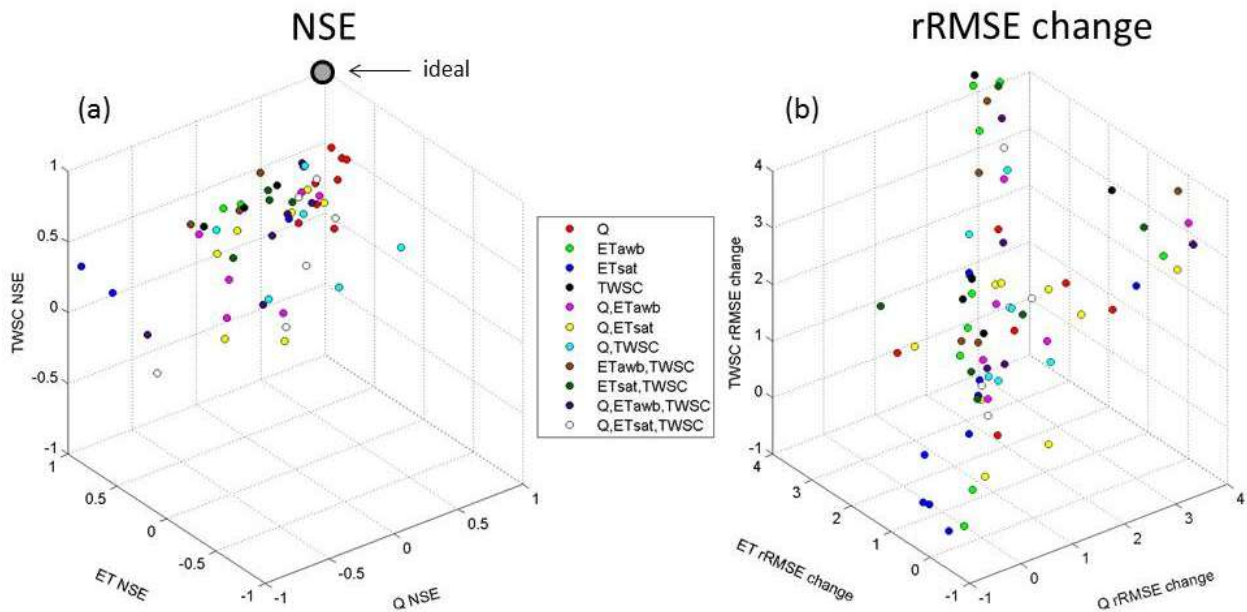


Figure 3.11: ULM calibrations over major basins towards combinations of Q,ET_{SAT}, ET_{AWB}, and TWSC at a monthly time step for the period 1991-2010, including (a) NSE values for each criteria (cutoff at -1 for clarity), and (b) differences in rRMSE for each criteria resulting from the respective calibrations. The entire set of results for these plots is included in Table 3.3 and Table 3.4.

Table 3.3: Summary of monthly skill scores and improvements from the single-criterion calibrations; numeric values show improvement, while dash cells indicate no improvement in model skill for the respective variable.

Underlined values denote the specific ET observation to which calibration was performed.

Calibration quantity	NSE skill					rRMSE improvement			
	Basin	Q	ET _{AWB}	ET _{SAT}	TWSC	Q	ET _{AWB}	ET _{SAT}	TWSC
Q	ARK	0.85	0.88	0.89	0.17	1.68	0.06	0.18	2.88
	RED	0.78	0.81	0.70	0.37	2.65	0.15	0.19	2.03
	CALI	0.94	0.75	0.10	0.53	0.48	0.20	0.02	4.19
	COLO	0.46	0.57	0.50	0.32	5.78	0.14	0.11	6.01
	CRB	0.78	0.50	0.63	0.69	0.77	0.06	0.14	7.30
	MO	0.87	0.77	0.74	0.61	1.76	-	-	11.49
	OHIO	0.86	0.68	0.76	0.43	0.21	-	0.02	0.80
	UP	0.72	0.54	0.56	0.20	0.46	-	-	2.60
	ET _{AWB}	ARK	-	0.93	0.76	0.03	-	0.11	0.08
RED		-	0.89	0.62	0.39	-	0.21	0.15	2.66
CALI		0.22	0.84	0.36	0.41	-	0.27	0.11	2.17
COLO		-	0.61	0.56	0.05	3.65	0.15	0.13	2.63
GBAS		-	0.62	0.43	0.57	-	0.21	0.23	3.23
CRB		-	0.63	0.54	0.67	-	0.13	0.08	6.96
LOW		-	0.92	0.76	0.42	0.00	0.05	0.04	6.17
MO		-	0.93	0.78	0.47	0.36	0.02	-	6.92
OHIO		0.15	0.92	0.74	0.37	-	0.05	0.00	-
ET _{SAT}	UP	-	0.93	0.82	0.04	-	0.10	-	-
	ARK	-	0.81	0.96	-	-	-	0.27	-
	RED	-	0.77	0.90	0.32	-	0.12	0.32	0.62
	CALI	0.45	0.45	0.65	0.31	-	0.03	0.24	0.75
	COLO	-	0.53	0.69	0.02	3.16	0.12	0.20	2.26
	GBAS	-	0.59	0.53	0.60	-	0.20	0.27	3.57
	CRB	-	0.45	0.65	0.27	0.05	0.04	0.15	1.43
	LOW	-	0.73	0.97	0.20	0.15	-	0.26	1.62
	MO	-	0.78	0.96	0.20	-	-	0.22	-
TWSC	OHIO	-	0.71	0.96	0.32	-	-	0.25	-
	UP	-	0.84	0.96	0.06	-	-	0.21	-
	ARK	-	0.80	0.87	0.37	-	-	0.16	11.49
	RED	-	0.55	0.24	0.57	-	0.02	0.00	8.38
	CALI	0.15	0.71	0.07	0.47	-	0.17	0.00	3.22
	COLO	-	0.11	0.26	0.19	2.53	0.00	0.01	4.25
	GBAS	-	0.59	0.48	0.59	-	0.20	0.25	3.52
	CRB	-	0.53	0.54	0.68	-	0.07	0.07	7.17
	LOW	-	0.77	0.63	0.58	-	-	-	9.97
MO	-	0.91	0.82	0.52	0.52	-	0.02	8.49	
OHIO	0.39	0.69	0.54	0.55	-	-	-	2.70	
UP	-	0.75	0.76	0.42	0.13	-	-	7.75	

Table 3.4: Same as Table 3.3, except for multi-criteria calibrations.

Calibration quantity	NSE skill				rRMSE improvement				
	Basin	Q	ET _{AWB}	ET _{SAT}	TWSC	Q	ET _{AWB}	ET _{SAT}	TWSC
QET _{AWB}	ARK	0.59	0.89	0.74	-	1.43	0.07	0.06	-
	RED	0.09	0.81	0.57	-	2.14	0.15	0.13	-
	CALI	0.68	0.64	0.27	0.40	0.13	0.13	0.08	2.04
	COLO	-	0.55	0.55	0.09	4.11	0.13	0.13	3.06
	CRB	-	0.16	0.26	0.41	0.21	-	-	3.10
	MO	-	0.87	0.77	0.29	1.24	-	-	2.06
	OHIO	0.74	0.89	0.76	0.47	0.12	0.01	0.02	1.40
	UP	0.71	0.86	0.81	0.31	0.45	0.02	-	5.18
QET _{SAT}	ARK	0.50	0.87	0.75	-	1.36	0.04	0.07	-
	RED	-	0.74	0.54	-	2.02	0.10	0.11	-
	CALI	0.71	0.45	0.62	0.35	0.15	0.03	0.22	1.29
	COLO	-	0.55	0.69	0.02	3.95	0.13	0.20	2.26
	CRB	-	0.19	0.58	0.42	0.35	-	0.10	3.31
	MO	-	0.86	0.72	0.22	1.25	-	-	0.25
	OHIO	0.69	0.78	0.77	0.38	0.09	-	0.03	0.04
	UP	0.60	0.88	0.82	0.23	0.39	0.04	-	3.35
Qtwsc	ARK	0.46	0.87	0.68	0.18	1.35	0.04	0.03	0.68
	RED	-	0.82	0.66	0.45	-	0.15	0.17	4.34
	CALI	0.71	-	-	0.38	0.17	-	-	1.81
	COLO	-	0.53	0.60	0.05	4.21	0.13	0.15	2.65
	CRB	0.09	-	0.01	0.40	0.39	-	-	3.04
	MO	0.06	0.87	0.75	0.27	1.30	-	-	1.67
	OHIO	0.73	0.85	0.71	0.50	0.11	-	-	1.82
	UP	0.55	0.63	0.65	0.32	0.37	-	-	5.45
ET _{AWB} TWSC	ARK	-	0.88	0.86	0.35	-	0.06	0.15	10.13
	RED	-	0.59	0.32	0.49	-	0.03	0.03	5.46
	CALI	0.15	0.76	0.11	0.43	-	0.21	0.02	2.47
	COLO	-	0.64	0.63	0.14	3.94	0.17	0.17	3.68
	GBAS	-	0.59	0.47	0.59	-	0.20	0.25	3.50
	CRB	-	0.56	0.56	0.69	-	0.09	0.09	7.30
	LOW	-	0.85	0.71	0.58	-	-	0.00	9.92
	MO	-	0.93	0.79	0.50	0.66	0.02	-	7.95
ET _{SAT} TWSC	OHIO	0.42	0.90	0.71	0.54	-	0.02	-	2.46
	UP	-	0.88	0.80	0.37	0.13	0.04	-	6.66
	ARK	-	0.89	0.89	0.32	-	0.05	0.18	8.08
	RED	-	0.79	0.79	0.43	-	0.13	0.24	3.62
	CALI	0.52	0.70	0.70	0.38	0.00	0.20	0.27	1.81
	COLO	-	0.71	0.71	0.10	3.31	0.12	0.21	3.23
	GBAS	-	0.50	0.50	0.59	-	0.12	0.26	3.53
	CRB	-	0.40	0.50	0.30	0.94	0.16	0.18	2.54
QET _{AWB} TWSC	LOW	-	0.77	0.77	0.52	-	-	0.05	8.40
	MO	-	0.82	0.82	0.49	0.55	-	0.02	7.65
	OHIO	0.39	0.79	0.79	0.48	-	-	0.04	1.46
	UP	0.42	0.81	0.81	0.38	0.32	-	-	6.88
	ARK	0.43	0.89	0.71	-	1.33	0.06	0.04	-
	RED	-	0.80	0.47	-	2.04	0.14	0.09	-
	CALI	0.63	0.64	0.41	0.37	0.09	0.13	0.13	1.59
	COLO	-	0.53	0.60	0.05	4.21	0.13	0.15	2.65
QET _{SAT} TWSC	CRB	-	0.11	0.39	0.63	0.31	-	-	6.36
	MO	-	0.92	0.80	0.40	0.54	0.11	0.14	1.83
	OHIO	0.73	0.88	0.72	0.51	0.11	0.01	-	1.95
	UP	0.53	0.77	0.77	0.27	0.36	-	-	4.13
	ARK	0.49	0.73	0.73	-	1.37	-	0.06	-
	RED	-	0.46	0.46	-	1.97	-	0.08	-
	CALI	0.63	0.41	0.41	0.37	0.09	0.06	0.13	1.59
	COLO	-	0.60	0.60	0.05	4.21	0.06	0.15	2.65
QET _{SAT} TWSC	CRB	0.09	0.01	0.01	0.40	0.39	-	-	3.04
	MO	-	0.80	0.80	0.30	1.04	0.11	0.09	2.83
	OHIO	0.74	0.74	0.74	0.45	0.12	-	0.01	1.12
	UP	0.63	0.79	0.79	0.34	0.41	-	-	5.76

The extent to which each criterion was improved through calibration is illustrated in Figure 3.11b, quantified by the rRMSE difference with each basins CONTROL simulation.

Examining this figure along with the accompanying tables (Table 3.3, 3.4), it is clear that calibrations to certain criteria have the potential to either improve or worsen model

performance towards other criteria. These tradeoffs should be distinguished from the implied tradeoffs in the Pareto front of the multi-objective calibrations, since the two are not strictly the same. Examining figure 3.11b, the results form a central cluster with three branches. The central cluster of simulations is comprised mostly of multi-criteria calibrations that exhibit modest improvements in each criterion. This modest improvement in each criterion is consistent with the degree of improvement noted by Gupta et al. (1999) for their multicriteria calibrations towards surface heat fluxes. The lower branch is made up mostly of single-criteria ET calibrations (ET_{SAT}, ET_{AWB}) that exclusively improve ET performance, for cases where the objective function conflicts with the other criteria, and hence worsens the performance in other criteria. The upper-left branch is made up of calibrations for which there is good agreement between the ET and TWSC data, and hence large improvements in these objective functions through calibration. The upper-right branch follows similarly except with agreements between TWSC and Q data.

This analysis suggests that at the regional scale (larger than $\approx 10^5 \text{ km}^2$), calibrations towards Q are generally more robust than those towards TWSC and ET in a multi-criteria context. Overall, the remote-sensing auxiliary criteria (ET_{AWB} , ET_{SAT} , TWSC) generally provide useful information regarding the seasonality of the terrestrial water balance.

However, these criteria alone or in combination do not appear sufficient to appreciably improve model simulations of Q, as may be the desire in an ungauged basin.

Figure 3.12 shows multi-criteria results for the tributaries and follows the same format as Figure 3.11 with considerably more data points for the Q and ET_{SAT} criteria. In contrast to the major basin results in Figure 3.11a, Figure 3.12a shows that the multi-criteria calibration (Q, ET_{SAT}) for the tributaries performs competitively with both single-criterion calibrations in terms of NSE for a large number of tributaries. For all calibration criteria, there are basins that perform poorer than climatology – i.e. $NSE < 0$ – however these are mostly for single-criterion calibrations relative to the other criterion. For example, it follows intuitively that the ET_{SAT} calibration has instances of poorer NSE with respect to Q, than does the Q, ET_{SAT} calibration. Figure 3.12b shows quantitatively greater improvements in Q performance than ET (note that the horizontal axes are not the same in this plot). This reflects the greater flexibility in model structure and (soil) parameter combinations considered here to influence Q outputs versus ET with relation to a given set

of atmospheric forcings. For both Q and ET_{SAT} , rRMSE improvements in single-criterion calibrations were frequently made at the expense of rRMSE of the other criterion. An interesting finding is that the top Q simulations from approximately one third of all tributaries (81) resulted from multi-criteria Q, ET_{SAT} calibrations. This is in direct contrast to the major basin calibrations, in which the top performing Q simulations resulted exclusively from single-criterion Q calibrations. For only six tributaries (~2 % of all tributaries), ET_{SAT} calibrations improved Q to a comparable degree to Q calibrations. Therefore, consistent with the major basin analysis, the use of only auxiliary remote-sensing criteria (in this case, only ET_{SAT}) was not sufficient to appreciably and reliably improve Q performance. The unique conclusion here is that the inclusion of an auxiliary remote sensing criterion (Q, ET_{SAT}) for the tributary basins ($<10^4$ km²) can improve calibration results *beyond* that of the single-criterion calibration.

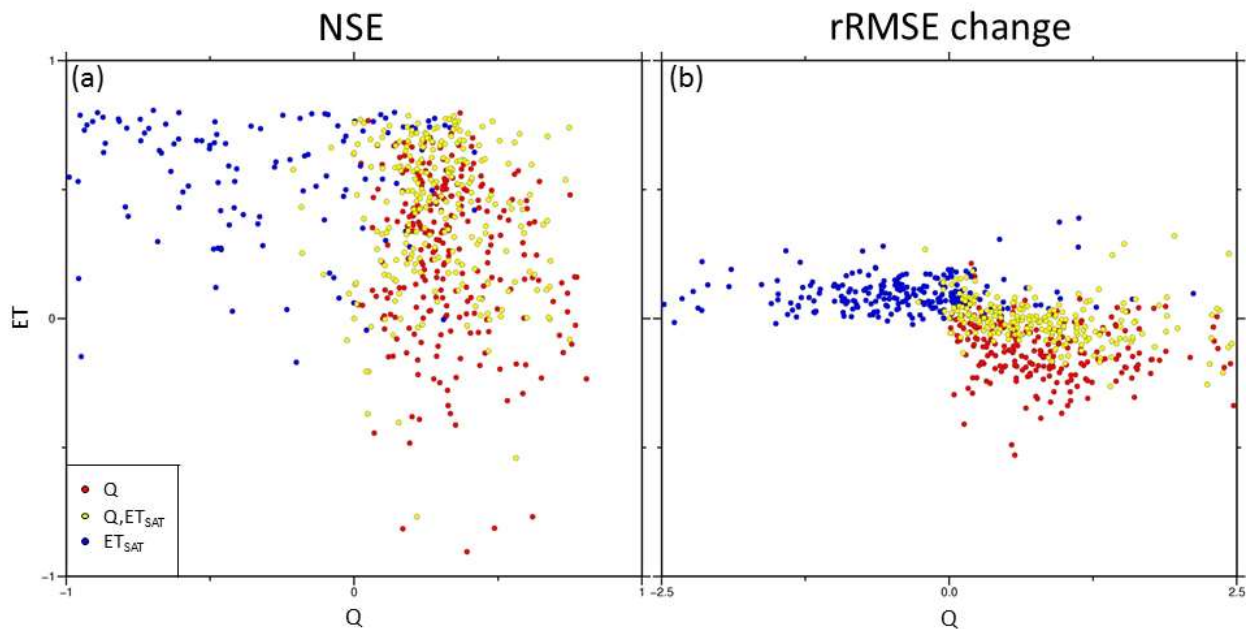


Figure 3.12: ULM calibrations over tributary basins towards combinations of Q, and ET_{SAT} at a daily time step for the period 1991-2010, including (a) NSE values for each criteria and (b) differences in rRMSE for each criteria resulting from the respective calibrations.

