ABSTRACT

A multi-sensor/multi-platform approach to water and energy cycle prediction is demonstrated in an effort to understand the variability and feedback of land surface and atmospheric processes over large space and time scales. Remote sensing based variables including soil moisture (from AMSR-E), evapotranspiration (from MODIS), rainfall (from TRMM) and microwave brightness temperature (from TMI) are combined with North American Regional Reanalysis derived atmospheric components to examine the degree of hydrological consistency throughout these diverse and independent hydrologic data sets. The study focuses on the influence of the North American Monsoon System (NAMS), and is timed to coincide with the SMEX04-NAME campaign over the Arizona portion of the NAME domain to help better characterize the hydrometeorological processes across Arizona during the summer monsoon period.

To broaden the integrated analysis of remote sensing observations, a data assimilation scheme employing a Particle Filter technique is implemented to incorporate the remotely sensed observations into a physically based land surface model at the regional scale. The merging remote sensing and land surface model predictions within a data assimilation system is a central focus of the NASA Energy and Water System (NEWS) program, and the results here showed that it can be used to obtain a comprehensive and hydrologically consistent characterization of the land surface water cycle; leading to an improved understanding of water and energy cycles within the NAME region.
MULTI-SENSOR REMOTE SENSING DATA FOR WATER AND ENERGY BALANCE STUDIES: TOWARDS HYDROLOGICAL CONSISTENCY THROUGH OBSERVATION AND DATA ASSIMILATION

McCabe, M. F. ¹, Pan, M. ¹, Wójcik, R. ¹, Sheffield, J. ¹, Gao, H. ², Su, H. ¹, and Wood, E. F. ¹

¹ Department of Civil and Environmental Engineering, Princeton University, Princeton
New Jersey, USA, 08542

² School of Earth and Atmospheric Sciences, Georgia Institute of Technology,
Atlanta, Georgia, USA, 30332

Submitted: March 31, 2006
1. INTRODUCTION

Documenting the global water and energy cycle through modeling and observations is a primary goal of the World Climate Research Programme’s (WRCP) Global Energy and Water Experiment (GEWEX). Such documentation is needed to enable enhanced understanding of Earth’s climate, including characterizing the memories, pathways and feedbacks between key water and energy cycle (WEC) components. With such enhanced knowledge, there is the potential to develop “improved, observationally based predictions of water and energy cycle consequences of Earth variability and change” (Belvedere et al., 2005); a central goal of the NASA Energy and Water cycle Study (NEWS) (NASA, 2004).

With NASA’s Earth Observation System, and similar programs by ESA in Europe and JAXA in Japan, there has been a significant increase in space-based observations that can advance our knowledge of the surface water and energy budgets. The inherent GEWEX strategy (as well as NEWS) is built around the retrieval of remotely sensed surface observations and their assimilation into process-resolving land surface modeling, since characterizing the surface water and energy budgets through in-situ observations alone is infeasible. This strategy recognizes that large-scale applications of energy and water cycle models are greatly complicated by difficulties in representing climate processes at large scales and the scarcity of land surface observations.

To address the latter and to help the former, the NASA/NEWS strategy includes the development and deployment of a space-based energy and water cycle global observing system. Of particular relevance to water and energy cycle observations are the following current space-borne systems: (1) the Tropical Rainfall Measurement Mission (TRMM) satellite that includes both a precipitation radar and a Microwave Imager (TMI), which measures surface microwave emissions from 10.65 to 85.5 GHz in nine frequency bands, for the retrieval of precipitation (Nesbitt et al., 2004) and for land surface monitoring (Bindlish et al., 2003; Gao et al., 2006b); (2) the Earth Observing System (EOS) Terra and Aqua platforms that pave the way to the next-generation NPOESS operational satellites, and have sensors across the visible, near-infrared and microwave frequency bands that allows for the monitoring and retrieval of incoming solar radiation, albedo, vegetation properties, surface temperature, surface emissivity, precipitation, atmospheric
water vapor and aerosols. Depending on the frequency, the retrieved surface emissivity can be used to estimate surface properties, surface soil moisture and snow properties; (3) the Gravity Recovery and Climate Experiment (GRACE), which measures the change in total column water mass at continental scales (Tapley et al., 2004); (4) QuikSCAT whose radar scatterometer measurements have been used to detect freeze-thaw transitions at high latitudes (Kimball et al., 2004); and (5) other relevant operational satellites and sensors including TOPEX-POSEIDON, which has been used to retrieve surface water stage (Birkett, 1998), GOES for solar radiation (Pinker and Laszlo, 1992), Landsat and EO-1 Earth surface imaging, SSM/I for atmospheric water vapor and precipitation, and AMSU and AIRS for atmospheric temperature and water vapor profiles.

Currently, research satellites and/or sensors are aimed at measuring specific components and/or processes of the global energy and water cycles. In fact historically, space agencies have created separate teams by sensor, focused on the retrieval and/or validation of individual water and energy cycle products. When satellite retrieved surface water and energy budget variables are combined with in-situ data like river discharge, budget closure is rarely if ever achieved, demonstrating a basic inconsistency among the retrieved variables (Pan and Wood, 2006) and highlighting a symptom of separate sensing programs. Some examples of consistency, which are examined in this paper, are: occurrence/retrieval of precipitation with a corresponding change in soil moisture; high soil water availability corresponding with higher evaporative fractions; and surface states consistent with atmospheric boundary properties like the convective triggering potential, humidity index or condensation lifting level.

The North American Monsoon Experiment (NAME) had a scientific focus of better understanding the hydrometeorology of the southwestern United States during the summer (monsoon) season, with particular attention “to determine the sources and limits of predictability of warm season precipitation over North America” (see description at http://www.etl.noaa.gov/programs/2004/name/). Of key interest is the role of the land surface, and its memory (Koster and Suarez, 2001), in describing seasonal to inter-annual variations in the North American monsoon system (NAMS)(Adams and Comrie, 1997; Higgins et al., 1998). To fully understand the hydrometeorology and surface conditions of the NAME domain, land surface water and energy cycle variables retrieved from space
observations must augment in-situ observations. As part of the NAME experiment, a soil moisture experiment (SMEX04) was undertaken to improve the validation of space-based retrievals of soil moisture that would be used by NAME scientists to better understand the role that surface soil moisture plays in land-atmosphere coupling, convection, and the maintenance of the NAMS (Small, 2001; Xu et al., 2004; Zhu et al., 2005).