3.4.3 Hydrologic response and model error analysis

Calibrated model parameters for this extended streamflow analysis were selected from section 3.4.2 based on the best performing Q calibrations. In the case where several of the best calibrations have similar skill in simulating Q (arbitrarily NSE values within 5% of

one another), the parameters associated with the simulation with higher performance in the auxiliary criteria were selected – i.e. ET_{SAT} , ET_{AWB} , and TWSC for major basins, ET_{SAT} only for tributaries. As part of this validation, basins were screened for a period of record that was considerably longer than the calibration window (18 years), chosen here to be ~70 years, to provide a robust characterization of their hydrologic response.

Table 3.5 shows the simulated and observed runoff efficiencies, lag-1 autocorrelations, and coefficients of variation for both major basins and tributaries. These variability components were computed using flows at a monthly time-scale to facilitate direct comparison between major and tributary flow responses, since most major basin streamflows were only available monthly for the cases of naturalized flows. Runoff efficiencies were fairly well matched by ULM across basins and scales, with a few exceptions, most notably COLO. For cases of large runoff efficiency discrepancy – i.e. larger than 10% – simulated runoff efficiencies were consistently higher than observed. This could result from model errors such as negative biases in ET estimates (noted for several basins in section 3.4.1), inadequate soil moisture storage capacity, or negative biases in the precipitation forcing, all of which could produce higher runoff efficiency than observed. Model persistence (i.e. lag-1 autocorrelation) follows observations reasonably well. For cases of notable disagreement, simulated persistence was most frequently higher than observed, which may be due in part to a lack of information of extreme/localized meteorological events in the forcing data. The major basins UP and CRB are unique in this regard, where the model is less persistent than observations. Persistence errors do not appear to be related to coefficient of variation errors, as modeled CV was both higher and lower than observations for basins where modeled flows were more persistent than observations. Modeled CV values were the most varied and did not show a systematic bias across basins or across scale.

Table 3.5: Variability analysis for observed followed simulated trends by major basin and tributary averages over a 70 year period, including runoff efficiency, R_e , lag-1 autocorrelation, r_1 , and the coefficient of variation, CV.

	Major Basin						Total sub- basins*	Sub-basin tributary averages					
	R_e		r_1		CV			R_e		r_1		CV	
	obs.	sim.	obs.	sim.	obs.	sim.		obs.	sim.	obs.	sim.	obs.	sim.
ARK	0.14	0.15	0.49	0.49	1.03	1.01	9/12	0.21	0.24	0.35	0.52	1.97	2.12
RED	0.12	0.14	0.46	0.48	1.14	1.02	4/5	0.16	0.15	0.52	0.77	1.38	1.61
CALI	0.46	0.45	0.65	0.65	1.02	1.05	7/11	0.41	0.49	0.60	0.69	1.77	1.39
COLO	0.10	0.14	0.68	0.72	0.99	0.92	2/2	0.41	0.67	0.55	0.68	1.39	1.14
CRB	0.45	0.45	0.72	0.66	0.80	0.85	9/18	0.36	0.41	0.63	0.64	1.11	1.09
MO	0.12	0.14	0.67	0.79	0.72	0.78	13/41	0.20	0.25	0.46	0.57	1.56	1.35
OHIO	0.41	0.40	0.63	0.71	0.74	0.60	46/66	0.41	0.45	0.48	0.60	0.95	0.75
UP	0.27	0.28	0.74	0.67	0.67	0.60	8/9	0.28	0.27	0.49	0.60	1.13	0.89
LOW	NA	NA	NA	NA	NA	NA	11/18	0.27	0.25	0.45	0.64	1.32	1.33
Other	NA	NA	NA	NA	NA	NA	54/68	0.34	0.39	0.48	0.58	1.05	1.05

*The number of tributaries was reduced to the first number from the second number with the requirement for ~70 year flow record

Two major basins were selected to examine streamflow errors more closely, the CRB and OHIO. To enable a visual comparison among basins with different flow magnitudes, the streamflows in Figure 3.13 were converted to z-scores, via subtraction of the long-term observed mean flow and division by the standard deviation. CRB has a variety of interesting hydroclimatic features such as alpine, maritime and arid regions and its tributaries possess the widest range of AI values of any region. Model errors for the major basin are concentrated near the time of peak flow, relating to snowmelt dynamics in this heavily snowmelt influenced region. The major basin model flows were less persistent with higher CV than observations, which is consistent with the sharper peak in the hydrograph. The time of peak flow comes on-average one month earlier in the tributaries, reflecting their rapid response and shorter times of concentration. Over the tributaries, the model tends to under (over) predict high (low) flows, such that beginning at the time of peak flow tributary errors tend to precede major basin errors by approximately one month. The range of AI values and snow versus rain dominated conditions between the major basin and its tributaries are depicted in the multiple hydrographs of the bottom panel, revealing that the

large snowmelt dominated component of the major hydrograph was only scarcely sampled by the tributaries in the study domain.

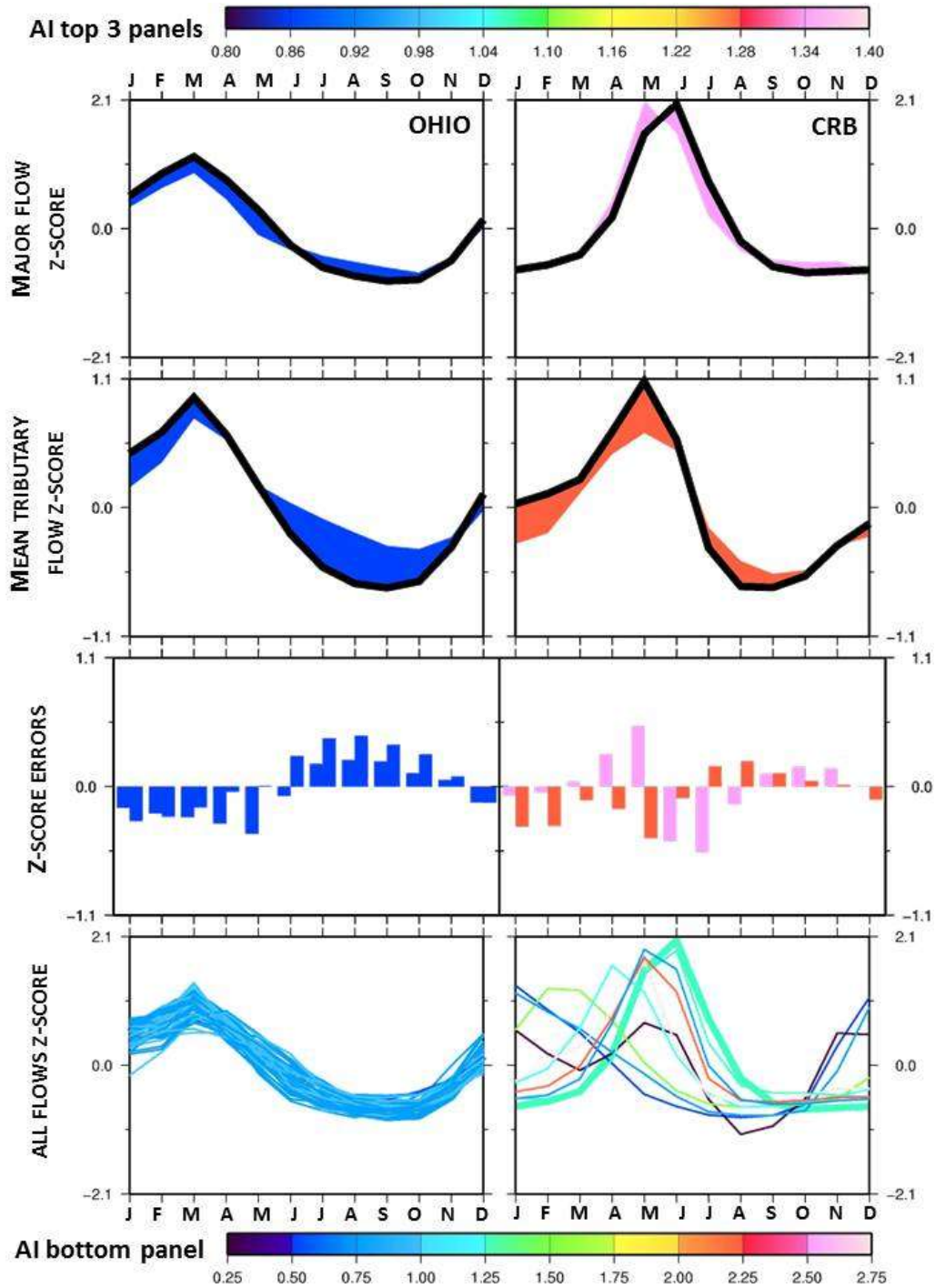


Figure 3.13: Comparison between major basin and mean tributary flows and errors. Flow data was converted to z-scores to allow for comparison among basins. The differences in aridity index (AI) are shaded according to the upper-scale for the top 3 panels and the lower scale for the bottom panel.

The Ohio River Basin is situated within a more uniform continental hydroclimatic regime than the CRB. Its tributaries are more numerous (46, versus 9 in CRB) and hence represent an even more comprehensive range of conditions specific to the region. The timing of maximum and minimum flows is remarkably similar between the mean of the tributaries and the major flows, consistent with the relative hydroclimatic homogeneity of the region. Similar to CRB, the model under (over) predicted high (low) flows, while high correlation among tributary streamflow is evident from their respective hydrographs. The smoother simulated hydrographs at both scales is consistent with the overestimated persistence and under estimated variance noted in Table 5.

Given the multiple data sets used in this study, it is essential to temper the findings with the impact of overall data uncertainty. To train the model, several independent data sets were used that could lead to offsetting errors across these datasets – i.e. ET versus TWSC – highlighting potential water budget inconsistencies and data uncertainties. This is an inherent potential pitfall in using independent datasets, however it may aid in ultimately bracketing true conditions. One technique to reconcile such inconsistencies is through redistributing the total water balance error from multiple sensors back to each of the individual components using a Kalman error approach (Pan et al., 2012). This approach is beyond the scope of this work; however it may offer a framework to further improve the consistency of the remote sensing water budget analyses in the future.

Overall sources of error and uncertainty are as follows. TWSC uncertainties were perhaps the largest within the study; evident in the disparity between mean monthly values from individual processing streams in Figure 3.8. A further uncertainty arose in comparing these data with ULM, given the different reference depths considered by each. ET_{AWB} errors were most likely to arise from the atmospheric components (left side of equation 1) that were contingent upon the NARR analysis increment, particularly problematic over coastal regions (Ruane, 2010); wherein adjustments to latent heating of the atmospheric column are made to overcome moisture excesses in the underlying Eta model. ET_{SAT} estimates were subject to uncertainty from the input MODIS skin temperatures, which Ferguson et al. (2010) described as being the largest source of error for a similar satellite-based ET product, in lieu of errors associated with emissivity and land-surface characteristics. Furthermore, the ET_{SAT} estimates are not strictly constrained by moisture availability that

could lead to further data uncertainty. Q uncertainties due to random errors in the USGS current meters or (for major basins) naturalization data and algorithms could skew the interpretation of the model performance and trend analysis. Albeit, it is not immediately apparent in which direction the skew would occur and it is expected – at least in the case of the in-situ USGS data – that these errors would be small relative to the greater complexities in the remote sensing data. Meteorological forcing errors may exist, particularly in regions of topographical complexity. Most notably, precipitation errors would prevent the model from matching streamflow timing, magnitude, and variability, while surface temperature and wind errors could translate into erroneous estimates of surface water and energy fluxes. Lastly, errors in model structure, or conceptualization errors may exist that ultimately prevent the model from correctly simulating certain processes, or achieve the correct results for the incorrect reason via calibration. Investigating these types of errors would require a more directed and rigorous error analysis including detailed measurements of surface fluxes of moisture and energy and their respective uncertainties.

3.5 Conclusions

We have exploited several observational data sets together with an LSM to estimate various components of the terrestrial water budget. The analysis focused on ways to train ULM to observational data sets to improve estimates of the water budget components. The results were presented to provide insight into tradeoffs in the performance with respect to each criterion. The single-best performing streamflow parameters for each basin were utilized to streamflow variability and hydrologic response. Finally, an examination into potential error sources was made to illustrate specific causes behind discrepancies in simulated streamflows and their relationship across scale. The most important conclusions of this analysis are:

1) Model calibrations towards a single-criterion had varied results. At large scales ($\geq 10^5$ km²) most basins were able to replicate Q, ET, and TWSC individually with reasonable skill, despite uncertainties in the data themselves and discrepancies between modeled and native retrieval resolutions. At 250 small-scale basins ($< 10^4$ km²) over daily time steps, ET calibrations generally scored higher than Q-calibrations, however for a small number of these (arid basins), strong disagreements between the model and remote-sensing product

lead to ET simulations that were poorer predictors than climatology, while Q calibrations always provided additional skill

2) At large-scales, calibrations towards multiple-criteria had the best overall performance when Q was included, followed by ET_{SAT} , ET_{AWB} , and TWSC. Altogether, calibrations towards Q alone had the best all-around performance in terms of the other criteria, while neither of the other criteria (ET, TWSC) alone or in combination was able to add appreciable skill to Q prediction, since this would be desirable in ungauged basins.

3) Multi-criteria performance at small scales followed similarly to the large-scale analysis with the notable exception that the multi-criteria calibration (Q and ET_{SAT} together) outperformed the single criterion Q-calibration in terms of Q performance at roughly one third of the basins. This suggests that traditional streamflow calibration stands to benefit from the inclusion of remote-sensing data.

4) The lack of a systematic bias in the satellite-ET product over a number of basins of varying VI and Ts diversity indicates that above a certain threshold, VI-Ts diversity alone may not be an adequate predictor of quality of the satellite-based ET product. Rather, the issue of unbounded ET estimates during summer was most detrimental to the quality of ET estimates.

5) The use of multiple criteria in the calibration procedure, at minimum serves to reduce the equifinality problem when choosing the ‘best’ instance of the model parameters.

6) Investigating model error sources revealed that simulations generally under (over) predicted high (low) flows. Comparing errors across scales also brought forth issues with travel times and integrating differing hydroclimatic conditions across basins.

IV. REGIONAL PARAMETER ESTIMATION FOR THE UNIFIED LAND MODEL

This chapter is in review by *Water Resources Research* (Livneh and Lettenmaier, 2012).

4.1 Introduction

The goal of parameter regionalization is to derive predictive relationships between observable catchment attributes and model parameters, and in so doing provide a basis for a) avoiding time consuming local parameter estimation when a model is applied to a new domain, and/or b) provide a basis for transferring parameters to ungauged basins. The most common approaches for transferring parameter information in past work have been synthetic unit hydrographs (Aron and White, 1982), multiple regression and interpolation (e.g. Magette et al., 1976, Karlinger et al., 1988, Post and Jakeman, 1996, Abdulla and Lettenmaier, 1997, Kull and Feldman, 1998, Post et al. 1998, Post and Jakeman 1999, Siebert, 1999, Fernandez et al. 2000, Merz and Blöschl 2004, Gan and Burges, 2006, Heuvelmans, 2006, Wagener and Wheeler, 2006, Boughton and Chiew, 2007, Goswami et al., 2007, Yadav et al., 2007, Viviroli et al., 2009) where the explanatory variables are catchment characteristics. Other common techniques include hydrologic classification and clustering methods (Vandewiele and Elias, 1995, Gupta et al., 1999, Nijssen et al., 2001, Koren et al., 2003, Merz and Blöschl, 2004, Pokhrel et al., 2008, Zhang et al., 2008), which essentially assign a priori model parameters to catchments either via grouping into hydrologically homogenous regions, by relating parameters to land-cover and climatic data, or by a combination of the two.

Singh et al. (2006) distinguish regionalization procedures for which site-by-site model calibration is followed by regionalization, from those that perform calibration and regionalization in a single combined step. Samaniego et al. (2010b) refer to the former as *postregionalization* and the latter as *simultaneous regionalization*. The latter has the benefit of incorporating additional geographical information (from nearby basins) into the parameter estimation procedure. A few recent studies have implemented simultaneous regionalization strategies, with varied results. Fernandez et al. (2000) attempted to optimize regional relationships and regional model parameters simultaneously for 33 catchments in

the southeastern United States, and concluded that improvements in regional relationships do not necessarily lead to improved model performance at ungauged sites. Kim and Kaluarachchi (2008) compared a simultaneous calibration procedure with five postregionalization techniques, and found modest improvements from the simultaneous calibration. Hundecha and Bárdossy, (2004), Götzinger and Bárdossy, (2007), Pokhrel et al. (2008) each had some success in simultaneous regionalization over different study domains; however all found that parameter transferability was limited by the use of discrete soil texture classes. Pokhrel et al. (2008) utilized the soil texture class relationships of Koren et al. (2003) to constrain parameters during calibration. Samaniego et al., (2010a,b) successfully applied a simultaneous regionalization procedure that considered the sub-grid variability of catchment attributes. This consideration has the advantage of enabling the regionalization to incorporate information from finer resolution data to estimate effective parameter values that are representative of the dominant hydrological processes at a coarser grid and across scales.

Collectively, the range of explanatory variables that have been used in the aforementioned studies include meteorological data (mean, variability and frequency information for precipitation, temperature, potential evapotranspiration, solar exposure, and surface wind), and land surface attributes (catchment geometry, aspect, and geomorphic data; geologic information, soil fractional composition, texture classes, hydraulic properties and depth; vegetation coverage, land-use information, and glaciation). Data sources have almost entirely been in situ; to date, only limited use has been made of remote sensing data as explanatory variables. In some cases, streamflow information has been used in regionalization (e.g. baseflow index, peak discharge and recurrence, runoff ratio, specific runoff), however this results in obvious limitations for parameter transfer to ungauged basins.

Our major objective in this paper is to extend previous model development and calibration efforts for the Unified Land Model (ULM – Livneh et al., 2011; Livneh et al., 2012a) to improve model applicability to new domains. The model parameters that serve as the basis for our regionalization relationships were derived through single and multi-criteria site-by-site calibrations described by Livneh et al. (2012a). These calibrations involved minimizing objective functions of errors between predicted streamflow, Q , and observations, as well as

in some cases, remote sensing estimates of evapotranspiration, ET. A secondary objective of our work is to evaluate different methods for organizing catchment attributes and selecting model parameters to increase the quality of regional relationships and enhance regional model performance.

Because there are many potential explanatory variables for regional parameter estimation, and because many of these attributes are correlated by construct, we used a principal components analysis (PCA) approach to maximize their explanatory skill and minimize potential redundancy. This approach technically falls into the category of ‘postregionalization’, however in two experiments (described in Section 4.2.5) we essentially retro-fit the data into a pseudo-simultaneous regionalization by conducting a limited number of additional simulations – termed here as ‘zonalization’. This procedure reevaluates the appropriateness of model parameter sets in the context of their performance over neighboring catchments (i.e. in spatial zones). Similarities exist between *zonalization* and other simultaneous regionalization approaches, but a key exception is that the regionalization takes place *a posteriori* with respect to model calibration

We further test this approach in the context of global parameter transfer, by restricting the regionalization procedure to only those catchment attributes with global coverage. This provides a broader context for hydrologic modeling in data poor regions; where stream gauges are not present, or for cases where site specific calibration is not computationally viable.

4.2 Methods

We describe in this section the ULM model and its parameters, along with the geospatial and hydrometeorological data needed to set-up and force the model. We also summarize the structure of the regionalization experiments, and the form of PCA and bias correction techniques used.

4.2.1 Study area and data sources

The study domain consists of 220 river basins with drainage areas in the range $10^2 - 10^4$ km² distributed across the continental United States (CONUS) (Figure 4.1). The 220 basins were selected to provide a broad cross section of hydroclimatic regimes (see Livneh et al., 2012a for details). The catchments are a subset of the MModel Parameter Estimation

EXperiment (MOPEX) data set (Schaake et al., 2006) which has been screened to assure an adequate density of precipitation gauges and minimal effects of upstream anthropogenic activities such as irrigation diversion and reservoir operations. Streamflow data were obtained directly from United States Geologic Survey (USGS) archives.

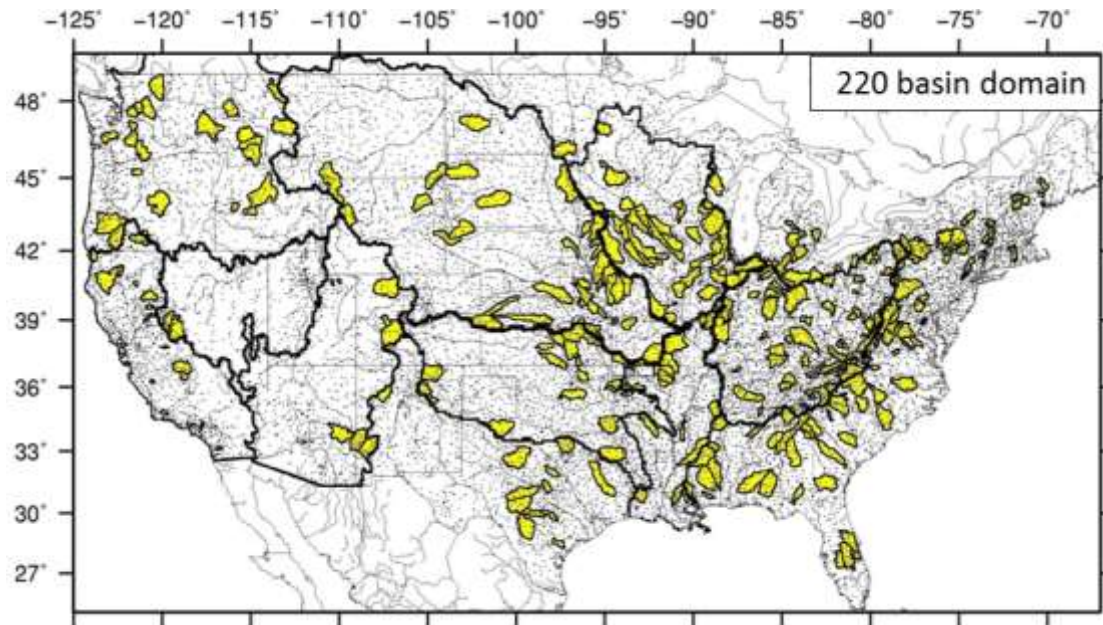


Figure 4.1: Map of the study domain, including 220 basins (yellow) and location of precipitation gages used in the forcing data set (fine black dots).

4.2.2 Model forcing data

The meteorological forcing data used in this study were derived by Livneh et al. (2012b) and are available at a $1/16^\circ$ resolution over the CONUS domain for the period 1915 – 2010. The gridded precipitation and daily minimum and maximum temperatures are based on approximately 20,000 NOAA Cooperative Observer (Co-op) stations (dots) shown in Figure 4.1. Wind data were linearly interpolated from a coarser (1.9° grid) NCEP–NCAR reanalysis grid (Kalnay et al. 1996), which also was used to produce a daily wind climatology for years prior to 1948.

4.2.3 Catchment attribute data

The catchment attribute data sets are summarized in Table 4.1 and serve as candidate predictor variables for the regionalization experiments. The first set of attributes correspond to the soil texture class relationships used by Koren et al. (2003) to estimate a set of *a priori* model parameters for the NWS Sacramento model (Sac). These conceptualized soil parameters are specific to the Sac model, which is the basis for the soil

hydrology in ULM. The soil texture relationships used by Koren et al, (2003) are readily estimated from STATSGO data (Schwarz and Alexander, 1995), and heretofore represent the default parameters for ULM.

The second set of catchment attributes includes the remaining land-surface characteristics that can be derived from inputs required by ULM. These include geomorphic variables (derived from the input DEM), vegetation information such as percent forest cover and seasonal greenness, as well as information pertaining to soil temperature climatology and seasonal land-surface albedo. The third set of attributes is derived from two remote sensing moisture flux products that are described in detail by Livneh et al. (2012a). These include the MODIS-based ET data product of Tang et al. (2009), as well as terrestrial water storage change (TWSC) based on Gravity Recovery and Climate Experiment (GRACE) data. Since the GRACE data are at coarser resolution ($\sim 1^\circ$) than the model spatial resolution ($1/16^\circ$), we compute a spatially weighted average TWSC value for each basin. The final set of attributes are taken from the GAGES-II data set, which includes information about basin morphology, climate, topography, soils, anthropogenic disturbance factors, as well as land use. Only floating-point basin attribute data in GAGES-II were considered, since integer-class attributes cannot readily be regressed, or averaged. Also, we did not consider streamflow-based attributes, (e.g. Baseflow Index) since these are not available for ungauged basins.

Table 4.1: Catchment attributes used as candidate explanatory variables in parameter regionalization.

Soil texture attributes	Description	Reference
Tension and free water storages, hydraulic conductivities, impervious areas, percolation constant, recession slope.	<i>a priori</i> values from soil texture relationships	Koren et al. (2003), Schwarz and Alexander (1995)
Geomorphic attributes		
Basin area, mean elevation, maximum relief, approx. length of main stream, relief ratio, shape factor, length-to-width ratio, elongation ratio	Defined from DEM and USGS GIS HUC 250K database	Seaber et al. (1987)
Land surface characteristic attributes		
Percentage of basin covered in forest; Satellite-based greenness fraction and albedo – monthly, seasonal, annual means, standard deviations, minimums, and maximums	Required as inputs into ULM	Gutman and Ignatov (1998)
Remote sensing attributes		
Evapotranspiration – monthly, seasonal, annual means, standard deviations, minima, and maxima	Derived entirely from satellite data (MODIS, SRB)	Tang et al. (2009)
TWSC – monthly, seasonal, annual means, standard deviations, minima, and maxima	GRACE data, mean of 3 processing streams*	Swenson and Wahr (2006)
Meteorological attributes		
Precipitation, Temperature, Wind – monthly, seasonal, annual means, standard deviations, minima, and maxima	Derived from station co-op data and reanalysis fields (wind only)	Livneh et al. (2012a)
GAGES-II attributes		
Soils data, climatic, land-use, morphology transitionary data, population density, drainage density classes, and anthropogenic disturbance factors	A single basin-average value for each field, only floating point data considered (i.e. no integer class data)	Falcone et al. (2010)

4.2.4 Land surface model

ULM is a merger of the land surface components from the Noah land surface model (LSM; Ek et al., 2003) – e.g., vegetation, ET computation, snow model, and algorithms for computing frozen soil, surface heat and radiative fluxes – and subsurface elements (soil moisture and runoff generation algorithms, as well as infiltration) from the NWS Sacramento Model (Burnash et al., 1973). The snow model is described by Livneh et al. (2010), which is the standard Noah snow model augmented to include time-varying albedo, partial snow cover, and retention of liquid water within the snowpack. Livneh et al. (2011)

evaluated ULM performance with respect to observed river discharge, flux towers measurements of surface heat fluxes, and soil moisture. Table 4.2 summarizes plausible ranges of the model soil parameters that constrained the parameter estimation here.

Table 4.2: List of ULM soil parameters from NWS Sacramento Model and their plausible ranges.

Parameters	Unit	Description	Plausible Range
UZTWM	mm	Upper zone tension water maximum storage	1.0 - 300
UZFWM	mm	Upper zone free water maximum storage	1.0 - 300
UZK	day ⁻¹	Upper zone free water lateral depletion rate	0.05 – 0.75
ZPERC	-	Maximum percolation rate	1.0 - 350
REXP	-	Exponent of the percolation curve equation	0.0 – 5.0
LZTWM	mm	Lower zone tension water maximum storage	1.0 - 500
LZFSM	mm	Lower zone free water supplemental maximum storage	1.0 – 1000
LZFPM	mm	Lower zone free water primary maximum storage	1.0 – 1000
LZSK	day ⁻¹	Depletion rate of the lower zone supplemental free water storage	0.01 – 0.8
LZPK	day ⁻¹	Depletion rate of the lower zone primary free water storage	0.0001 – 0.025
PFREE	-	Percolation fraction going directly from upper zone to lower zone free water storages	0.0 – 0.8
PCTIM	-	Impervious fraction of the ground surface	0.0 – 0.1
ADIMP	-	Maximum fraction of additional equivalent impervious area caused by land surface saturation	0.0 – 0.45

4.2.5 Regionalization procedure

The regionalization approach seeks to leverage the site-by-site calibrations performed by Livneh et al. (2012a). In that work, each basin underwent a multi-objective calibration involving approximately 2000 simulations per basin, from which a set of Pareto-optimal parameter sets, θ_P , we identified which minimize streamflow prediction errors. Given the large inherent data-storage requirements, only summary data from these calibrations were retained for each basin; these consist of the roughly 2000 parameter sets and their associated daily performance statistics. The major performance statistics used were the components of the Nash-Sutcliffe coefficient (NSE – Nash and Sutcliffe, 1970) pertaining to differences in simulated and observed streamflows (Gupta et al., 2009). These include the Pearson correlation coefficient, R , the difference in mean flows, α , and the difference in standard deviations, or range-shift, β . An important point here is that when calibrating the three components of the NSE in a multi-objective context, the resulting

Pareto set of solutions have statistics that are non-dominant with respect to each other (i.e. there are tradeoffs between R , α , β). However, Livneh et al. (2012a) observed that the effective NSE for these parameter sets are not necessarily equal, and some sets may have slightly higher or lower NSE than others.

The pairs of parameter sets and performance statistics from Livneh et al. (2012a) were reanalyzed in two ways that address the findings of previous regionalizations (e.g. Fernandez et al., 2000) detailed in section 4.1. The assertion of that work is that a strong predictive relationship between catchment attributes (predictors) and calibrated model parameters (predictands) will not necessarily lead to improved model performance using regionalized parameters. Therefore we designed four experiments to test the impact of predictive relationship strength on regionalized model performance by selecting predictands and predictors in several ways that alter the predictive relationships. The predictive relationship between each predictor/predictand set was derived using PCA (described in section 4.2.6) and the resulting ULM performance using regionalized model parameters was compared for each experiment. The first two experiments (Table 4.3) contrast parameter selection (predictands), based on either local or *zonal* representativeness, illustrated in Figure 4.2. Local parameters were selected based on the NSE for the basin of interest, whereas *zonal* parameters were selected based on the average NSE that resulted from iteratively simulating each Pareto-optimal parameter set, θ_P , from the basin of interest, at its neighboring basins (which we defined as being all basins for which the gauge was within a 5° latitude-longitude of the target basin gauge). The first experiment used locally optimized parameters, $\theta_{P-LOCAL}$, and thus followed a classic post-regionalization approach, where a predictive relationship was derived between local catchment attributes and locally optimized model parameters. In the second experiment, we *zonalized* the model parameters prior to regionalization, (i.e. $\theta_{P-ZONAL}$), which is anticipated to produce more spatially representative model parameters and test the assertion above.

The main points of the zonalization procedure for a given basin are:

- (1) Begin with ten Pareto-optimal sets per basin θ_P ;
- (2) Compute the NSE for each parameter set at the local basin. Select the set with the highest NSE to be the local optima $\theta_{P-LOCAL}$;
- (3) Run each parameter set at all neighboring basins within a 5 zone window;

(4) Average the resulting NSE values for each parameter set across neighboring basins and select the parameter set with the highest average NSE as the zonal optima $\theta_{P-ZONAL}$.

The above procedure was repeated for every basin in the domain. The third and fourth experiments (Table 4.3) were similar to the first two experiments, except that the zonal procedure was extended to the catchment attributes, η , where each basin's catchment attributes (η_{LOCAL}) replaced by their mean values within a 5° radius (η_{ZONAL}).

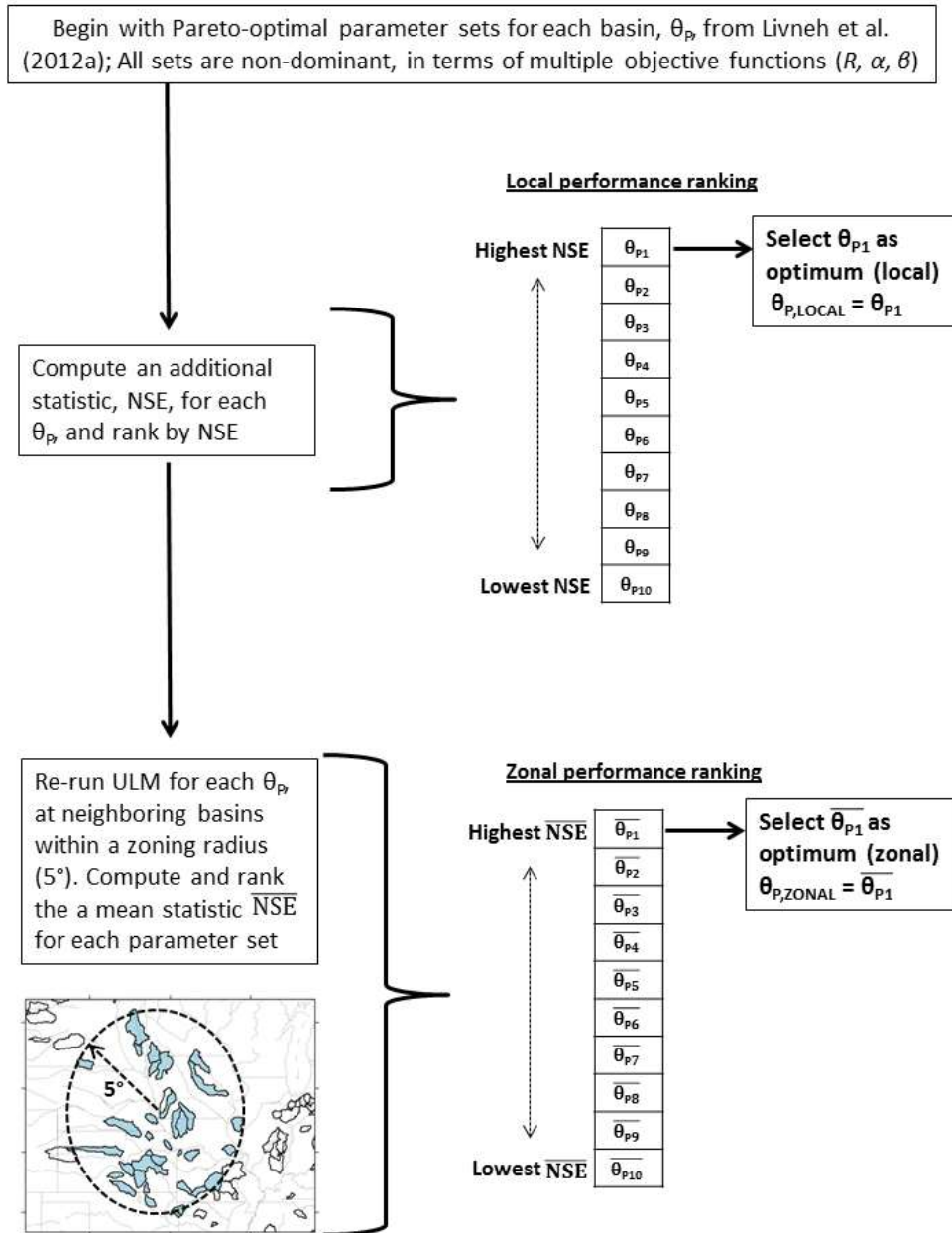


Figure 4.2: Flow chart illustrating the procedure for selecting locally and *zonally* optimized model parameters based on ranking Nash-Sutcliffe efficiency (NSE) from Pareto-optimal parameter sets that were non-dominant in terms of Pearson correlation, R , difference in means, α , and difference in standard deviation, β .

Table 4.3: Regionalization experiments considering either local or zonal predictands (ULM parameters, θ_P) and predictors (catchment attributes, η).