This paper has two main objectives. The first is an evaluation of the consistency of retrieved surface water and energy cycle variables from space-borne sensors using observations over the Arizona domain of the NAME campaign (a portion of the Tier 1 study area). The retrieved variables include precipitation from the Tropical Rainfall Measurement Mission (TRMM), soil moisture from the Advanced Microwave Scanning Radiometer (AMSR-E), and evapotranspiration derived from MODIS measurements on board both EOS-Terra and Aqua. Atmospheric variables assimilated into the NCEP Eta model and available from the North American Regional Reanalysis (NARR) project are used to better understand the consistency between the surface water and energy cycle variables and the atmospheric boundary layer variables that indicate the potential for convection.

The second objective of the paper is assessing improved estimation of the surface water and energy budgets through assimilating the space-retrieved variables into a land surface model. To date little work has been reported on the assimilation of multi-sensor retrieved variables into land surface models, especially at regional scales. Besides the difficulties arising from the differing spatial and temporal scales of the space observations, the issue of budget closure is addressed through imposing a closure constraint within the assimilation system (Pan and Wood, 2006). The water and energy budget variables resulting from application of the assimilation system provide more accurate fields that can be used for further NAME research.

This paper provides a first assessment of two scientific goals of NEWS: an assessment of a water and energy cycle observing system, and the evaluation of a regional land and atmospheric data assimilation system for water and energy cycle variables. The paper is arranged as follows: Section 2 discusses the data and methodology used for the study, with particular emphasis on the remote sensing data and retrievals. Section 3 presents the
analysis of hydrological consistency amongst remotely sensed hydrologic variables, and also an extension of this idea to examine feedback relationships between select land surface and atmospheric variables. Section 4 outlines the data assimilation approach to incorporate diverse hydrologic observations, and Section 5 concludes with an overview of the research and a synopsis of the research questions addressed.

2. DATA AND METHODOLOGY

2.1 NLDAS Model Forcing

The North American Land Data Assimilation System (NLDAS) (Mitchell et al., 2004) is a multi-institutional effort to provide high quality, spatially continuous meteorological forcing data collated from best available operational observations (Cosgrove et al., 2003). A variety of forcing and output data suitable for use in land surface and other model simulations is accessible from the system, providing a data source to understand regional scale processes – particularly where extensive ground based records are scarce.

A number of key variables were utilized from the NLDAS for comparison with remote sensing retrievals and for use in the data assimilation study. Primarily, the data included meteorological forcings such as precipitation, wind velocity, humidity, pressure, air temperature and downward shortwave and longwave radiation. Depending on the resolution requirements of the derived variables (see details below) the native NLDAS spatial resolution of 0.125 degree was either aggregated (to 0.25 degree), or interpolated (to 0.05) using a simple nearest neighbor scheme to minimize interpolation effects.

2.2 Remote Sensing Observations

1) Surface heat fluxes derived from MODIS measurements on EOS-Terra and Aqua

Estimates of the latent and sensible heat flux were determined using the Surface Energy Balance System (SEBS) model (Su, 2002). SEBS was developed to predict heat fluxes using combinations of satellite earth observation data and routinely available meteorological forcing. So far, the SEBS model has been tested over a number of land surface types and scales (Su et al., 2005; McCabe and Wood, 2006; Su et al., 2006).
Further details on the physical basis of the model can be found in the listed references, since only a brief description is offered here.

SEBS requires three broad sets of information to enable the estimation of surface fluxes including; A) data on the **land surface condition** consisting of surface albedo, emissivity, surface temperature, fractional vegetation coverage and leaf area index, along with height of the vegetation; B) **meteorological data** including pressure, air temperature, humidity, and wind speed at a reference height and; C) **radiation data** comprising downward solar radiation and downward long-wave radiation. Given the large-scale application of SEBS in this study (SEBS was run across the conterminous United States), a focus was placed on utilizing large-scale operational data sets for flux prediction.

The data included a combination of NLDAS meteorological forcing; 0.05 degree Climate Modeling Grid (CMG) data from MODIS (Land Cover Type (MOD12C1), land surface temperature and emissivity (MOD/MYD11C1); the University of Maryland vegetation scheme (Hansen et al., 2000) and associated look up tables for vegetation structure and surface parameters; and NLDAS database on Leaf Area Index (LAI). The data sets were assembled to run SEBS across the United States, and are summarized in Table 1.

SEBS constrains the surface heat flux estimates by considering dry-limit and wet-limit conditions, thus differentiating the upper and lower boundaries on the sensible heat flux estimation. For the dry-limit case (i.e. evident in semi-arid environments), latent heat is assumed zero due to the limitation of soil moisture, and the sensible heat flux is at its maximum value (limited by the available energy – the difference between the net radiation and ground heat flux). Under the wet-limit case, the evaporation takes place at a potential rate ($\lambda E_{\text{wet}}$) (i.e. the evaporation is limited only by available energy, under the given surface and atmospheric conditions), and the sensible heat flux takes its minimum value ($H_{\text{wet}}$), which can be estimated using a Penman-Monteith parameterization (1981). The dry and wet limit constraints allow an expression for the actual evapotranspiration (ET) to be formulated from knowledge of these bounds. Further details on the approach are outlined in Su (2002).
Here, surface temperature and emissivity data from the MODIS sensor on board EOS-Terra (~11 a.m.) and Aqua (~2 p.m.) were used to provide heat flux estimates approximately two times per day (dependent on cloud cover, which limits the availability of the MODIS measurements).

2) Soil Moisture from the Advanced Microwave Scanning Radiometer (AMSR-E)

Near surface soil moistures were derived from the descending orbit of the AMSR-E satellite between Aug. 1-31, 2004. Early morning overpasses of the AMSR-E satellite (~2 a.m.) were chosen to minimize the influence of daytime surface temperature spatial variability and fluctuations (likely in the semi-arid Arizona environment) and to maximize the potential of observing incident precipitation from afternoon thunderstorms prevalent over Arizona during the NAMS season.

The Land Surface Microwave Emission Model (LSMEM) (Drusch et al., 2004; Gao et al., 2004) was used to estimate soil moisture from 0.25 x 0.25 degree 10.65 GHz brightness temperatures, which were combined with ancillary information required by the model. LSMEM employs an iterative technique to estimate the soil moisture. In the first step, a modeled brightness temperature is calculated, corresponding to an estimated moisture (based on antecedent conditions), early morning air temperature (NLDAS), land cover characteristics derived from MODIS data, and model parameters describing the atmosphere and land surface condition. Successive model iterations are performed by varying the estimated soil moisture, until convergence between the calculated and observed horizontal brightness temperature is achieved. Gao et al. (2004) and McCabe et al. (2005b) provide further details on model implementation and a description of LSMEM parameterizations.