		ULM parameters (predictands)	
		$\theta_{P-LOCAL}$	$\theta_{P-ZONAL}$
Catchment attributes (predictors)	η_{LOCAL}	Experiment 1	Experiment 2
	η_{ZONAL}	Experiment 3	Experiment 4

4.2.6 Principal Components Analysis (PCA)

PCA was used to develop predictive relationships between catchment attributes and model parameters for each experiment listed in Table 4.3. Garen (1992) developed a PCA regression procedure to improve streamflow volume forecasting that included a systematic search for optimal or near-optimal combinations of variables. The procedure has since been used for applications related to hydrologic data reconstruction, reservoir modeling, and water supply forecasting (e.g. Hidalgo et al., 2000, Rosenberg et al., 2011). Hidalgo et al. (2000) found this method to produce more parsimonious results than other PCA-regression based models. To date, this method has not been used specifically for LSM parameter regionalization, although the method is suitable for incorporating a large number of predictor variables (i.e. candidate catchment attributes).

Therefore, we applied the Garen (1992) approach as implemented by Rosenberg et al. (2011) with the exception that we considered all attributes with non-zero correlations with the model parameters (as opposed to considering only positively correlated attributes as is typically done). The procedure includes an iterative series of t-tests between catchment attributes and model parameters, ultimately preserving only those principal components (i.e. combinations of attributes) that are statistically significant ($\alpha = 0.1$). A jack-knifing approach was used to predict parameter values for each basin based on its catchment attributes, such that the predictive equation is derived exclusively from information from

the other basins. This procedure was chosen to emulate the prediction of model parameters for ungauged basins.

4.3 Results and discussion

We evaluated the variability and spatial coherence of the regionalization input data, followed by an examination of the tradeoffs in model performance that result from using locally versus zonally optimized inputs (θ and η). We then compared ULM performance from all regionalization experiments to understand which strategy produces the best results. Finally, model simulations from each experiment were used in retrospective flood forecasts and were contrasted with a bias correction method to further quantify the potential for using regionalized model parameters.

4.3.1 Spatial Coherence

Figure 4.3 shows the inputs to the four regionalization experiments. The western U.S. is enlarged to illustrate the spatial coherence of zonal model parameters. Livneh et al. (2011) found ULM to be highly sensitive to the parameter shown in Figure 4.3 (UZTWM). This suggests that model parameters chosen on the basis of zonal performance indeed have detectable spatial coherence and may be linked to processes with length scales larger than those of an individual basin. This is an encouraging preliminary result, given that our ultimate goal is to find a set of regional equations that describe model parameter variations across large spatial scales.

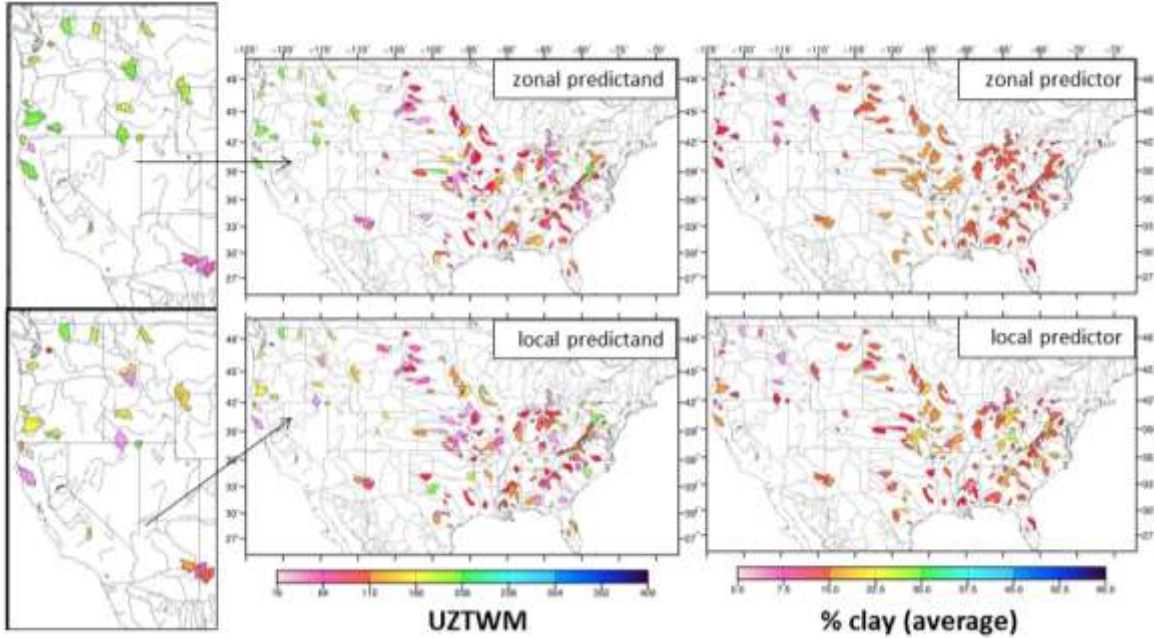


Figure 4.3: Example illustrating the spatial coherence of a set of candidate inputs for the regionalization experiments, which regionalize predictors (catchment attributes) and predictands (ULM parameters) that were selected either zonally or locally (e.g. Exp. 1 uses local predictands and local predictors as inputs to the PCA regionalization, see Table 4.3 for other experiments). The western U.S. is enlarged to show the spatial coherence of the zonal parameter value, UZTWM.

One way to quantify the coherence of a phenomenon in space (parameter variability) is by constructing an experimental variogram, $\gamma^*(\mathfrak{S}_k)$. This provides a measure of the average dissimilarity of a vector class, \mathfrak{S}_k , as a function of distance, h , by computing the dissimilarity between all pairs of samples within a region, i.e.:

$$\gamma^*(\mathfrak{S}_k) = \frac{1}{2n_c} \sum_{\alpha=1}^{n_c} (z(x_{\alpha} + h) - z(x_{\alpha}))^2 \quad (4.1)$$

Where $z(x_{\alpha})$ represents a parameter value in space for all samples, n_c . The experimental variogram is typically computed using vectors, h , of a length less than half the diameter of the region (Wackernagel, 2003). The experimental variograms for the locally optimized and zonally optimized parameters are shown in Figure 4.4. For ease of viewing dissimilarities, were binned by 1° intervals, and dissimilarities were normalized by the square of the mean of each parameter value to facilitate inter-parameter comparison. Two important variogram features are apparent. The first is the dissimilarity value in the bin closest to the origin, which denotes how abruptly the values of the variable changes at a very small scale. This is called the *nugget-effect*, which draws its name from the field of

gold mineral exploration. The second important feature of the variogram, the *sill*, is the distance beyond which increases in variability become negligible. This distance is called the *range*, and essentially represents the length scale of spatial coherence for a given parameter.

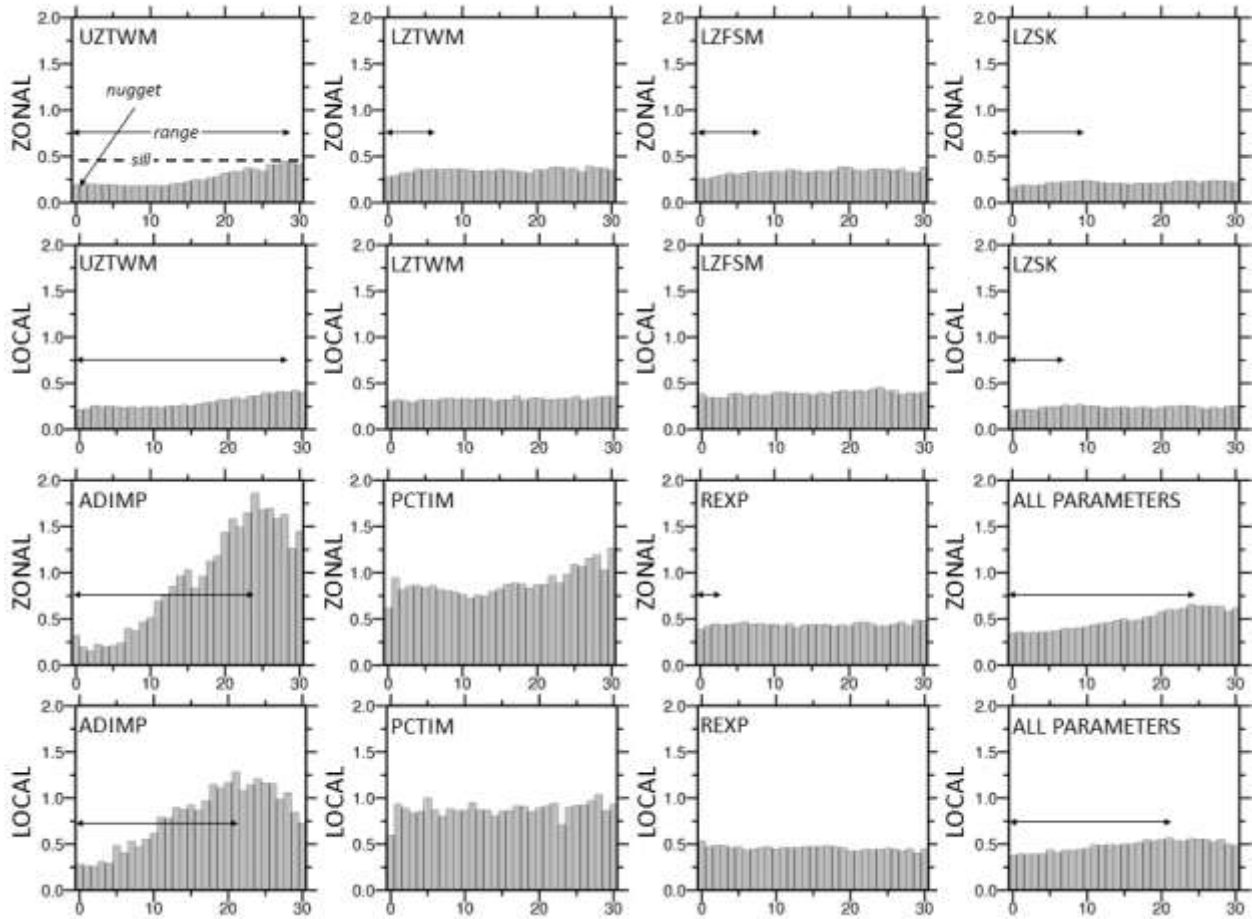


Figure 4.4: Experimental variograms for both zonal and local model parameters, illustrating greater spatial coherence for zonal parameters shown. Only those parameters with a detectable range are included, which is consistently present for zonal parameters.

Figure 4.4 shows only those parameters with a range that could be detected graphically. In all cases, the zonally optimized parameters have ranges that are greater than those of the locally optimized parameters and in some cases no sill was detected for locally optimized parameters, whereas one was for zonal optimizations. Although this should follow for all zonally optimized parameters by construct, roughly half of the parameters did not have detectable ranges, which may indicate that model performance is not very sensitive to their values, or alternatively that parameter values may be correlated with fields

that are not spatially coherent. The cases where no sill was detected for locally optimized parameters (while one was in fact detected for zonal optimization) were for instances of small spatial coherence, where the range was entirely contained within the 5° zoning window (for parameters LZTWM, LZFSM, REXP). This suggests that the size of the selected zoning window (5°) could impact the extent of the range. The presence of the nugget effect for all parameters indicates considerable variability even at very small scales. The nugget-effect is frequently smaller in zonal than local parameters, but not always, which is likely caused by the combination of parameter uncertainty and model streamflow prediction errors (i.e. imperfect optimizations). Important geographical boundaries may be crossed within the zoning radius (i.e. continental divide), which could contribute to a larger nugget-effect for zonal parameters. Furthermore, the parameter PCTIM was shown to be model-sensitive, although it lacks strong spatial coherence as illustrated in the short range of Figure 4.4. Overall, the parameters with detectable ranges in Figure 4.4, especially ADIMP and UZTWM, are consistent with those identified by Livneh et al. (2011) to which ULM was most sensitive.

4.3.2 Simulated streamflow performance

The tradeoffs in model performance associated with using zonal as contrasted with locally optimized parameters are shown in Figure 4.5. For approximately 20% of the basins, the best zonal performance resulted from the best locally optimized parameters – i.e. zonal and local parameters produced essentially the same result. For the remaining ~80% of basins, Figure 4.5 shows that the penalty for using zonal parameters for a given basin (i.e. locally) is comparatively smaller than the penalty for using local parameters zonally. Kumar and Samaniego (2011) found an analogous result for an LSM calibrated over a number of basins in Germany, with the aim of not over-fitting parameters to an individual basin. We infer from these results that model performance using zonalized parameters has a comparatively smaller penalty than local optimization, while lessening the degree of over-fitting parameters to any single basin.

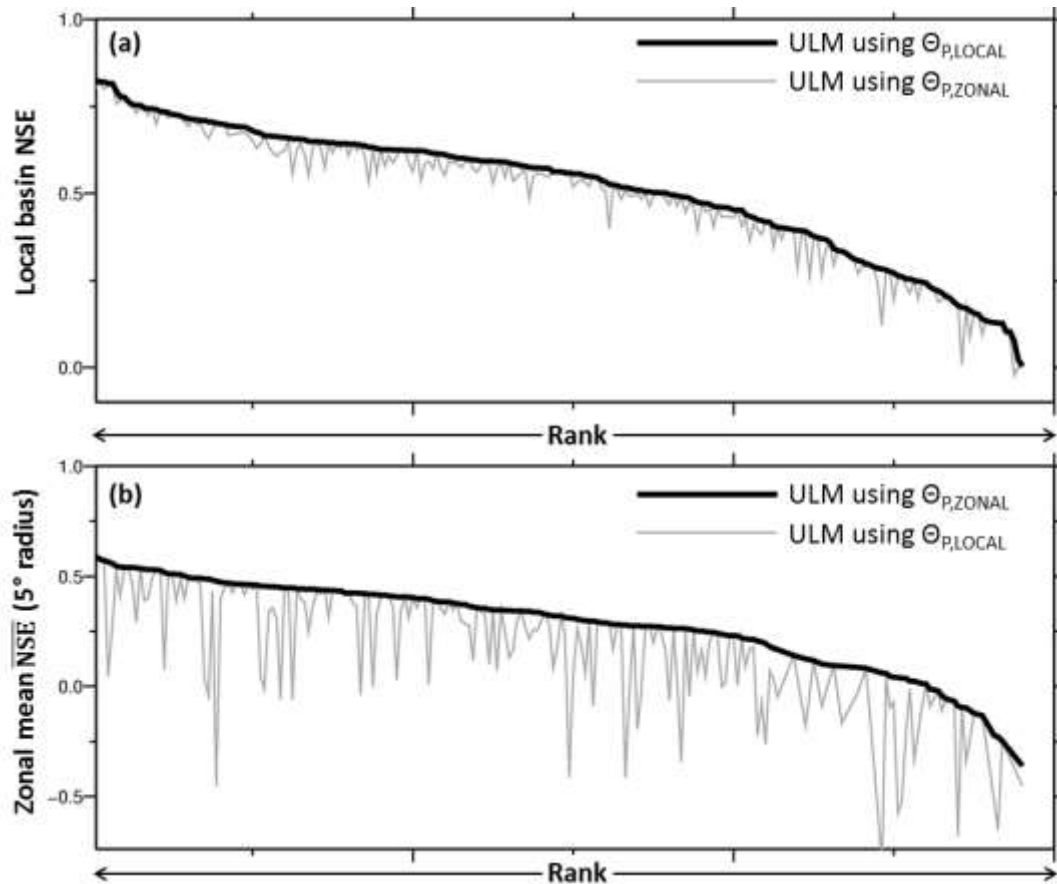


Figure 4.5: Illustration of tradeoffs in model performance when running (a) zonal parameters ($\theta_{P,ZONAL}$) locally and (b) running local parameters ($\theta_{P,LOCAL}$) zonally (averaged NSE over a 5° latitude-longitude window – see Figure 4.2 for definitions). The solid-black line was drawn connecting ranked Nash-Sutcliffe Efficiency (NSE) for 220 basins and represents the upper-envelope for model performance, either locally (a), or zonally (b), while the thin gray lines show that the penalty in local performance for using $\theta_{P,ZONAL}$ is much smaller than the penalty in zonal performance using $\theta_{P,LOCAL}$.

Figure 4.6 compares skill scores from the four regionalization experiments to local optimization. Differences in skill vary between regionalization experiments; however skill scores tend to be lowest relative to local calibration for basins where local optimization was itself the least skillful (i.e. on the right-most tail of the plots). An interesting result is that for several cases, the regionalized model outperformed the local optimization – most frequently for the case of zonalized parameters with local catchment attributes. The complete results from the calibration period (1991-2010) and a validation period of equal length (1971-1990) are tabulated in Table 4.4. For both time periods, regionalization using zonal rather than locally optimized parameters scored slightly higher, while the opposite was true for catchment attributes – experiments using local (zonal) catchment attributes had

slightly higher (lower) skill. This finding supports a hypothesis that model parameters may in fact be zonally representative, given their function of integrating model physics with hydro-meteorological processes. These processes frequently have length-scales larger than an individual catchment (e.g. seasonal frontal precipitation over the central and eastern U.S.). Alternatively, catchment attributes generally represent spatially-fixed local phenomena that are not necessarily well-expressed through areal averaging. However, it is worth noting that the spatially averaged zonal catchment attributes were not a direct analogue to the zonal parameters, which were selected following a non-linear transformation through ULM and a subsequent streamflow comparison.

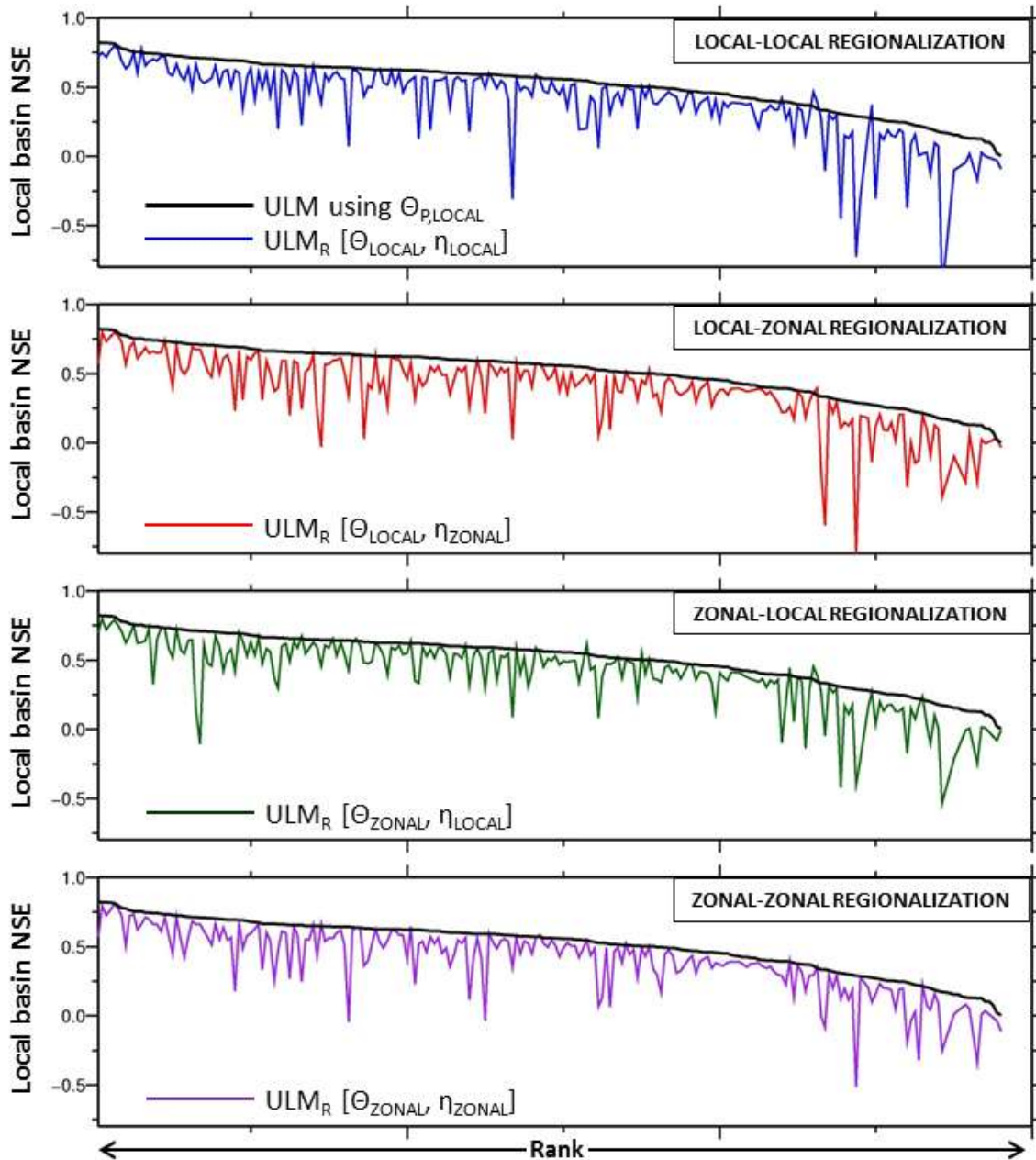


Figure 4.6: Comparison of the four regionalization experiments with local optimizations. The solid black line represents the NSE of each basin (ranked) as in Figure 4.5a, whereas the colored lines show regionalized model skill (ULM_R) for each experiment. The first word in the panel labels refers to which parameters, θ , were used, while the second refers to the catchment **attributes**, η , such that, for example, “ZONAL-LOCAL” represents the regionalization using zonal model parameters with local catchment **attributes**.

Table 4.4: Model performance (in terms of NSE) for calibrations and regionalization experiments.

Simulation type	Calibration Period		Validation Period	
	Mean	Std. deviation	Mean	Std. deviation
Locally Optimized	0.53	0.56	0.52	0.55
Zonally Optimized	0.51	0.54	0.44	0.48
$\theta_{P-ZONAL} - \eta_{ZONAL}$ Regionalization	0.43	0.48	0.44	0.48
$\theta_{P-ZONAL} - \eta_{LOCAL}$ Regionalization	0.43	0.49	0.44	0.48
$\theta_{P-LOCAL} - \eta_{ZONAL}$ Regionalization	0.41	0.47	0.42	0.47
$\theta_{P-LOCAL} - \eta_{LOCAL}$ Regionalization	0.43	0.48	0.43	0.48

The validation period is useful as a test of the robustness of model parameters and is important for model studies dealing with hydroclimatic sensitivities. Both the locally and zonally optimized skill scores are smaller during the validation period than in the original period used for parameter estimation, but the drop for zonally optimized parameters is more marked. Somewhat surprisingly, model skill from the regionalization experiments was slightly higher in the validation period than in the calibration period from which their predictive relationships were derived. Despite the differences in model skill between the two time periods, a paired t-test was performed which showed that none of the differences listed in Table 4.4 was statistically significant.

4.3.3 Principal components and catchment attributes

The final equations used to predict model parameters were made up of combinations of statistically significant principal components (PCs), which themselves were composed of catchment attributes.. Table 4.5 summarizes the number of catchment attributes, PCs, and the PCA parameter prediction errors, expressed as a normalized standard error:

$$\overline{SE} = \frac{s/\sqrt{n}}{\bar{\theta}} \quad (4.2)$$

Where s is the standard deviation of parameter estimation errors, n is the number of basins, and $\bar{\theta}$ is the mean value of the parameter being estimated. The number of PCs needed to estimate a given parameter varied from 1 to 26, with an average of approximately 10, while the number of catchment attributes used in estimation ranged from 17 to 47 with an average of 27. Quantitatively, these numbers did not appear to have an impact on the overall quality of parameter estimates. The $\theta_{P-ZONAL} - \eta_{LOCAL}$ regionalization had the smallest parameter prediction error and the best regionalized model performance. The predictive errors and

regionalized model performance from the other experiments intuitively followed similarly. Therefore, although it was called into question by Fernandez et al. (2000), this conclusion appears to hold in this case, namely higher quality regionalization relationships ultimately produce better model simulations.

Table 4.5: Counts of principal components and catchment **attributes** needed to for the predictive equations for each model parameter listed below; normalized standard error (Equation 4.2) was computed from the differences between the predictand (either $\theta_{P-LOCAL}$, or $\theta_{P-ZONAL}$) and the PCA generated estimated value for each regionalization experiments, where the first letter in the heading refers to parameter optimization, θ_P , and the second refers to the catchment attribute, η – i.e. Z=“zonal”, L=“local”.

Experiment	Principal Components				Catchment attributes				Normalized Standard Error, \overline{SE}			
	LL	LZ	ZL	ZZ	LL	LZ	ZL	ZZ	LL	LZ	ZL	ZZ
UZWIM	19	15	17	20	28	52	31	35	0.421	0.456	0.391	0.373
UZFWM	9	9	12	13	37	44	28	27	0.567	0.566	0.530	0.548
LZTWM	11	7	10	8	43	24	22	30	0.523	0.539	0.537	0.552
LZFPM	20	15	26	14	28	27	40	22	0.432	0.514	0.369	0.426
LZFSM	16	9	12	10	36	28	34	33	0.522	0.572	0.468	0.529
UZK	7	9	11	7	33	31	36	29	0.614	0.608	0.543	0.578
LZSK	21	18	22	17	31	26	32	34	0.326	0.395	0.322	0.370
LZPK	8	6	10	10	44	23	28	24	0.520	0.525	0.502	0.502
ADIMP	22	16	23	26	31	24	35	44	0.868	0.925	0.735	0.740
PCTIM	11	9	22	13	27	17	45	32	0.847	0.871	0.727	0.817
REXP	11	7	8	5	28	31	28	27	0.607	0.643	0.619	0.645
PFREE	11	4	8	1	25	24	32	17	0.544	0.581	0.578	0.631
ZPERC	13	7	7	5	47	26	30	27	0.450	0.470	0.501	0.498
Mean	11.93	8.73	12.53	9.93	29.2	25.13	28.07	25.4	0.483	0.511	0.455	0.481

Table 4.6 shows the overall frequency and use of attribute variables in terms of their respective classes. Attributes from the GAGES-II database far outnumber all others, and were also used most frequently for parameter predictions. The next most frequently used attributes were the GRACE-based TWSC, which were used nearly twice as often as the other remote sensing data set (ET), which was least frequently used overall.

Table 4.6: Summary of catchment attributes used in regionalization, including the average number of parameters each attribute was used to predict (frequency), and the total number of attributes used from each class.

Attribute class	Mean frequency of attributes -class in predictions	Fraction of attributes used (from total)
Soil texture	2.0	9/19
Geomorphic	2.5	8/8
Meteorological	2.1	10/16
ET	1.4	7/8
TWSC	2.6	5/8
GAGES-II	2.8	274/313
<i>Mean total</i>	2.23	<u>313/372</u>

Table 4.7 provides insights into the most explanatory catchment attributes for each parameter in the regionalization process; computed as the product of the attributes coefficient (in its respective PCs) and the mean attribute value across all catchments ($\bar{\theta}$). Every category of catchment attributes (summarized in Table 4.2) was represented within the most significant set of attributes shown in Table 4.7. Somewhat surprisingly, soil-based attributes were not ubiquitously among the most explanatory attributes, and were not among the three most predictive attributes for the lower zone soil moisture storage parameters (LZFSM, LZFBM). Also noteworthy was the frequent occurrence of temperature-related attributes, which may reflect their connection to radiation and the ensuing effect on model ET. Similarly, relative humidity and remote-sensing ET were found to be explanatory attributes for several cases. A notably intuitive relationship resulted between a related attribute and parameter, namely the topographical wetness index and the parameter ADIMP, which represents the maximum fraction of additional impervious area caused by saturation. Finally, several a priori ULM parameters (from the Koren et al., 2003 Sacramento Model parameter estimation) were found to be explanatory predictors. Somewhat unexpectedly, the explanatory a priori predictors were not of the same parameter. This can be partially reconciled by the fact the a priori parameters themselves were derived from the same soils data base (STATSGO) and they frequently represent inter-related processes. An example is the a priori value of PFREE (representing the percolation fraction going directly from upper zone to lower zone free water storages) that was an explanatory attribute for REXP (the exponent of the percolation curve equation), which are both computed from the estimated soil wilting point in the original

derivation of Koren et al. (2003). Lastly, the use of seasonally averaged catchment attributes (such as greenness fraction, or TWSC) are implicitly tied to a stationary climate and land cover, and would require careful implementation when applying these methods to predict future climate and land-use scenarios.

Table 4.7: The three most explanatory catchment attributes for each predicted model parameter, based on the product of the regression coefficients and the mean attribute value (all attributes below were part of statistically significant PCs in the prediction equations). For each parameter the attributes are listed in order of their explanatory strength. Results are shown only for the case of zonal parameters with local attributes.

Parameter	Catchment attribute	Explanation	Source
UZTWM	max_inter-monthly_tmin	Maximum inter-monthly daily minimum temperature	Met. Data
	max_inter-monthly_tmax	Maximum inter-monthly daily maximum temperature	Met. Data
	CLAYAVE	Average value of clay content (percentage)	GAGES-II
UZFWM	RH_BASIN	Watershed average relative humidity (percent)	GAGES-II
	ZPERC	A priori value of maximum percolation rate coefficient	Koren et al. (2003)
	NO4AVE	Average value of percent by weight of soil material less than 3 inches in size and passing a No. 4 sieve (5 mm)	GAGES-II
LZTWM	BAS_COMPACTNESS	Watershed compactness ratio, = area/perimeter ²	Geomorph.
	HGB	Percentage of soils in hydrologic group B. Hydrologic group B soils have moderate infiltration rates. Soils are moderately deep, moderately well drained, and moderately coarse in texture.	GAGES-II
	max_inter-monthly_tmin	Maximum inter-monthly daily minimum temperature	Met. Data
LZFPM	APR_TMP7100_DEGC	Average April air temperature for the watershed (degrees C)	GAGES-II
	mean_monthly_greenness	Mean monthly value of basin-wide greenness fraction	Land. surf.
	T_MIN_BASIN	Watershed average of minimum monthly air temperature (degrees C)	GAGES-II
LZFSM	RH_BASIN	Watershed average relative humidity (percent)	GAGES-II
	MAM_albedo	Average seasonal basin-wide albedo (Mar., Apr., May)	Land. surf.
	MAINSTEM_SINUOUSITY	Sinuosity of mainstem stream line. Defined as curvilinear length of the mainstem stream line divided by the straight-line distance between the end points of the line.	GAGES-II
UZK	MAY_PPT7100_CM	Mean May precip (cm) for the watershed	GAGES-II
	MAINS800_21	Mainstem 800m buffer "urban", 2001 era. Sum of MAINS800_21, 22, 23, and 24. Buffer is the area 800m each side of stream centerline	GAGES-II
	maxInterTWSC	Maximum inter-monthly terrestrial water storage change	Remote sens.
LZSK	MAM_greenness	Average spring basin-wide greenness fraction (Mar., Apr., May)	Land. surf.
	sd_monthly_albedo	Standard deviation of monthly albedo	Land. surf.
	NO200AVE	Average value of percent by weight of soil material less than 3 inches in size and passing a No. 200 sieve (.074 mm)	GAGES-II
LZPK	WDMAX_BASIN	Watershed average of monthly maximum number of days (days) of measurable precipitation	GAGES-II
	BAS_COMPACTNESS	Watershed compactness ratio, = area/perimeter ²	GAGES-II
	SON_greenness	Average autumn basin-wide greenness fraction (Sept., Oct., Nov.)	Land. surf.
ADIMP	TOPWET	Topographic wetness index	GAGES-II
	max_inter-monthly_tmax	Maximum inter-monthly daily maximum temperature	Met.
	RIP800_52	Riparian 800m buffer percent Shrubland	GAGES-II
PCTIM	LST32F_BASIN	Watershed average of mean day of the year (1-365) of last freeze	GAGES-II
	MAM_albedo	Average seasonal basin-wide albedo (Mar., Apr., May)	Land. surf.
	T_MAX_BASIN	Watershed average of minimum monthly air temperature (degrees C)	GAGES-II
REXP	PCT_2ND_ORDER	Percent of stream lengths in the watershed which are second-order streams (Strahler order); from NHDPlus	GAGES-II
	PFREE	Apriori value of percolation fraction going directly from upper zone to lower zone free water storages	Koren et al. (2003)
	ROADS_KM_SQ_KM	Road density, km of roads per watershed sq km, from Census 2000 TIGER roads	GAGES-II
PFREE	UZTWM	Apriori value of upper zone tension water capacity	Koren et al. (2003)
	LZTWM	Apriori value of lower zone tension water capacity	Koren et al. (2003)
	S4ET	Mean evapotranspiration in autumn (September, October, November)	Remote sens.
ZPERC	elongation_ratio	Diameter of a circle with basin area divided by the maximum transect.	Geomorph.
	PCT_3RD_ORDER	Percent of stream lengths in the watershed which are third-order streams (Strahler order);	GAGES-II

4.3.4 Global parameter estimation experiment

To emulate parameter estimation in data-poor regions, we repeated the most effective regionalization from section 4.3.2 ($\theta_{P-ZONAL}-\eta_{LOCAL}$) as well as the classic postregionalization ($\theta_{P-LOCAL}-\eta_{LOCAL}$) using only globally available catchment attributes. The two experiments chosen represent the recommended and conventional regionalizations, respectively. They exclude the GAGES-II attributes (which comprised a large number of explanatory catchment attributes in each original experiment, but are available only for the CONUS). The total number of candidate catchment attributes was reduced to 65 for these tests, after removing the GAGES-II attributes. Figure 4.7 compares ULM performance as for Figure 4.6, however, with the addition of the global coverage experiments. Both of the global experiments perform remarkably closely to the experiments in section 4.3.2 with very modest reductions in both mean and standard deviation of the skill scores (NSE listed on Figure 4.7). This preservation of NSE skill is attributable to the robustness of the PCA method in maximizing explanatory skill and minimizing redundancy. Stated alternatively, the original experiment was highly redundant, and used a large number of correlated attributes (section 4.3.2), while much of the explanatory information was extractable from the smaller set of attributes that are available globally (65).