Applications of LSMEM over the Southern Great Plains (Gao et al., 2003; Gao et al., 2004) and Iowa (during SMEX02) show that the model provides soil moisture retrievals within 4% vol./vol. when compared to coincident ground and airborne measurements (McCabe et al., 2005b). The retrievals are also consistent with observed precipitation pattern (McCabe et al., 2005d). LSMEM makes assumptions in estimating the soil moisture that have been shown to hold true over the sparse vegetation (Jackson et al., 1995; Jackson et al., 1999) representative of the Arizona region.
3) Precipitation from the Tropical Rainfall Measurement Mission (TRMM)

Satellite based estimates of precipitation provide the only viable means to determine rainfall distributions over large regions of the earth that do not have sufficient in-situ gauge measurement. As such, they form a particularly useful data set for advancing global hydrometeorological observations. Data from the TRMM 3B-42 merged high quality infrared precipitation product (Huffman et al., 1995) were used to map rainfall patterns and amounts over the study domain. The TRMM based product (http://trmm.gsfc.nasa.gov/) provides 3-hourly 0.25 x 0.25 degree gridded estimates of global precipitation, over a latitudinal range of ±50 degrees, derived from a variety of satellite and other data sources.

TRMM rainfall estimates are produced in a number of stages. First, available high quality passive microwave data from the TRMM Microwave Imager, as well as SSMI and AMSR-E, are calibrated and converted to precipitation estimates using probability matching of precipitation rate histograms derived from coincident data. For the infrared calibrations, merged infrared data provided to the Climate Prediction Centre (CPC) from a variety of satellites (e.g. NOAA/GOES), are averaged to 0.25 degree resolution and combined into hourly files. Microwave and infrared estimates are then combined to provide a ‘best’ estimate of rainfall in any 3 hour period. Monthly rescaling to observed records of precipitation is the final step in producing the merged product. All available microwave and infrared estimates are summed over a calendar month, producing a monthly multi-satellite product. Available gauge (in-situ) data are combined with the multi-satellite product to create a post real-time monthly satellite-gauge combination, which is ultimately used to rescaled the 3 hourly fields, providing the instantaneous precipitation rate at the nominal observation time (see detailed description of the 3B42 algorithm at http://trmm.gsfc.nasa.gov/3b42.html).

4) Brightness Temperature from the TRMM Microwave Imager (TMI)

Microwave brightness temperatures were obtained from the Tropical Rainfall Measuring Mission (TRMM), and used in the data assimilation portion of the study. TMI brightness temperatures are measured using nine-channel (frequency) passive microwave radiometer, but only the horizontally polarized brightness temperature data from the
10.65 GHz channel are used in the data assimilation analysis. TRMM is in a sun-
asynchronous orbit, resulting in multiple overpasses each day for the NAME region because its near the northern boundary of the TRMM orbit. This differs from the sun-
synchronous polar orbital characteristics of EOS-Aqua platform that carries the AMSR-E radiometer, which provide a maximum of two measurements per day for a particular location - one from the ascending orbit and one on the descending orbit. As a result, for the NAME region TRMM offers a unique data source for the temporal evolution of rainfall (Kummerow et al., 2000) and for soil moisture retrievals (Bindlish et al., 2003; Gao et al., 2006b); making it particularly suitable in data assimilation.

2.3 Derived Atmospheric Variables

Data from the North American Regional Reanalysis (NARR) were used to predict two atmospheric indices: the Convective Triggering Potential (CTP) and the Humidity Index (HI). These variables are used to assess the consistency of the surface fluxes, soil moisture and precipitation, with respect to diagnosing land-atmospheric coupling. The formal definitions of both indices are provided below.

1) Convective Triggering Potential (CTP)

The CTP represents a measure of the temperature lapse rate between 100-300 mb (approximately 1 and 3 km above the land surface) and provides insight into the boundary layer response to surface flux development. The temperature lapse rate offers a means for determining the atmosphere’s capacity for entrainment, and hence boundary layer growth. Findell and Eltahir (2003b) describe the CTP as “the area between the observed temperature sounding and a moist adiabat originating at the observed temperature, 100mb above the surface”. The formulation can be expressed as follows:

\[
CTP = \int_{z_{100mb}}^{z_{300mb}} g \left( \frac{T_{\text{parcel}} - T_{\text{env}}}{T_{\text{env}}} \right) dz
\]

where \( z \) is the pressure level above the surface, \( g \) is gravity, \( T_{\text{parcel}} \) is the parcel temperature, which is the moist adiabat that is defined by the observed temperature at 100 mb, and \( T_{\text{env}} \) is the temperature of the environment. Fundamentally, the formulation for the CTP follows that of the Convective Available Potential Energy (CAPE), a product of
the NARR data, with the difference being primarily the interval over which the integral is taken.

In terms of relative values of CTP and their physical consequence, the CTP is large when the lapse rate is close to dry adiabatic (~10°C/km). When the lapse rate is closer to moist adiabatic (~5°C/km), a smaller but still positive CTP is resolved. A negative CTP identifies a temperature inversion in the atmosphere, indicating that the atmosphere would be too stable for the development of rain. The positive degree of CTP also determines whether sensible heat (higher +CTP) or latent heat (lower +CTP) provide a convective advantage.

As for the Humidity Index (HI\textsubscript{low}) described below, NARR data from 6 a.m. local time (13 UTC) vertical profiles are used in calculating the CTP.

2) Humidity Index (HI)

The Humidity Index (HI\textsubscript{low}) is defined in Findell and Eltahir (2003b) as the sum of the dew-point depressions 50 and 100 mb above the ground surface:

$$HI_{\text{low}} = (T_{950} - T_{d,950}) + (T_{850} - T_{d,850})$$

where \( T_p \) is the temperature at pressure level \( p \), and \( T_{d,p} \) is the dew-point temperature at pressure level \( p \). HI\textsubscript{low} is a generalized variation of the Lytinska et al. (1976) original definition as the sum of the dew-point depressions at 850, 700 and 500 mb above the surface, and is derived to be appropriate for use in all regions. Findell and Eltahir (2003b) use the index (in combination with the CTP) to predict the likelihood of a precipitation event occurring in a particular location, based on early morning soundings of the atmosphere.

In the original version of the Humidity Index (Lytinska et al., 1976), a threshold for rain was established at HI \( \leq 30^\circ \). In the generalized version employed here, the value is reduced to HI\textsubscript{low} \( \leq 15^\circ \). As will be seen in Section 3, rainfall events as determined from TRMM data are observed to occur for values slightly above this limit. Here, the indices serve as a proxy for assessing whether remote sensing observations of the land surface (soil moisture and evapotranspiration) impact the developing atmosphere. Further, they may provide a direct link to illustrate land-surface–atmosphere feedback. Indirectly, they
also serve to validate (through TRMM observations) the capacity of the NARR based measures to predict precipitation events.