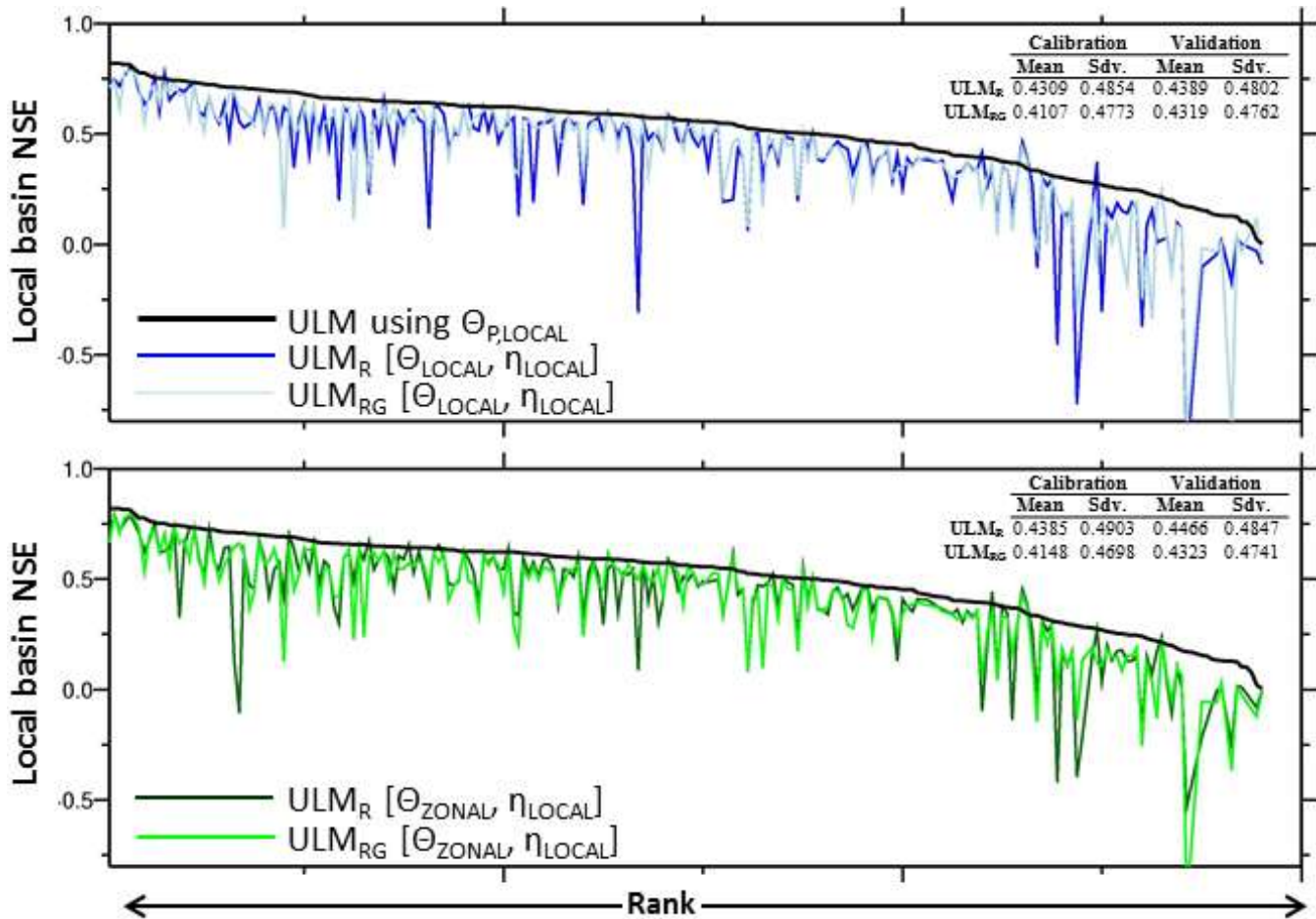


Figure 4.7: Comparison of ULM using locally optimized parameters with the original regionalization experiments (ULM_R, section 4.3.2) and the global experiments (ULM_{RG}, section 4.3.4). The mean daily NSE for all basins for ULM_{RG} were only slight reduced from the values listed in Table 4.4.

In the absence of GAGES-II catchment attributes, the PCA procedure identified alternative explanatory catchment attributes in place of those used in the original experiments (i.e. described in Table 4.7). Some of the most apparent replacements (not tabulated) for ULM-sensitive parameters (as identified by the experimental variograms) were: topographic wetness index was replaced by soil porosity for ADIMP; average clay content was replaced by mean monthly precipitation for UZTWM; and mean monthly temperature replaced relative humidity for LZFSM. Meanwhile the most explanatory attributes for PFREE remained unchanged. Altogether, in the absence of GAGES-II data, the PCA procedure was robust in preserving much of the explanatory information to estimate ULM parameters.

In each regionalization experiment, a small number of predictive relationships were found between catchment attributes and ULM parameters that were difficult to reconcile. These either lacked a physical basis, or would lead to circular arguments as to their link to the model parameter. Examples of the former in Table 4.7 are the relationship between the basin compactness ratio with LZTWM, and the basin elongation ratio with ZPERC. These relationships are most likely through the indirect effect of basin shape on the steepness or character of the hill slope, which could have a secondary impact on model parameters. Examples of the latter are the relationship between the a priori value of ZPERC and UZFWM and the a priori values of UZTWM with PFREE. ZPERC controls the percolation rate to the lower zone, so it is conceivable that a larger storage reservoir (UZFWM) could compensate for this. PFREE is entirely in the lower zone, and controls how much percolation goes to free water recharge, so again it is conceivable that UZTWM (which controls percolation rate) could bear on this, but both of these relationships are highly circular. For the above cases, it is most likely that these relationships are essentially mathematical artifacts of the regionalization. Siebert (1999) noted several regionalization relationships that lacked a physical basis in an 18 catchment experiment. For instance, lake area was found to be an explanatory variable, despite the fact the model structure did not explicitly consider lakes. One approach for dealing with such problems is to post-edit candidate catchment attributes for implausible relationships with model parameters, and to reprocess using only candidate attributes that appear to have physically plausible relationships with the model parameters.

4.4 Summary and conclusions

We have described a methodology for regionalizing ULM parameters based on a set of parameter optimizations and ancillary (predictor) variables for 220 catchments located across the CONUS. Both local and zonal parameterization approaches were developed, and were evaluated in a series of regionalization experiments that ultimately compared the impact of initial parameter and catchment attribute selection on regionalized model performance. A PCA approach constructed predictive relationships between locally or zonally optimized model parameters and PCs consisting of catchment attribute variables

that include soil texture, geomorphic, meteorological, and land surface features, as well as two remote sensing data sources and the GAGES-II data set. Our main conclusions are:

1. The penalty in streamflow prediction skill for using zonal parameters at an individual basin (i.e. locally) is comparatively smaller than the penalty for using local parameters zonally. This suggests that it is possible to avoid over-fitting model parameters to individual basins, while preserving a significant amount of predictive skill.
2. The experiments showed that the quality of regionalized model performance is directly related to the strength of parameter predictive relationships. Therefore, to be most effective, future regionalization efforts should seek ways to pair model parameters (predictands) and catchment (attributes) prior to regionalization (as done here through *zonalization*) to further improve regionalization quality.
3. Over the 20-year training and validation periods, the most skillful model performance resulted from regionalizations that used zonal model parameters and local catchment attributes as inputs for the PCA procedure. Both the calibrated and regionalized parameter sets were temporally robust, since differences in performance between the training and validation periods were not statistically significant.
4. The approach worked surprisingly well when only globally available data sources were used. Although many of the best predictors in the original experiment were from the GAGES-II data set (which is only available for CONUS), other parameters displaced those based on GAGES-II, with little loss in accuracy.

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V. CONCLUSIONS

The research reported in this dissertation addresses the four science questions from Chapter I, specifically: (i) Which ULM structures produce the most realistic simulations of surface hydrology and land-atmosphere interactions?, (ii) How well can the ULM structures be used to accurately estimate the terrestrial water balance at both catchment and regional scales?, (iii) Can the use of ground-based and satellite observations provide a physically consistent framework from which to derive model parameters that result in realistic water balance estimates?, and (iv) To what extent can parameter information from ULM simulations ($10^2 - 10^4 \text{ km}^2$) be transferred to other catchments through predictive relationships derived exclusively from directly observable catchment attributes? The development and implementation of the model took place in three stages that first addressed model structure, followed by model parameters, and finished with model regionalization.

The initial objective of the model development effort was to evaluate the potential of ULM to improve weaknesses of its parent models, Noah and Sac, while taking advantage of their respective strengths. It was shown that ULM more accurately simulates the soil drying cycle than does Noah, which has implications for drought monitoring applications. The improvements in hydrology did not hinder surface heat flux estimates, which were similar or modestly superior to Noah. This is relevant to coupled land-atmosphere applications (i.e., numerical weather prediction) and is significant in a benchmarking context, which implies that updates to one aspect of model physics need not come at the expense of another. In order to adequately capture streamflow dynamics, limited parameter tuning was needed. One key finding is that there is a need for a representative set of ULM parameters, and that simply utilizing native Sac soil parameters within the ULM structure does not necessarily lead to realistic model responses.

Another goal of this dissertation was to incorporate in situ and remote sensing observations of the land surface water budget into ULM parameter estimates. The challenge of how best to combine these data into regional parameter estimation approaches was addressed through a set of single and multi-criteria model calibrations in which streamflow was deemed the least uncertain criterion, and hence most reliable as the overall

validation metric. At the largest scales ($\geq 10^5 \text{ km}^2$), calibrations were performed to several objective function combinations (Q, ET_{SAT} , ET_{AWB} , TWSC) with varying results. Although ULM was able to replicate these criteria reasonably well individually, certain combinations of criteria (e.g. ET_{AWB} and TWSC) lead to large errors in other criteria. A shortcoming in the use of remote sensing data (from either single or multiple sensors) was that these information sources are not constrained by water balance closure, leading to inconsistent results in certain cases of predictive variables and objective functions.

Overall, large-scale performance was generally superior when Q was included in the objective function, and especially when it was the single criterion. This showed that as of yet, non-streamflow related quantities (i.e. ET and TWSC) alone do not contain sufficient information and agreement to significantly improve streamflow predictions, which is desirable for prediction in ungauged basins. At smaller scales ($10^2 - 10^4 \text{ km}^2$), the number of samples (basins) was much larger, while the number of potential predictors was smaller (Q and a single ET product). The results contrasted somewhat with the large-scale findings; specifically, for roughly one-third of all basins simulated streamflow performance was higher when calibrating to both Q and ET simultaneously than when using Q as the sole objective function. Therefore, this testing showed that although the inclusion of remote sensing data together with gauge-based streamflow can improve simulated response, remote-sensing data by themselves were incapable of producing parameter estimates that could result in adequate streamflow simulations.

Another way to improve the quality of simulations in ungauged basins is by transferring geophysical information within a parameter regionalization framework. A series of regionalization experiments conducted using this paradigm should be relevant both to ungauged basins and for more general interpretation and estimation geospatial patterns.

This work sought to determine whether strong predictive relationships between catchment attributes (predictors) and calibrated model parameters (predictands) will necessarily lead to improved regional model performance (as measured by the model's ability to reproduce observed hydrologic fluxes). Given the large number of potential explanatory variables for regional parameter estimation, and because many of these attributes are correlated by construct, a principal components analysis (PCA) approach was

used. It was shown that regionalizations were most effective when the more conventional procedure of using locally optimized parameters as predictands was replaced by an approach that searches for *zonally* representative parameter values, using limited additional simulations. This preliminary step also revealed that the penalty in streamflow prediction skill for using zonal parameters at an individual basin (i.e. locally) is comparatively smaller than the penalty for using local parameters zonally. This suggests that it is possible to avoid over-fitting model parameters to individual basins, while preserving a significant amount of predictive skill. A spatial length for zoning was defined based on basins for which the gauge was within a 5° latitude-longitude radius of the target basin gauge.

The potential for transferring parameters globally was examined by repeating the regionalization using only catchment attributes derived from globally available data. Model simulations using these parameters based on a reduced number of candidate catchment attributes performed surprisingly well.

Overall, the experiments showed that the quality of regionalized model performance is directly related to the strength of parameter predictive relationships. Therefore, to be most effective, future regionalization efforts should seek ways to pair model parameters (predictands) and catchment attributes (predictors) prior to regionalization, as was done here through zonalization.

VI. REFERENCES

- Abdulla, F.A., and D.P. Lettenmaier, 1997: Development of regional parameter estimation equations for a macroscale hydrologic model, *J. Hydrol.*, **197**, 230–257.
- Anderson E. A., 1973: National Weather Service River Forecast System—Snow Accumulation and Ablation Model. NOAA Tech. Memo. NWS HYDRO-17, 217 pp.
- Anderson R.M., V.I. Koren and S.M. Reed, 2006: Using SSURGO data to improve Sacramento model *a priori* parameter estimates, *J. Hydrol.*, **320(1)**, 103–116.
- Aron, G., White, E.L., 1982. Fitting a Gamma distribution over a synthetic unit hydrograph. *Water Resour. Bull.* 18 (1), 95–98.
- Arora, V.K., 2001: Streamflow simulations for continental-scale river basins in a global atmospheric general circulation model, *Adv. Water Resour.*, **24(7)**, 775-791.
- Baldocchi, D. D., 2003: Assessing the eddy-covariance technique for evaluating the carbon dioxide exchange rates of ecosystems: Past, present and future, *Glob. Change Biol.*, **9**, 479– 492.
- Baldocchi, D. D., J. Finnigan, K. Wilson, K. T. Paw U, and E. Falge, 2000: On measuring net ecosystem exchange over tall vegetation on complex terrain, *Boundary Layer Meteorol.*, **96**, 257– 291.
- Bastidas, L. A., T. S. Hogue, S. Sorooshian, H. V. Gupta, and W. J. Shuttleworth 2006: Parameter sensitivity analysis for different complexity land surface models using multicriteria methods, *J. Geophys. Res.*, **111**, D20101, doi:10.1029/2005JD006377.
- Betts, A. K., J. H. Ball, A. C. M. Beljaars, M. J. Miller, and P. A. Viterbo 1996: The land surface-atmosphere interaction: A review based on observational and global modeling perspectives, *J. Geophys. Res.*, **101(D3)**, 7209–7225.
- Beven, K.J., and A. Binley, 1992: The future of distributed models – model calibration and uncertainty prediction. *Hydrological processes*, **6 (3)**, 279–298.
- Beven, K.J., and J. Freer, 2001: Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology, *Journal of Hydrology*, **249**, 11-29.

Birkel, C., D. Tetzlaff, S.M. Dunn, and C. Soulsby, 2010: Towards simple dynamic process conceptualization in rainfall-runoff models using multi-criteria calibration and tracers in temperate, upland catchments, *Hydrological Processes*, **24**, 260–275.

Bohn T.J., M.Y. Sonessa, and D.P. Lettenmaier, 2010: Seasonal Hydrologic Forecasting: Is there a role for multimodel ensemble methods?, *J. Hydrometeorol.*, **11**, 1358-1372.

Bonan G.B., D. Pollard, and S.L. Thompson, 1992: Effects of boreal forest vegetation on global climate, *Nature*, **359**, 716-718.

Boughton, W., Chiew, F., 2007. Estimating runoff in ungauged catchments from rainfall, PET and the AWBM model. *Environ. Modell. Softw.* **22**, 476–487.

Budyko, M.I., 1974: *Climate and Life*. Academic Press, New York, 508.

Burnash, R.J.C., R.L. Ferral, and R.A. McGuire, 1973: A generalized streamflow simulation system - Conceptual modeling for digital computers. Technical Report, Joint Federal and State River Forecast Center, U.S. National Weather Service and California Department of Water Resources, Sacramento, 204pp.

Chen F., K.E. Mitchell, J. Schaake, Y. Xue, H.-L. Pan, V. Koren, Q.Y. Duan, M.B. Ek, and A. Betts, 1996, Modeling of land-surface evaporation by four schemes and comparison with FIFE observations, *J. Geophys. Res.*, **101**, 7251-7268.

Chen F., Z. Janjic, and K.E. Mitchell, 1997, Impact of atmospheric surface-layer parameterizations in the new land-surface scheme of the NCEP mesoscale Eta model, *Boundary Layer Meteorol.*, **85**, 391-421.

Crow, W.T., E.F. Wood, and M. Pan, 2003: Multiobjective calibration of land surface model evapotranspiration predictions using streamflow observations and spaceborne surface radiometric temperature retrievals, *J. Geophys Res.*, **108(23)**, 4725. doi:10.1029/2002JD003292.

Daly, C., R. P. Neilson, and D. L. Phillips, 1994: A statistical topographic model for mapping climatological precipitation over mountainous terrain., *J. Appl. Meteor.*, **33**, 140–158.

D'Odorico, P., K. Caylor, G. S. Okin, and T. M. Scanlon 2007: On soil moisture–vegetation feedbacks and their possible effects on the dynamics of dryland ecosystems, *J. Geophys. Res.*, **112**, G04010, doi:10.1029/2006JG000379.

Duan Q., S. Sorooshian, and V.K. Gupta 1994: Optimal use of the SCE-UA global optimization method for calibrating watershed models, *J. Hydrol.*, **158** (3-4), 265-284.

Eltahir, E. A. B., Ek, M. B., K. E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, and G. Gayno, 1998: A soil moisture–rainfall feedback mechanism 1. Theory and observations, *Water Resour. Res.*, **34**, 765–776.

Ek, M.B., and A.A.M. Holtslag, 2004: Influence of soil moisture on boundary layer cloud development, *J. Hydrometeorol.*, **5** (1), 86–99.

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 Centers for Environmental Prediction operational mesoscale Eta model, *Journal of Geophysical Research*, D22 (108), 8851, doi:10.1029/2002JD003296.

Falcone J.A., D.M. Carlisle, D.M. Wolock, and M.R. Meador, 2010: GAGES: A stream gage database for evaluating natural and altered flow conditions in the conterminous United States. *Ecology* 91:621.

Falge, E., D. Baldocchi, R.J. Olson, P. Anthoni, M. Aubinet, C. Bernhofer, G. Burba, R. Ceulemans, R. Clement, H. Dolman, A. Granier, P. Gross, T. Grünwald, D. Hollinger, N.O. Jensen, G. Katul, P. Keronen, A. Kowalski, C. Ta Lai, B.E. Law, T. Meyers, J. Moncrieff, E. Moors, J.W. Munger, K. Pilegaard, Ü. Rannik, C. Rebmann, A. Suyker, J. Tenhunen, K. Tu, S. Verma, T. Vesala, K. Wilson, and S. Wofsy, 2001: Gap filling strategies for long term energy flux data sets, *Agric. For. Meteorol.*, **107**, 71–77.

Ferguson, C.R., J. Sheffield, E.F. Wood, and H. Gao, 2010: Quantifying uncertainty in a remote sensing based estimate of evapotranspiration over the continental United States. *Int. J. Remote Sens.*, **31:14**, 3821-3865.

Fernandez, W., R.M. Vogel, and A. Sankarasubramanian, 2000: Regional calibration of a watershed model, *Hydrological Sciences Journal*, 45(5), 689-707.

Finnerty, B.D., M.B. Smith, D.J. Seo, V.I. Koren, and G. Moglen, 1997: Sensitivity of the Sacramento soil moisture accounting model to space–time scale precipitation inputs from NEXRAD, *J. Hydrol.*, **203**(1–4), 21–38.

Gan, T. Y., and S. J. Burges, 2006: Assessment of soil-based and calibrated parameters of the Sacramento model and parameter transferability, *J. Hydrol.*, **320**(1 –2), 117– 131.

Garen, D. C. 1992: Improved techniques in regression-based streamflow volume forecasting, *J. Water Resour. Plan. Manag.*, **118**(6), 654–670.

Goldstein A. H., N. E. Hultman, J. M. Fracheboud, M. R. Bauer, J. A. Panek, M. Xu, Y. Qi, A. B. Guenther, and W. Baugh, 2000: Effects of climate variability on the carbon dioxide, water, and sensible heat fluxes above a ponderosa pine plantation in the Sierra Nevada (CA), *Agric. For. Meteorol.*, **101**(2-3), 113-129.

Götzinger, J., and A. Bárdossy, 2007: Comparison of four regionalization methods for a distributed hydrological model, *J. Hydrol.*, 333, 374–384.

Gupta H.V., S. Sorooshian, and P.O. Yapo, 1998: Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information, *Water Resour. Res.*, **34**, 751–763.

Gupta, H. V., L. A. Bastidas, S. Sorooshian, W. J. Shuttleworth, and Z. L. Yang, 1999: Parameter estimation of a land surface scheme using multicriteria methods, *J. Geophys. Res.*, **104**(19), 491-503.

Gupta H.V., H. Kling, K.K. Yilmaz, and G.F. Martinez, 2009: Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modeling, *Journal of Hydrology*, **377**(1-2), 80-91.

Gutman, G., and A. Ignatov, 1998: The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models, *Int. J. Remote Sensing*, **19**, 1533-1543.

Heuvelmans G., B. Muys, and J. Feyen J, 2004: Evaluation of hydrological model parameter transferability for simulating the impact of land use on catchment hydrology, *Phys. Chem. Earth*, **29** (11-12 SPEC. ISS.), 739-747.

Heuvelmans, G., Muys, B., Feyen, J., 2006. Regionalization of the parameters of a hydrologic model: comparison of linear regression models with artificial neural nets. *J. Hydrol.* 319, 245–265.

Hidalgo H.G., T.C. Piechota, and J.A. Dracup, 2000: Alternative principal components regression procedures for dendrohydrologic reconstructions, *Water Resources Research*, 36(11), 3241-3249.

Hollinger, S. E., and S. A. Isard, 1994: A soil moisture climatology of Illinois. *J. Climate*, **7**, 822-833.

Hollinger D. Y., S. M. Goltz, E. A. Davidson, J. T. Lee, K. Tu, and H. T. Valentine 1999: Seasonal patterns and environmental control of carbon dioxide and water vapour exchange in an ecotonal boreal forest, *Glob. Change Biol.*, **5(8)**, 891-902.

Hundecha, Y., and A. Bárdossy, 2004: Modeling effect of land use changes on runoff generation of a river basin through parameter regionalization of a watershed model, *J. Hydrol.*, **292**, 281–295.

Jarvis, P. G., 1976: The interpretation of leaf water potential and stomatal conductance found in canopies in the field, *Philos. Trans. Roy. Soc. London*, **273B**, 593–610.

João E., 2002: How scale affects environmental impact assessment, *Environmental Impact Assessment Review*, **22**, 289-310.

Johansen, O., 1977, Thermal conductivity of soils (in Norwegian), Ph.D., thesis, Univ. of Trondheim, Trondheim, Norway, 1975. (English Translation, No. 637, *Cold Reg. Res. And Eng. Lab.*, Hanover, NH, 1977).

Kalma, J.D., T.R. McVicar, and M.F. McCabe, 2008: Estimating land surface evaporation: a review of methods using remotely sensed surface temperature data, *Surveys in Geophysics*, **29**, 421–469.

Kalnay, E., and Coauthors, 1996: The NCEP/NCAR 40-Year Reanalysis Project, *Bull. Amer. Meteor. Soc.*, **77**, 437–471.

Kampf, S.K., and S.J. Burges, 2007: Parameter estimation for a physics-based distributed hydrologic model using measured outflow fluxes and internal moisture states, *Water Resources Research*, **43**, W12414, doi:10.1029/2006WR005605.

Kampf, S.K., and S.J. Burges, 2010: Quantifying the water balance in a planar hillslope plot: Effects of measurement errors on flow prediction, *Journal of Hydrology*, **280**, 191-202.

Karlinger, M.R., D.P. Guertin, and B.M. Troutman, 1988: Regression estimates for topological-hydrograph input, *Journal of Water Resources Planning and Management*, **114**, 446-456.

Khu S.T., H. Madsen, and F. di Pierro, 2008: Incorporating multiple observations for distributed hydrologic model calibration: an approach using a multi-objective evolutionary algorithm and clustering, *Advances in Water Resources* **31**: 1387–1398.

Kingston D.G., D.M. Hannah, D.M. Lawler, and G.R. McGregor, 2011 Regional classification, variability, and trends of northern North Atlantic river flow, *Hydrological Processes*, **25**, 1021–1033.

Klees, R., X. Liu, T. Wittwer, B.C. Gunter, E.A. Revtova, R. Tenzer, P. Ditmar, H.C. Winsemius, and H.H.G. Savenije, 2008: A Comparison of Global and Regional GRACE Models for Land Hydrology. *Surv. Geophys.*, **29(4–5)**, 335–359, doi:10.1007/s10712-008-9049-8.

Koren, V., J. Schaake, K. Mitchell, Q.-Y. Duan, F. Chen, and J.M. Baker, J. M., 1999, A parameterization of snowpack and frozen ground intended for NCEP weather and climate models. *J. Geophys. Res.*, **104(D16)**, 19569–19585.

Koren, V.I., M. Smith, D. Wang, and Z. Zhang, 2000: Use of soil property data in the derivation of conceptual rainfall-runoff model parameters, Preprints, 15th Conference on Hydrology, Long Beach, CA, *Amer. Meteor. Soc.*, **10(14)**, 103–106.

Koren V.I., M. Smith and Q. Duan, 2003: Use of *a priori* parameter estimates in the derivation of spatially consistent parameter sets of rainfall-runoff models. In: Q. Duan, S. Sorooshian, H. Gupta, H. Rosseau and H. Turcotte, Editors, *Calibration of Watershed Models, Water Science and Applications vol. 6*, AGU, pp. 239–254.

Koren, V.I., Parameterization of frozen ground effects: sensitivity to soil properties, in Predictions in Ungauged Basins: Promises and Progress (Proceedings of symposium S7 held during the Seventh IAHS Scientific Assembly at Foz do Iguaçu, Brazil, April 2005). *IAHS Publ. 2006*, **303**, 125-133.

Koster, R.D., P.A. Dirmeyer, Z.C. Guo, G.Bonan, E. Chan, P. Cox, C.T. Gordon, S. Kanae, E. Kowalczyk, D. Lawrence, P. Liu, C.H. Lu, S. Malyshev, B. McAvaney, K.E. Mitchell, D. Mocko, T. Oki, K. Oleson, A. Pitman, Y.C. Sud, C.M. Taylor, D. Verseghy, R. Vasic, Y.K. Xue, and T. Yamada, 2004: Regions of strong coupling between soil moisture and precipitation, *Science*, **305**, 1138–1140.

Kumar, R. and L. Samaniego, 2011: A regional calibration scheme for a distributed hydrologic model based on a copula dissimilarity measure, poster presented at the AGU Fall Meeting, San Francisco, California, USA.

Liebenthal, C., B. Huwe, and T. Foken, 2005: Sensitivity analysis for two ground heat flux calculation approaches, *Agric. Forest. Meteorol.*, **132**, 253–262.

Lischeid G., 2008: Combining hydrometric and hydrochemical data sets for investigating runoff generation processes: tautologies, inconsistencies and possible explanations, *Geography Compass* **2**(1): 255–280, 10.1111/j.1749– 8198.2007.00082.x.

Livneh, B., Y. Xia, K.E. Mitchell, M.B. Ek, and D.P. Lettenmaier, 2010, Noah LSM Snow Model Diagnostics and Enhancements, *J. Hydrometeorol.*, **11**(3), 721-738.

Livneh, B., P.J. Restrepo, and D.P. Lettenmaier, 2011: Development of a Unified Land Model for prediction of surface hydrology and land-atmosphere interactions, *Journal of Hydrometeorology*, **12**(6), 1299-1320, doi: 10.1175/2011JHM1361.1.

Livneh B., E.A. Rosenberg, C. Lin, V. Mishra, K.M. Andreadis, and D.P. Lettenmaier, 2012b: Extension and spatial refinement of a long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States, *Journal of Climate (in preparation)*.

Livneh, B. and D.P. Lettenmaier, 2012a: Multi-criteria parameter estimation for the unified land model, *Hydrol. Earth Syst. Sci. Discuss.*, **9**, 4417-4463, doi:10.5194/hessd-9-4417-2012.

Lo, M., J.S. Famiglietti, P.J.-F. Yeh, and T.H. Syed, 2010: Improving parameter estimation and water table depth simulation in a land surface model using GRACE water storage and estimated base flow data, *Water Resour. Res.*, **46**, W05517, doi:10.1029/2009WR007855.

Loescher, H. W., B. E. Law, L. Mahrt, D. Hollinger, J. L. Campbell, and S. E. Wofsy, 2006: Uncertainties in, and interpretation of, carbon flux estimates using the eddy covariance technique, *J. Geophys. Res.*, **111**, D21S90, doi:10.1029/2005JD006932.

MacLean, A.J., B.A. Tolson, F.R. Seglenieks, and E. Soulis, 2010: Multiobjective calibration of the MESH hydrological model on the Reynolds Creek Experimental Watershed, *Hydrol. Earth Syst. Sci. Discuss.*, **7**, 2121–2155.

Magette, W.L., V.O. Stanholz, and J.G. Cair, 1976: Estimating selected parameters for the Kentucky watershed from watershed characteristics, *Water Resources Research*, **12**, 472- 476.

Mahmood, R. and K.G. Hubbard, 2003: Simulating sensitivity of soil moisture and evapotranspiration under heterogeneous soils and land uses, *J. Hydrol.*, **280**, 72-90.

Mahrt, L., and H.L. Pan, 1984: A two-layer model of soil hydrology, *Boundary Layer Meteorol.*, **29**, 1– 20.

Mahrt, L., and M. Ek, 1984: The influence of atmospheric stability on potential evaporation, *J. Clim. Appl. Meteorol.*, **23**, 222– 234.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen, 2002: A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States, *J. Climate*, **15**, 3237–3251.

McCabe, M.F., S.W. Franks, and J.D. Kalma, 2005: Calibration of a land surface model using multiple datasets, *J. of Hydrolog.*, **302**, 209-222.

McCumber, M., and R.A. Pielke, 1981: Simulation of effects of surface fluxes of heat and moisture in a mesoscale numerical model. Part 1: Soil layer, *J. Geophys. Res.*, **86C**, 9929-9938.

Merz, R. and G. Blöschl, 2004: Regionalisation of catchment model parameters, *Journal of Hydrology*, **287**, 95-123.

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P.C. Shafran, W. Ebisuzaki, D. Jovic, J. Woollen, E. Rogers, E.H. Berbery, M.B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, and W. Shi, 2006: North American Regional Reanalysis. *Bull. Amer. Met. Soc.*, **87(3)**, 343-360.

Miller, D. A. and R. A. White, 1999: A Conterminous United States multi-layer soil characteristics data set for regional climate and hydrology modeling, *Earth Interactions*, **2**, (available at <http://EarthInteractions.org>).

Milly, P.C.D., J. Betancourt, M. Falkenmark, R.M. Hirsch, Z.W. Kundzewicz, D.P. Lettenmaier, and R.J. Stouffer, 2008, Stationarity is dead: whither water management?, *Science*, **319**, 573-574.

Milzow, C., Krogh, P.E., and Bauer-Gottwein, P., 2011: Combining satellite radar altimetry, SAR surface soil moisture and GRACE total storage changes for hydrological

model calibration in a large poorly gauged catchment, *Hydrol. Earth Syst. Sci.*, **15**, 1729–1743.

Mishra, V, K.A. Cherkauer, and S. Shukla, 2010: Assessment of Drought due to Historic Climate Variability and Projected Future Climate Change in the Midwestern United States, *J. Hydrometeorol.*, **11(1)**, 46-68.

Mitchell, K.E., and Coauthors., 2004: The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, *J. Geophys. Res.*, **109**, D07S90, doi:10.1029/2003JD003823.

Murphy, A. H., 1988: Skill scores based on the mean square error and their relationships to the correlation coefficient, *Mon. Weather Rev.*, **116**, 2417-2424.

Nandagiri, L., 2007: Calibrating hydrological models in ungauged basins: possible use of areal evapotranspiration instead of streamflows, Predictions In Ungauged Basins: PUB Kick-off (Proceedings of the Kick-off meeting held in Brasilia, 20-22 November 2002) IAHS.

Nash, J. E. and J. V. Sutcliffe, 1970: River flow forecasting through conceptual models part I — A discussion of principles, *J. Hydrol.*, **10(3)**, 282–290.

Nijssen, B., G.M. O'Donnell, D.P. Lettenmaier, D. Lohmann, and E.F. Wood, 2001: Predicting the discharge of global rivers, *Journal of Climate*, **14**, 3307-3323.

Nishida, K., Nemani, R.R., Running, S.W., and Glassy, J.M., 2003: An operational remote sensing algorithm of land surface evaporation, *J. Geophys. Res.*, **108(D9)**, 4270, doi:10.1029/2002JD002062.

Niyogi D., J.G. Alfieri, P.D. Blanken, F. Chen, M.A. LeMone, K.E. Mitchell, and M.B. Ek, 2008: Estimation of the Minimum Canopy Resistance for Croplands and Grasslands Using Data from the 2002 International H2O Project, *Mon. Weather Rev.*, **136**, 4452-4469.

Oki, T., Musiaka, K., Matsuyama, H., and Masuda, K., 2005: Global atmospheric water balance and runoff from large river basins. *Hydrological Processes*, **9**, 655–678. doi: 10.1002/hyp.3360090513.

Pan, H.L., and L. Mahrt, 1987: Interaction between soil hydrology and boundary layer development, *Boundary Layer Meteorol.*, **38**, 185– 202.

Pan, M., Sahoo, A.K., Troy, T.J., Vinukollu, R., Sheffield J., and Wood, E. F., 2011: Multi-source estimation of long-term Terrestrial Water Budget for major global river basins, *J. Clim.*, (*in press*).

Pielke, R. A., R. Avissar, M. Raupach, A. J. Dolman, X. Zeng, and A. S. Denning, 1998: Interactions between the atmosphere and terrestrial ecosystems: Influence on weather and climate, *Glob. Change Biol.*, **4**, 461–475.

Pinker, R.T., and Laszlo, I., 1992: Modeling surface solar irradiance for satellite applications on a global scale, *J. Appl. Meteorol.*, **31**, 194–211.

Pokhrel, P., H. V. Gupta, and T. Wagener, 2008: A spatial regularization approach to parameter estimation for a distributed watershed model, *Water Resour. Res.*, **44**, W12419, doi:10.1029/2007WR006615.

Post, D.A. and A.J. Jakeman, 1996: Relationships between catchment attributes and hydrological response characteristics in small Australian mountain ash catchments, *Hydrological Processes*, **10**, 877-892.

Rasmussen, E., 1967: Atmospheric water vapor transport and the water balance of North America: Part I. Characteristics of the water vapor flux field, *Mon. Wea. Rev.*, **95**, 403–426, doi: 10.1175/1520-0493.

Rasmussen, E.M.: Atmospheric water vapor transport and the water balance of North America, **2**, Large-scale water balance investigations, 1968: *Mon. Weather Rev.*, **96**, 720-734.

Reed, S., V. Koren, M. Smith, Z. Zhang, F. Moreda, and D.-J. Seo, 2004: Overall distributed model intercomparison project results, *J. Hydrol.*, **298**, 27– 60.

Ropelewski, C.F., and Yarosh, E.S., 1998: The observed mean annual cycle of moisture budgets over the central United States (1973– 92). *J. Climate*, **11**, 2180–2190.

Rosen, R.D., and Omolayo, A.S., 1981: Exchange of water vapor between land and ocean in the Northern Hemisphere, *J. Geophys Res.*, **86**, 12147-12152.

Rosenberg, E. A., A. W. Wood, and A. C. Steinemann, 2011:, Statistical applications of physically based hydrologic models to seasonal streamflow forecasts, *Water Resour. Res.*, **47**, W00H14, doi:10.1029/2010WR010101.

Rosero, E., L.E. Gulden, Z.-L. Yang, L.G. De Goncalves, G.-Y. Niu, and Y.H. Kaheil, 2011, Ensemble Evaluation of Hydrologically Enhanced Noah-LSM: Partitioning

of the Water Balance in High-Resolution Simulations over the Little Washita River Experimental Watershed, *J. Hydrometeorol.*, **12**(1), 45-64.

Ruane, A.C., 2010: NARR's atmospheric water cycle components — Part II: Summertime mean and diurnal interactions. *J. Hydrometeorol.*, **11**, 1220-1233, doi:10.1175/2010JHM1279.1.

Samaniego, L., A. Bárdossy, and R. Kumar, 2010a: Streamflow prediction in ungauged catchments using copula-based dissimilarity measures, *Water Resour. Res.*, **46**, W02506, doi:10.1029/2008WR007695.

Samaniego L, R. Kumar, and S. Attinger, 2010b: Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *WaterResources Research* **46**(:): W05523 DOI: 10.1029/2008wr007327.

Schaake, J.C., V.I. Koren, Q.-Y. Duan, K.E. Mitchell, and F. Chen, 1996, Simple water balance model for estimating runoff at different spatial and temporal scales, *J. Geophys. Res.*, **101**, 7461-7475.

Schaake, J., Q. Duan, V. Koren, and A. Hall, 2001: Toward improved parameter estimation of land surface hydrology models through the Model Parameter Estimation Experiment (MOPEX), IAHS Publ., 270, 91– 97.