NARR fields are based on the National Centers for Environmental Prediction (NCEP) operational Eta model. Results have a nominal spatial resolution of 32 km, provide data across 45 vertical layers and return information with a temporal resolution of 3 hours. To collocate fields with the AMSR-E derived soil moisture and TRMM precipitation data, the derived variables were resampled to conform to a 0.25 degree regular grid. Data were interpolated using a nearest neighbor technique, minimizing possible smoothing of the original NARR data.

3. HYDROLOGICAL CONSISTENCY AND ATMOSPHERIC FEEDBACK RELATIONSHIPS IN OBSERVED VARIABLES

3.1 Hydrological Consistency Between Remotely Sensed Data

There exists considerable uncertainty in quantifying the role that land surface-atmosphere feedbacks have on NAMS precipitation. In previous analysis of the NAMS (e.g. Higgins et al., 1998; Hu and Feng, 2002; Zhu et al., 2005), studies have tended to focus on output from numerical weather prediction models to characterize the nature of the system. To date there has been limited effort to undertake a similar assessment using currently available satellite retrievals - a consequence of a lack of coincident data and lack of focus on integrated retrievals as part of broader energy and water cycle system. The remote sensing data assembled here provide a unique opportunity to characterize consistency and feedback relationships in the NAMS system, using available hydrological observations and derived atmospheric variables collected as part of the NAME campaign.

Central to assessing hydrologic consistency, is the inherent difficulty in validating remote sensing measurements; in part because the ground ‘validation’ data represents different spatial scales and, often, different measurements (e.g. gravimetric soil moisture versus soil emissivity.) Generally, there exist few avenues to robustly evaluate remote observations. Those available include validation/evaluation through; 1) intensive field campaigns that are both expensive and spatially/temporally constrained (e.g. HAPEX/MOHIBLY, FIFE/BOREAS, SMEX campaigns, etc.) (Kanemasu et al., 1992;
Jackson et al., 2004; Kustas et al., 2005); 2) distributed networks of in-situ point measurements (e.g. AmeriFlux, CEOP) (Western et al., 1999; Gao et al., 2006b; Su et al., 2006), which are limited by their spatial representativeness and; 3) comparison with model output. While valuable insights have resulted from such comparisons, each approach has particular restrictions making their use difficult for a thorough evaluation of remote sensing observations and retrievals.

Our assessment is that the inconsistency in the spatial and temporal scales between the remote sensing observations and the measurements available to evaluate them is a major unresolved problem. The outputs from land surface models, forced by observations, approach the necessary time and space scales similar to remote sensing measurements, but are limited by resolution differences (models are necessarily coarse over large scales, compared with multi-resolution satellite data) and issues of instantaneous satellite measurements versus time averaged model output. Also, model output is possibly the least desirable source of evaluation information given concerns about the ability to model land surface processes, and the landscape, completely.

Here, a simple approach towards assessing hydrological consistency is presented, outlining a qualitative examination of multi-sensor/multi-platform equivalence. To identify hydrological consistency within the independent remote sensing retrievals, a number of conditions should be satisfied. With respect to the remote sensing variables developed here, these criteria include:

   a. The surface soil moisture condition (wet or dry) should relate to precipitation (or lack) in the hours preceding the AMSR-E observation;

   b. The sensible heat flux, H (estimated from MODIS), should correspond to the AMSR-E moisture condition i.e. low H for an increased soil moisture anomaly; high H for dry areas;

   c. Given a), the surface condition (wet) from AMSR-E should show strong spatial correlation with the HI_{low} and CTP relations identified in (Findell and Eltahir, 2003b) – given that these indices can capably predict the atmospheric state;
Knowledge of the spatial correlation among HI_{low} and CTP and AMSR-E should provide information on the nature of feedback relations between the surface and the atmosphere boundary layer.

The following sections explore these criteria by analyzing the degree of hydrological consistency across three independently derived remote sensing hydrological data sets: precipitation, surface soil moisture and surface evapotranspiration. These data sets are also combined with the NARR-derived atmospheric variables (Section 2.3) to provide insight into the nature of the land-atmosphere feedback mechanisms across the Arizona region of the NAME domain.

1) AMSR-E Soil Moisture and TRMM Rainfall

The AMSR-E 10.65 GHz radiometer can be used to retrieve near daily global soil moisture at resolutions suitable for regional water balance studies. To distinguish between wet and dry regions and their potential impact on the NAME region hydrometeorology, the AMSR-E data are recast in terms of their anomaly from the monthly average soil moisture. For all available overpasses in August, an average soil moisture estimate was determined for each pixel (32 x 28 0.25 degree pixels across Arizona). The AMSR-E anomaly was then calculated by subtracting daily observations from the mean. Analyzing results in this way allows for the differentiation of consistently wet or dry areas from those responding to particular precipitation events. To seek consistency and validation of the AMSR-E soil moisture anomaly, TRMM derived rainfall amounts were processed for 3, 6, 9 and 12 hours preceding the 2 a.m. AMSR-E overpass time (descending orbit). It is expected that the time span of precipitation should be sufficient to capture the afternoon storms characteristic of the NAMS.

Fig. 1 details selected positive AMSR-E anomaly events (wet soil) distributed throughout the month of August observations. A clear coherence between wet (dark) areas and coincident precipitation is evident throughout the temporal distributions of TRMM data. In the majority of cases, there is also a strong degree of spatial correlation, particularly evident in the pattern of Aug. 12, where two localized anomalies are represented by an equivalent structure in the TRMM precipitation (see also Aug. 2, 5, 7). In other instances, components of the AMSR-E anomalies are well represented, while others are less so. On
Aug. 14 and 16 for instance, there is strong agreement between AMSR-E and TRMM rainfall patterns in the southern portion of the image. However, the precipitation identified in portions of the TRMM image fail to leave a corresponding imprint on the surface (see central western precipitation in -12 hour TRMM image for Aug. 14). When the converse applies (as in the Aug. 16 AMSR-E anomaly for central eastern Arizona; i.e. wet AMSR-E anomaly but no TRMM correspondence), these are more likely evidence of rainfall occurring prior to the 12 hour time frame examined here (see Fig. 4).

The precipitation process is both highly variable in space and time, spanning a broad range of possible values and intensities (light–heavy rain/short–long duration). On the other hand, while soil moisture is also spatially variable, it has a smaller time varying component (temporally stable) and its value is bounded by soil physical properties (soil water potential and porosity), limiting the range expected from remote observation. Given the competing natures of the hydrological processes, it seems more likely that anomalous AMSR-E data could occur with no observed rain event (Aug. 16), than TRMM data imply significant rainfall but show no corresponding soil moisture anomaly (Aug. 14). The contention is further strengthened by considering that instantaneous rainfall rates are only available at 3 hourly intervals, increasing the possibility of missed rain events during this time. Indeed, further investigation of the Aug. 16 anomaly verified a precipitation event in the TRMM data for Aug 15 (06 UTC) – before the four successive rain events considered here.

While strong spatial coherence is evident in the patterns of AMSR-E anomaly and TRMM rainfall, the magnitudes of the events are also important in identifying hydrological consistency. To classify this, regions where the soil moisture anomaly was greater than 10% vol./vol. were discriminated from the AMSR-E data. Likewise, rainfall totals for the four 3-hourly TRMM data (Fig. 1), corresponding to these locations were extracted for the 7 days of measurement presented here, with results plotted in Fig. 2. While the 10% volumetric limit may seem arbitrary, the intention was to discriminate against low rain-rate events and focus only on significant precipitation rates – and hence anomaly inducing storms. As noted previously, while general spatial correlation is good between the soil moisture-rainfall distributions, there is not a pixel-to-pixel scale
equivalence. To examine this further, both raining and non-raining cells were identified when mapping the AMSR-E anomaly locations to the TRMM rainfall amounts.

Data is expressed in ranges of 5% AMSR-E anomaly change, up to a maximum of 35% positive anomaly (difference from the monthly mean soil moisture). Precipitation values represent the average rain-rate corresponding to the specific anomaly range, for rain days identified in Fig. 1. Standard deviations (± 0.5 st.dev) are plotted to detail the rainfall variability. There is no substantial difference between results for all TRMM cells (i.e. all cells where AMSR-E anomaly > 10% vol./vol.) (Fig. 2a) and TRMM cells where rain rates > 0 mm/3hr (Fig. 2b). Considering the histogram results of Fig. 2d, it is apparent that when soil moisture anomaly is greater than 15% vol./vol., there are comparatively few non-raining cells corresponding to observed soil moisture anomalies, illustrating the strong dependency between these two data sets.

Similar comparisons emerge upon refinement of the criteria for raining cells, with additional constraint for rain-rates greater than 5 and 10 mm/3hrs specified. From Fig. 2c a different, but still consistent pattern emerges. As in the preceding analysis, increased anomaly is linked strongly with increased rain-rates, reflecting physical expectation. Histograms of these results indicate that for increased AMSR-E anomaly, the number of contributing cells tends to equivalence.

2) AMSR-E Soil Moisture and MODIS Based Sensible Heat Flux

AMSR-E anomalies exhibit strong correlation with TRMM precipitation totals upon examination of rainfall observation over the preceding 12 hours. As a consequence, improved confidence can be placed in the fidelity of both remote sensing products. In terms of hydrological consistency, the soil moisture-precipitation correlation should also be evident in remote measures of the surface heat fluxes. Using the MODIS sensor on board Terra and Aqua, insight into the changing spatial patterns of surface fluxes can be observed. Measurements of the sensible heat in the morning and afternoon following the AMSR-E anomaly were combined (Fig. 3) to characterize spatial flux distribution.

For each of the AMSR-E anomalies, there is considerable agreement with the available sensible heat predictions. Dark areas in Fig. 3 represent regions of low sensible heat (increased evaporative fraction). Regions where no data exist are the result of cloud
contamination of the infrared bands on MODIS. Microwave frequencies (i.e. AMSR-E) are not subject to the same atmospheric influences as infrared bands, and incomplete coverage in infrared data is common – particularly when examining periods in the region of precipitation events. Both Aug. 2 and 5 display increased evaporation (relative to other areas) in the southeast corner, corresponding well to significant rain events in Fig. 1. Likewise, Aug. 7, 14 and 16 patterns are strongly related with soil moisture distributions. The spatial flux from Aug. 12 is masked by cloud cover over the rainfall areas from Fig. 1. However, rainfall occurring in the 3 hours following the AMSR-E overpass (not included in Fig. 1) indicates excellent spatial correlation with the observed flux pattern (see Fig. 4).

While all land surface variables examined here qualify as ‘fast’ components of the hydrological cycle, their degree of time stability differ, decreasing from soil moisture (relatively stable), to evapotranspiration (less stable), to the highly time variable precipitation (unstable). While it might be expected that rainfall imparts a footprint onto the near surface soil moisture, extracting a corresponding signal from the surface flux is not necessarily assured. The AMSR-E anomaly represents (at best) the top 1-2 cm of the surface layer, and has been observed (Fig. 1) to illustrate a strong response to precipitation. However, the evaporative process accounts for transpiration from vegetation, evaporation from the canopy and also soil storage. While direct evaporation from the near surface moisture storage is likely (see Fig. 3), vegetation and biophysical influences may hinder a similar consistency in remote observation in areas other than semi-arid environments.

3.2 Consistency and Feedback Between the Land Surface and Atmosphere

Considerable spatial coherence and hydrological consistency between independent remote sensing data was observed in the previous analysis. However, these studies do not address the occurrence of land-atmospheric feedbacks; another measure of coherence. For this, a proxy for the atmospheric component of the water and energy cycles that can describe the link to the surface state is required.

Humidity indices (described in Section 2.3) serve as indicators of the atmospheric state, characterizing conditions when the atmosphere may be too dry for the development of
precipitation. However, if considered separately, the indices’ ability to do so under more humid conditions is not as robust (Mueller et al., 1996). Findell and Eltahir (2003b) suggest that when the Convective Triggering Potential (CTP) is coupled with a humidity index (HI$_{low}$), an increased ability to identify regions of convection from early morning atmospheric soundings can be achieved.

Unique criteria used to describe the likelihood of precipitation using HI-CTP relationships have been developed (Findell and Eltahir, 2003b) and include:

- HI$_{low}$ ≥ $15^\circ$ or CTP < 0 J.kg$^{-1}$: atmosphere very dry and very stable so rainfall cannot occur;
- HI$_{low}$ ≤ $5^\circ$ and CTP > 0 J.kg$^{-1}$: atmosphere very humid and unstable, so rainfall can occur over wet and dry soils;
- $5^\circ$ ≤ HI$_{low}$ ≤ $15^\circ$ and CTP > 0 J.kg$^{-1}$: the land surface can significantly influence the likelihood of rainfall. Here, rainfall over dry soils is more likely for high CTP – high HI$_{low}$ values, while rainfall over wet soils is more likely in the low CTP – low HI$_{low}$ pairs;

Spatially distributed HI$_{low}$ and CTP data are plotted in Fig. 3 together with AMSR-E anomaly and MODIS sensible heat flux. HI$_{low}$ values from a 6 a.m. sounding for both the morning preceding the AMSR-E overpass, and also immediately after (approximately 4 hours) are included for comparison. CTP data from the previous morning sounding are also presented.