Schaake, J., S. Cong and Q. Duan, 2006: The U. S. MOPEX Data Set, IAHS Red Book #307.

Schwarz, G. E., and R. B. Alexander, 1995: State soil geographic (STATSGO) database for the conterminous United States, *U.S. Geol. Surv. Open File Rep.*, 95-449.

Seaber, P.R., F.P. Kapinos, and G.L. Knapp, 1987: Hydrologic Unit Maps: U.S. Geological Survey Water-Supply Paper 2294, 63 pp.

Seneviratne, S.I., T. Corti, E.L. Davin, M. Hirschi, E.B. Jaeger, I. Lehner, B. Orlowsky, and A.J. Teuling, 2010: Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Sci. Rev.*, **99**(3-4), 125-161.

Shukla, S, Steinemann, A.C., and Lettenmaier, D.P., 2011: Drought Monitoring for Washington State: Indicators and Applications. *J. Hydrometeor* , **12**, 66–83.doi: 10.1175/2010JHM1307.1.

Siebert, 1999: Regionalisation of parameters for a conceptual rainfall-runoff model, *Agricultural and Forest Meteorology*, 98-99, 279-293.

Singh, V. P., and D. K. Frevert, 2006: Watershed Models, Taylor and Francis, Philadelphia, Pa. Swenson, S. C. and J. Wahr, 2006: Post-processing removal of correlated errors in GRACE data, *Geophys. Res. Lett.*, **33**, L08402, doi:10.1029/2005GL025285.

Smith, M. B., D. P. Laurine, V. I. Koren, S. M. Reed, and Z. Zhang, 2003: Hydrologic model calibration in the National Weather Service. Calibration of Watershed Models, Q. Duan et al., Eds., Water Science and Application, Vol. 6, Amer. Geophys. Union, 133–152.

Smith, M. B., D. Seo, V. I. Koren, S. M. Reed, Z. Zhang, Q. Duan, F. Moreda, and S. Cong, 2004: The distributed model intercomparison project (DMIP): Motivation and experiment design, *J. Hydrol.*, **298**, 4–26.

Son K, and Sivapalan, M., 2007: Improving model structure and reducing parameter uncertainty in conceptual water balance models through the use of auxiliary data, *Water Resour. Res.*, **43**: WO1415. DOI: 10.1029/2006WR005032.

Sridhar, V., Elliot, R. L., Chen F., and Botzge, J. A., 2002: Validation of the NOAA-OSU land surface model using surface flux measurements in Oklahoma, *J. Geophys. Res.*, **107(D20)**.

Starr, V.P., Peixoto, J.P., and Crisi, H.R., 1965: Hemispheric water balance for the IGY. *Tellus*, **17**, 463–472.

Syed, T. H., Famiglietti, J.S., Chen, J., Rodell, M., Seneviratne, S.I., Viterbo, P., and Wilson, C.R., 2005: Total basin discharge for the Amazon and Mississippi river basins from GRACE and a land-atmosphere water balance, *Geophys. Res. Lett.*, **32**, L24404, doi:10.1029/2005GL024851.

Tang, Q., Peterson, S., Cuenca, R.H., Hagimoto, Y., and Lettenmaier, D.P., 2009: Satellite-based near-real-time estimation of irrigated crop water consumption, *J. Geophys. Res.* **114**, D05114, doi: 10.1029/2008JD010854.

Tateishi, R. and Ahn, C. H., 1996: Mapping evapotranspiration and water balance for global land surfaces., *J. Photogr. Rem. Sens.*, **51**, 209-215.

Taylor, C.M., and R.J. Ellis, 2006: Satellite detection of soil moisture impacts on convection at the mesoscale, *Geophys. Res. Lett.*, **33 (3)**, L03404.

Thiemann, M., M. Trosset, H. Gupta, and S. Sorooshian, 2001: Bayesian Recursive Parameter Estimation For Hydrologic Models, *Water Resour. Res.*, **37(10)**, 2521–2535.

Turnipseed A. A., P. D. Blanken D. E. Anderson, and R. K. Monson, 2002, Energy budget above a high-elevation subalpine forest in complex topography. *Agric. Forest. Meteorol.*, **110(3)**, 177-201.

van Werkhoven, K., T. Wagener, P. Reed, and Y. Tang, 2008: Characterization of watershed model behavior across a hydroclimatic gradient, *Water Resour. Res.*, **44**, W01429, doi:10.1029/2007WR006271.

Vandewiele, G.L. and A. Elias, 1995: Monthly water balance of ungauged catchments obtained by geographical regionalization, *Journal of Hydrology*, 170, 277-291.

Vano, J., Das, T., and Lettenmaier, D.P., 2012: Hydrologic sensitivities of Colorado River runoff to changes in precipitation and temperature. *J. Hydrometeor.*, doi:10.1175/JHM-D-11-069.1 (*in press*).

Verseghy, D., 1996: Preliminary Considerations for Runoff Modelling in GCMS, *Nord. Hydrol.*, **27(1-2)**, 144 p.

Viviroli, D., Mittelbach, H., Gurtz, J., and Weingartner, R., 2009: Continuous simulation for flood estimation in ungauged mesoscale catchments of Switzerland – Part II: Parameter regionalization and flood estimation results, *J. Hydrol.*, 377, 208–225.

Vrugt J.A., Gupta H.V., Dekker S.C., Sorooshian S., Wagener T., Bouten W., 2006: Application of stochastic parameter optimization to the Sacramento Soil Moisture Accounting model, *J. Hydrol.*, **325(1-4)**, 288-307.

Vrugt, J.A., Gupta, H.V., Bastidas, L.A., Bouten, W., and Sorooshian, S., 2003: Effective and efficient algorithm for multi-objective optimization of hydrologic models, *Water Resour. Res.*, **39(8)**, 1214, doi:10.1029/2002WR001746.

Wackernagel, H. 2003: *Multivariate Geostatistics*, 3rd ed., 387 pp., Springer-Verlag, New York.

Wang, W., and A. Kumar, 1998: A GCM assessment of atmospheric seasonal predictability associated with soil moisture anomalies over North America. *J. Geophys. Res.*, **103**, 28637–28646.

Wei H., Xia, Y., Mitchell, K.E., and Ek, M.B., 2012: Improvement of the Noah Land Surface Model for Warm Season Processes: Evaluation of Water and Energy Flux Simulation, *Hydrological Processes*, DOI: 10.1002/hyp.9214 (*in press*).

Werth, S., and Guntner, A., 2010: Calibration analysis for water storage variability of the global hydrological model wghm, *Hydrol. Earth Syst. Sc.*, **14(1)**, 59–78.

Wetzel, P. J., S. Argentini, and A. Boone, 1996: Role of land surface in controlling daytime cloud amount: Two case studies in the GCIP-SW area, *J. Geophys. Res.*, **101(D3)**, 7359–7370.

Wilson, K., et al., 2002: Energy balance closure at FLUXNET sites, *Agric. For. Meteorol.*, **113(1–4)**, 223–243.

Xia Y., Mitchell, K., Ek, M., Cosgrove, B., Sheffield, J., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Duan, Q., and Lohmann, D., 2012: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System Project Phase 2 (NLDAS-2), part 2: Validation of Model-simulated streamflow, *Journal of Geophysical Research*, 117, doi:10.1029/2011JD016051.

Xiu, A., and J. E. Pleim, 2001: Development of a land surface model. Part I: Application in a mesoscale meteorological model, *J. App. Meteorol.*, **40**, 192–209.

Yadav, M., Wagener, T., and Gupta, H., 2007: Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins, *Adv. Water Res.*, 30, 1756–1774.

Yapo, P.O., Gupta, H.V. and Sorooshian, S., 1998: Multi-objective global optimization for hydrologic models, *J. Hydrol.*, **204**, 83-97.

Yeh, P.J.F., and Famiglietti, J.S., 2008: Regional terrestrial water storage change and evapotranspiration from terrestrial and atmospheric water balance computations, *J. Geophys. Res.*, 113, D09108, doi:10.1029/2007JD009045.

Yeh, P.J.F., Irizarry, M., and Eltahir, E.A.B., 1998: Hydroclimatology of Illinois: A comparison of monthly evaporation estimates based on atmospheric water balance and soil water balance, *J. Geophys. Res.*, 103, 19823–19837.

Zhang, L., W. R. Dawes, and G. R. Walker, 2001: Response of Mean Annual Evapotranspiration to Vegetation changes at Catchment Scale, *Water Resour. Res.*, **37(3)**, 701–708.

Zhang, Z., Wagener, T., Reed, P., and Bhushan, R., 2008: Reducing uncertainty in predictions in ungauged basins by combining hydrologic indices regionalization and

multiobjective optimization, *Water Resour. Res.*, 44, W00B04,
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- B.E.Sc. Civil and Environmental Engineering, University of Western Ontario, 2004
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- M.E.Sc. Civil and Environmental Engineering, University of Western Ontario, 2006
Emphasis: Geotechnical Engineering
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POSITIONS HELD:

- 2006- Research Assistant, Civil and Environmental Engineering, University of Washington.
- 2008, 2010, 2011 Adjunct Professor, Civil and Environmental Engineering, Seattle University.
- 2006 Design and CAD Engineer, Lican Developments, Windsor, ON.
- 2003-2006 V.P. Sales and Engineering, Univercycle Recycling Co., Windsor, ON; Jiang Ying, China.
- 2004-2006 Graduate Teaching Assistant, Civil and Environmental Engineering, Univ. of Western Ontario
- 2002 Engineer Assistant, Quality Engineering Company, Southfield, MI.

TEACHING

Graduate Teaching Assistant: Environmental Hydraulics, Environmental Design, Land Surveying, and Geotechnical Engineering – undergraduate courses at the University of Western Ontario.

Adjunct Professor: Applied Hydraulics, Fluid Mechanics Laboratory (*teaching evaluations available by request, mean score > 4.2/5.0*) – undergraduate courses at Seattle University.

Other: Assisted in generating assignments for graduate course in Precipitation Analysis, at the University of Washington.

PROFESSIONAL MEMBERSHIPS

- American Geophysical Union (AGU)
American Water Resources Association (AWRA)
European Geosciences Union (EGU)
American Society for Civil Engineers (ASCE)

SERVICE AND ACHIEVEMENTS

- 2011 - Vice President, Chi Epsilon, University of Washington Chapter.
- 2009 - Reviewer: *Nature Climate Change, Journal of Geophysical Research, Climatic Change, Journal of Climate, Hydrologic Processes, Geophysical Model Development.*
- 2007 - 2010 Graduate and Professional Student Senate representative on the Student Technology Fee Committee, University of Washington: Review and approval of proposals for technology budget across campus.
- 2005/2006 Departmental Teaching Assistant Award – University of Western Ontario, CEE.

- 2004 Co-winner of the 4th year Student Design Project for the design of a waste water treatment facility, University of Western Ontario.
- 2004 Dean's Honor List, at B.E.Sc. graduation, University of Western Ontario.
- 2002 Université de Montréal, French Summer Language Bursary Program.

PUBLICATIONS

Livneh, B. and D.P. Lettenmaier, **2012**: Multi-criteria parameter estimation for the unified land model, *Hydrol. Earth Syst. Sci. Discuss.*, 9, 4417-4463, doi:10.5194/hessd-9-4417-2012.

Mahanama, S.P., **B. Livneh**, R.D. Koster, D.P. Lettenmaier, and R.H. Reichle, **2012**: Soil Moisture, Snow, and Seasonal Streamflow Forecasts in the United States, *Journal of Hydrometeorology*, 13, 189-203, 10.1175/JHM-D-11-046.1.

Xia Y., K. Mitchell, M. Ek, J. Sheffield, B. Cosgrove, L. Luo, C. Alonge, H. Wei, J. Meng, **B. Livneh**, D.P. Lettenmaier, V. Koren, Q. Duan, K. Mo, Y. Fan, and D. Mocko, **2012**: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System Project Phase 2 (NLDAS-2), part 1: intercomparison and application of model products, *Journal of Geophysical Research*, 117, doi:10.1029/2011JD016048.

Xia Y., K. Mitchell, M. Ek, B. Cosgrove, J. Sheffield, L. Luo, C. Alonge, H. Wei, J. Meng, **B. Livneh**, Q. Duan, and D. Lohmann, **2012**: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System Project Phase 2 (NLDAS-2), part 2: Validation of Model-simulated streamflow, *Journal of Geophysical Research*, 117, doi:10.1029/2011JD016051.

Livneh, B., P.J. Restrepo, and D.P. Lettenmaier, **2011**: Development of a Unified Land Model for prediction of surface hydrology and land-atmosphere interactions, *Journal of Hydrometeorology*, 12(6), 1299-1320, 10.1175/2011JHM1361.1.

Livneh, B., Y. Xia, K.E. Mitchell, M.B. Ek, and D.P. Lettenmaier, **2010**: Noah LSM Snow Model Diagnostics and Enhancements, *Journal of Hydrometeorology*, 11(3), 721-738.

Koster, R.D., S.P. Mahanama, **B. Livneh**, D.P. Lettenmaier, and R.H. Reichle, **2010**: Skill in Streamflow Forecasts Derived from Large-Scale Estimates of Soil Moisture and Snow, *Nature Geoscience* doi:10.1038/ngeo944.

Barlage, M., F. Chen, M. Tewari, K. Ikeda, D. Gochis, J. Dudhia, R. Rasmussen, **B. Livneh**, M. Ek, and K. Mitchell, **2010**: Noah Land Surface Model Modifications to Improve Snowpack Prediction in the Colorado Rocky Mountains, *Journal of Geophysical Research*, 115, doi:10.1029/2010JD13470.

Casola, J.H., L. Cuo, **B. Livneh**, D.P. Lettenmaier, M. Stoelinga, P.W. Mote and J. M. Wallace, **2009**: Assessing the Impacts of Global Warming on Snowpack in the Washington Cascades, *Journal of Climate*, 22(10), 2758-2772.

Munoz-Arriola, F., S. Shukla, T. Bohn, C. Zhu, **B. Livneh**, D.P. Lettenmaier, R. Lobato-Sanchez, A. Wagner-Gomez, **2009**. Prediccion de la Hidrologia Superficial en Norte America, *Resumen del Clima de la Frontera*, Julio 13: 1-5.

Livneh B., and M.H. El Naggar, **2008**: Axial testing and numerical modeling of square shaft helical piles under compressive and tensile loading, *Canadian Geotechnical Journal*, 45(8), 1142-1155.

In press:

Sheffield, J., **B. Livneh**, and E.F. Wood, **2012**: Representation of Terrestrial Hydrology and Large Scale Drought of the Continental US from the North American Regional Reanalysis, *Journal of Hydrometeorology* (*in press*).

Xia Y., M. Michael Ek, J. Sheffield, **B. Livneh**, H. Wei, S. Feng, L. Luo, J. Meng, and E. Wood, **2012**: Validation of Noah-simulated Soil temperature in the North American Land Data Assimilation System Phase 2, *Journal of Applied Meteorology and Climatology* (*submitted*).

Working papers:

Livneh B., E.A. Rosenberg, C. Lin, V. Mishra, K.M. Andreadis, and D.P. Lettenmaier, **2012**: Extension and spatial refinement of a long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States, *Journal of Climate* (*in preparation*).

Bohn T. J., **B. Livneh**, J. Olyer, D. P. Lettenmaier, and S. Running, **2012**: Global evaluation of MTCLIM daily temperature range algorithm, *Journal of Hydrometeorology*, (*in preparation*).

Livneh B., and D.P. Lettenmaier, **2012**: Land surface model parameter regionalization via principal components analysis in the context of flood forecasting, *Water Resources Research*, (*in preparation*).

SELECTED PRESENTATIONS

Livneh, B., and D.P. Lettenmaier, AGU Fall Meeting, San Francisco, CA., Dec. **2011**, Land Surface Model parameter regionalization via remote sensing and observations (*poster*).

Livneh B. (co-presented with T.J. Bohn), University of Washington Hydrology Seminar, Aug. **2011**, Evaluating performance of MTCLIM and other hydrometeorological algorithms against a global set of station data.

Livneh, B., P.J. Restrepo, and D.P. Lettemnaier, 91st AMS Annual Meeting, Seattle, WA, Jan. **2011**, Application of a Unified Land Model for estimation of the terrestrial water balance (*poster*).

Koster, R. D., S. Mahanama, **B. Livneh**, D. P. Lettenmaier, and R. H. Reichle, 91st AMS Annual Meeting, Seattle, WA, **2011**, [Predicting hydrological drought: relative contributions of soil moisture and snow information to seasonal streamflow forecast skill.](#)

Livneh, B., P.J. Restrepo, and D.P. Lettemnaier, AGU Fall Meeting, San Francisco, CA., Dec. **2010**, Exploring terrestrial and atmospheric constraints in land surface model validation (*poster*).

Livneh, B., D.P. Lettenmaier and K.E. Mitchell, University of Washington Climate Impacts Group, Seattle, WA, Jan. **2010**, Noah LSM Snow Model Diagnostics and Enhancements.

Livneh, B., and D.P. Lettenmaier, UBC-UW Hydrology Symposium, University of British Columbia, Vancouver, BC, Canada, 25 Sep. **2009**, [Evapotranspiration Partitioning in Land Surface Models.](#)

Livneh, B., Y. Xia, K.E. Mitchell, M.B. Ek, and D.P. Lettenmaier, CPPA PI's Meeting, Washington, DC, Sep **2008**, [Noah LSM snow model diagnostics and enhancements](#) (*poster*).

Livneh, B., E.P. Salathe, and D.P. Lettenmaier, UW/UBC, Hydrology Conference, Seattle, WA, Sep. **2008**, [Understanding the sensitivity of Washington State snowpacks to climate change](#).

Livneh, B., D.P. Lettenmaier and K.E. Mitchell, AGU Fall Meeting, San Francisco, CA., Dec. **2007**, [Diagnosis of Performance of the Noah LSM Snow Model](#).