The HI$_{low}$ displays considerable spatial agreement with the AMSR-E anomaly, with low values of the index (HI$_{low}$ ≤ $15^\circ$) particularly well correlated with subsequent AMSR-E anomaly (and hence rainfall distribution). The ability of the HI$_{low}$ to predict future (+1 day) rainfall events is considerable. Particularly strong relationships are evident on Aug. 5, 7 and 15, with slightly reduced levels on Aug. 2, 12 and 14 (satisfying $15^\circ$ ≤ HI$_{low}$ ≤ $20^\circ$). In terms of the CTP data for Arizona, values routinely exceed 1000 J.kg$^{-1}$, which are considerably greater than ranges identified in Findell and Eltahir (2003b). Differences are likely due to disparity between the station data used in the analysis of Findell and Eltahir (2003b), and the model assimilated NARR output values developed here. Overall, for the
NARR derived CTP, the prevailing response is rarely less than 400 J.kg\(^{-1}\), conditions associated with lapse rates approaching dry adiabatic and indicating a convective advantage favoring sensible heat flux.

These results are seemingly in conflict with the criteria outlined above and the HI\(_{\text{low}}\)-CTP distributions noted in Fig. 13 of Findell and Eltahir (2003b). As observed from Fig. 3, the HI\(_{\text{low}}\) values for soundings after the AMSR-E anomaly routinely indicate rainfall potential over wet areas – in apparent contradiction to the correspondingly high values of CTP in the same areas, which should favor negative feedback (i.e. rainfall over dry soils). Only data for August 16 indicates convection favoring latent heat, with regions on the southeast border with New Mexico illustrating CTP values < 300 J.kg\(^{-1}\). Since the CTP values used here were calculated independently of previous works, no direct comparison is possible. Regardless, the data illustrate that HI\(_{\text{low}}\) is an effective predictor of precipitation in semi-arid environments. In terms of describing, or at least identifying feedback, the HI\(_{\text{low}}\)-CTP relationship would indicate that the land surface has a significant influence on triggering potential precipitation events. However, characterizing the dominant mode of this mechanism in Arizona is beyond the scope of this research, given the limited number of incidents with which to base conclusion.

One means of establishing periods of either positive or negative feedback though, is through examining the HI\(_{\text{low}}\) data and its ability to predict subsequent rain events. General analysis of the southwest (see Fig. 2 in Findell and Eltahir, 2003a) suggest that the region is dominated by negative feedback – although Arizona is also overlapped by an atmospherically controlled region. Atmospherically controlled regions describe a range of possible land surface-atmosphere interactions, from very dry and/or very stable atmospheres (no surface influence) to conditions that might provoke rainfall over any land condition (wet or dry). To identify whether the data here favor one or another state, HI\(_{\text{low}}\) values and TRMM data from 11 a.m. to 11 p.m. of the same day were analyzed, with results plotted in Fig. 5. By identifying soundings immediately following AMSR-E anomaly days (Fig. 1), one can possibly discriminate between positive and negative feedback – since both states are represented (i.e. as opposed to just using dry days). Ranges of humidity index were plotted, with HI\(_{\text{low}}\) values less than 15ºC shown in white circles and 15º \(\leq\) HI\(_{\text{low}}\) \(\leq\) 20º presented in red.
Results from Fig. 5 present some interesting trends. Immediately apparent is the strong link between wet-areas (AMSR-E anomaly) and patterns of the humidity index. That the index would relate the potential of rainfall occurring over the previous days rain event, suggests some degree of positive feedback. However, unless rainfall does indeed fall upon these regions, the atmospheric component of the feedback is not fulfilled. Through examination of the subsequent TRMM data for the afternoon and evening following the morning sounding, one can observe the relatively good prediction of precipitation corresponding to the location of HI_{low}. While precipitation does indeed occur over many of the wet areas, it is possibly equally represented over dry areas. Of primary interest though, is the fact that the HI_{low} is convincingly associated with AMSR-E anomaly values – which were also accurately predicted from the previous mornings sounding (Fig. 3) – indicating that the remote measures of the land surface do indeed have significant coupling with model derived atmospheric variables.

3.3 Summary of Hydrological Consistency and Feedback

In order to increase the accuracy in modeling land surface processes, one can develop more physically descriptive representations, increase the accuracy of measurements, or improve knowledge through observation of variables not currently observed. Here, a month of coincident remotely sensed observations of the hydrological cycle were examined for their consistency among component variables. Independent retrievals of soil moisture, evapotranspiration, sensible heat flux and precipitation were assessed in terms of their spatial correlation and shown to exhibit significant agreement. In particular, the spatial distribution of TRMM based precipitation illustrated excellent accord with AMSR-E soil moisture anomalies for August 2004, a period coinciding with the NAME-SMEX campaign. Spatial distributions of sensible heat flux were also well represented in the rainfall-soil moisture relationship, displaying significant response to moisture forcing. Increased confidence in the capacity to monitor individual hydrological variables emerged as a consequence of their high level of agreement.

The signature of soil moisture is strongly represented in the semi-arid Arizona environment, due in part to the intermittent nature of rainfall and the high evaporative demand of the atmosphere. During the NAMS, these conditions are not always evident,
with increased frequency of rainfall and a humid atmosphere not uncommon. Still, a clear link between hydrological components is observed in the remote sensing data. Previous studies demonstrated a significant AMSR-E soil moisture – rainfall link over more heavily vegetated environments (McCabe et al., 2005d). In such conditions, it might not be expected that a consistent relationship between the soil moisture and evapotranspiration would exist, since the vegetation layer acts to diminish and mask this response. Rather, evaporative response is more likely a function of vegetation type, particularly when moisture availability is not limited (McCabe and Wood, 2006). However, the ability of remote sensing products to detect hydrological response over a variety of surface types and conditions indicates their utility for broader scale application.

Identifying possible feedback relationships between hydrological variables was undertaken using NARR based atmospheric indices. Using NARR derived variables to describe the state of the early morning atmosphere, indices were correlated with both past and future precipitation events and subsequent soil moisture anomalies, offering a pathway towards characterizing the degree of feedback within the NAMS system. Particularly strong correlation was observed between the Humidity Index and AMSR-E soil moisture anomaly for key rainfall events during August 2004. Further, the Humidity Index was observed to persist over wet-regions, identifying a possible positive feedback mechanism during the summer monsoon period over Arizona. An extended analysis of this data over longer time periods is required to elucidate more clearly the nature of this feedback response, particularly since CTP data indicated a persistent convective advantage favoring sensible heat (i.e. negative feedback) – an outcome that was not completely supported by coincident remote sensing observations.

Knowledge of the spatial distributions of individual observation should allow for improved characterization of all observations, given the physical link between the processes. However, determining the most appropriate means to utilize the rich spatial information present in remote sensing data requires additional investigation. Multi-objective model calibration techniques (Franks et al., 1998; Gupta et al., 1998; McCabe et al., 2005a) offer one means towards achieving this – although how the spatially distributed information available from remote sensors can be best integrated into such frameworks requires additional research (see McCabe et al., 2005c). Data assimilation
schemes on the other hand are particularly suited to incorporating the spatial context of remote sensing data into land surface models to improve their prediction accuracy. Following is an application of data assimilation which seeks to explore the potential for incorporating diverse remote sensing data into a regionally scaled hydrological model. The work addresses the second objective of this research: to improve estimation of the surface water and energy budgets through assimilating space-retrieved variables into a land surface model.

4. DATA ASSIMILATION OF REMOTE SENSING OBSERVATIONS

A data assimilation experiment was performed across the Arizona domain using the remotely sensed observations described in Section 2. In general, data assimilation techniques are used to constrain/improve a models’ predictions by accounting for measurements of a physical phenomenon of interest. An attractive property of these methods is their capability to address uncertainties in both state variables and measurements (Reichle et al., 2001; McLaughlin, 2002). This makes them particularly suited to incorporate remote sensing data into hydrological models. The current data assimilation experiment is designed to illustrate the potential for incorporating multiple sources of remote sensing data into a land surface model to provide better estimation of the underlying physical processes.

4.1 Data Assimilation and the Particle Filter Approach

The data assimilation system has several components – a physical land surface model, which simulates the hydrological states and fluxes, the meteorological data required to force the land surface model, remote sensing observations to be assimilated into the model, and the statistical techniques used to assimilate (merge) the observations into the model. In this experiment, meteorological data is extracted from both the North American Land Data Assimilation System (NLDAS) (Mitchell et al., 2004) and TRMM rainfall products (see descriptions in Section 2.1). Remote sensing sources include the TMI 10.65GHz brightness temperature measurements and evapotranspiration data derived from the SEBS model (Su, 2002) and MODIS observations (see Section 2.2 and Su et al., 2005). The land surface model employed is the Variable Infiltration Capacity (VIC)
model (Wood et al., 1992; Liang et al., 1994; Liang et al., 1999), a multi-scale land
surface model which has been extensively discussed in the literature (e.g. Maurer et al.,
2001; Luo et al., 2003). The LSMEM model (Drusch et al., 2004, Gao et al., 2004,
2006b) was used to simulate the brightness temperature (\( T_b \)) given VIC surface states.

The core of the data assimilation system is the method employed for assimilation. In
hydrological investigations using detailed physical models, Monte Carlo assimilation
methods are often used e.g. the Ensemble Kalman Filter (EnKF) (Evensen, 1994; Reichle
et al., 2001), to reduce the complexity of the assimilation problem and also the
computational burden (McLaughlin, 2002). In this study, the Particle Filter (PF)
(Kitagawa, 1996; Doucet, 1998) approach has been selected as the most appropriate
assimilation technique. The Particle Filter approach belongs to a category of so called
Sequential Monte Carlo Methods for Bayesian estimations (Doucet, 1998). Here, a
variant of Particle Filter methods known as Sampling Importance Resampling (SIR)
(Arulampalam et al., 2002) is implemented.

Particle Filter methods propagate a Monte Carlo sample of points through a model by
preferentially re-selecting them according to likelihood values computed for each point
against an observation. In essence, a point closer to the observation will have a larger
likelihood value and thus will be preferentially selected. Particle Filter methods have
several advantages over alternative techniques such as Ensemble Kalman Filtering
including: (1) the filtering procedure is not linear, thus suiting the nonlinear nature of the
underlying hydrologic systems (methods like EnKF assume linear observation equations
and Gaussian measurement error distributions and become sub-optimal if these
assumptions are relaxed); (2) they filter by preferentially selecting from prior sample
points, instead of modifying the point, thus preserving the physical consistency of the
state values of the sample (this may also be a disadvantage since discrete resampling of
the ensemble at each update step may result in rapid loss in ensemble diversity i.e. in the
extreme case, you may end up with only one ensemble member); (3) they not only find
the best estimate of the state variable, but also identify the most probable forcing from a
cloud of inputs e.g. identify an improved estimate of antecedent rainfall by comparing
soil moisture results to satellite observations. Apart from these advantages, the particle
filter technique has some significant drawbacks due to its selection strategy that can
cause its failure, especially when the input noise is small. Additional Monte Carlo sample points can remedy this, but necessarily increase the computation burden.

The likelihood functions in the particle filter are modeled using the Copula approach (Sklar, 1959). Copula methods model a joint probability distribution in two separate and independent steps. First, the marginal distributions of each variable are fitted with an arbitrary type of parametric distributions individually. Following this step, the dependency structure is modeled using a parametric copula function (Sklar, 1959). The Copula approach is considered more flexible than the regularly used joint Gaussian distribution, as it allows assignment of arbitrary marginal distributions and a flexible dependency structure (see for e.g. Gao et al., 2006a).

4.2 Composing Discrete Assimilation Experiments

The data assimilation exercise consists of three individual experiments. In the first, VIC simulations are forced using NLDAS data as input, to provide a benchmark run against which subsequent analysis can be compared (Experiment 1). In the second experiment, VIC simulations are run with NDLAS data and satellite derived TRMM rainfall (Experiment 2). Lastly, the TRMM driven simulation from Experiment 2 is assimilated with both TMI brightness temperatures (to determine soil moisture using the LSMEM forward model) and MODIS derived evapotranspiration (Experiment 3) from Terra and Aqua. TRMM rainfall is a much lower quality product than the corresponding NLDAS rainfall data (positive bias), so Experiment 2 represents an ‘open-loop’ or initial guess solution. Experiment 3 is the data assimilation component, and improvements compared to Experiment 2 should be expected.

The VIC model was run at an hourly time step in order to utilize the instantaneous TRMM brightness temperature observations. The 3-hourly TRMM rainfall data were disaggregated to hourly. The experiment was simulated at 0.25 degrees (constrained by the TRMM data resolution), so additional parameters and observations were rescaled when necessary. Assimilation was performed for August 2004 to correspond with the NAME experiment. Meteorological and TRMM brightness temperature data were collected for 2 years prior to this and used as ‘training data’, to derive the copula-based likelihood functions necessary for the Particle Filter data assimilation. To decrease the
dimensionality of the assimilation problem, the likelihood functions were estimated for each grid cell separately (see McLaughlin, 2002).

Fig. 6 presents an overview of the data assimilation experiments together with time series of regionally averaged (i.e. entire Arizona domain) values of the top 10cm soil moisture and evapotranspiration. Additionally, for assimilations with TMI brightness temperature and MODIS evapotranspiration, the regional average standard deviation band is shown. For soil moisture, the band is narrower in wet periods than in dry-down periods, whereas for latent heat flux the uncertainty increases during the noon time and quickly diminishes afterwards, in line with the diurnal cycle of the process. As noted above, TRMM rainfall retrievals tended to have a positive bias over the study region compared to the higher quality NLDAS data. As a result, the TRMM driven open loop simulation (red line) for the 10 cm soil moisture are wetter than the corresponding NLDAS bench mark run (black line) for much of the month – excluding a short period from Aug. 5-12.

When TMI brightness temperatures (T_b) were assimilated into the VIC model, they tended to decrease the moisture in the soil column, resulting in a reduced assimilated moisture (blue line) relative to the unassimilated TRMM run (red line). The first few days of the study period do not reflect this trend, with assimilated values higher than the TRMM run. During and after the rainfall events around Aug. 15, the assimilation results indicated moisture values between the unassimilated TRMM run and the NLDAS benchmark run. Overall, the TMI observations are observed to impart a significant influence on the assimilation experiment, with assimilated soil moisture values regularly below the benchmark run.

In the second panel (evapotranspiration), both the open loop TRMM run (Experiment 2) and assimilation run (Experiment 3) yield higher ET estimates relative to the NLDAS driven bench mark due to the increased TRMM precipitation. However, assimilation of MODIS based evapotranspiration does not shift the ET values towards the benchmark run – on the contrary, they are increased above NLDAS-VIC model simulations. As can be observed in Fig. 6, the assimilation run develops spikes around noon-time (center of the two ET assimilations) for nearly every day. In this instance, the disparity between modeled and remotely measured variables is more clearly understood. Mitchell et al.
(2004) and Haddeland et al. (2006) identified problems with the VIC model NLDAS calibration that have lead to underestimating evapotranspiration for regions of the US, like the southwest. As will be discussed below, this calibration problem will affect flux partitioning and limit improvements from assimilation.

Spatial maps of total monthly rainfall for August and averaged soil moisture for the period following the rainfall events (August 15-20) are presented in Fig. 7. When comparing the model simulated brightness temperature to TMI measurements, the Particle Filter tended to identify slightly smaller rainfall amounts, as observed through differences between the TRMM rainfall and the assimilated rainfall in the left column. Corresponding with these rainfall differences is a small shift towards lower soil moisture values (described above), evidence of which can be discerned in the right column of Fig. 7. Significantly, no obvious pattern of difference exists between soil moisture from NLDAS and that from the TRMM simulations, indicating that TRMM rainfall has most of its errors in the magnitude, rather than the spatial pattern – an observation made through independent analysis of hydrological consistency between AMSR-E data and TRMM rainfall in Section 3.1.

Identifying the influence of evapotranspiration assimilation proved to be more challenging. MODIS based ET is available at approximately 11am and 2pm local time, but unlike TMI, is not spatially available due to intermittent cloud cover (Fig. 3); thus, affecting the retrieval ability. Fig. 8 displays the average noon-time latent heat flux (W/m²) for each of the three simulation experiments, together with direct observations from the MODIS sensor for Aug. 15-20. Clearly, MODIS retrievals produce considerably higher flux values across the entire Arizona domain. Assimilation of MODIS data elevated the latent heat by a relatively small amount compared to the benchmark run – highlighting one of the limitations of the Particle Filter method. Since the VIC model under predicts the latent heat flux (i.e. it is unable to reproduce the higher latent heat fluxes in the prior samples), the Particle Filter has an insufficient range from which to select ‘better’ assimilation values. As a result, only marginal improvement can be achieved. Additional research is being carried out regarding this issue.

### 3.3 Summary of Data Assimilation Experiments
The data assimilation experiment was performed to illustrate a mechanism through which distributed, diverse and hydrologically consistent remote sensing observations may be merged into a predictive framework – a key component of the NEWS strategy. Using the VIC land surface model, observations of the TMI brightness temperature and MODIS evapotranspiration were assimilated into an open-loop model forced with TRMM based precipitation and NLDAS meteorological data. The procedure verified the potential of merging diverse remote sensing observations and to provide insight into the underlying physical processes. Improvements relative to the open-loop run were observed upon assimilation of the TMI brightness temperatures, with 10 cm soil moisture values shifting towards the benchmark NLDAS based model run. However, assimilating the remotely sensed evapotranspiration did not significantly improve the predictive capacity of the model. In this instance, a calibration deficiency in the land surface scheme was identified as the key limitation to increasing predictive skill, serving to highlight a significant issue regarding estimating and specifying the uncertainty attributed to land surface model outputs relative to the uncertainty in the retrieved remote sensing variables. Further research in alternative forms of data assimilation (i.e. Regularized Particle Filter) and in estimating the relative uncertainty between model predictions and observations will address this problem.

Assimilation represents only one means of improving process representation. The accuracy of distributed modeling to predict, and therefore gain knowledge about, land surface processes rely greatly on the correct specification of rainfall amount and location. A possible development of the relationships observed here will lead to improvements of individual hydrological components through knowledge of physically related processes. For instance, spatial mismatch between the AMSR-E data and the TRMM rainfall (excluding uncertainties in the geo-registration of AMSR-E data) is a likely indicator of spatial misrepresentation in the rainfall distributions. Likewise, the magnitude of the soil moisture anomaly has been observed to correlate well with rainfall amount. As a result, it would seem that merging these products would allow for improved spatial description of the precipitation patterns and increased accuracy of the rainfall amount.
5. CONCLUSION

A fundamental consideration in establishing an integrative observation and modeling approach to water and energy cycle systems is understanding the capacity to which; 1) independent observations of the hydrological cycle display consistency among linked surface and atmospheric processes and; 2) observed variables can be merged into a framework designed to enhance knowledge of earth-climate dynamics. The North American Monsoon System (NAMS) provides an ideal test-bed under which these concepts can be developed and, through the NAME and SMEX programs, allows for direct insight into the interaction with land surface and atmospheric processes.

Numerous modeling based studies have sought to explore these relationships, focusing on longer temporal periods and spatial extents than are explored here (e.g. Higgins et al., 1998; Hu and Feng, 2002; Zhu et al., 2005). In most of these and similar works on the NAMS, soil moisture, surface heat fluxes and precipitation data consist almost exclusively of output from numerical weather prediction (NWP) or similar model results. Here, remote sensing observations of surface and atmospheric variables were analyzed for their hydrological consistency, offering the potential to explore feedback relationships in a more realistic manner than is available through model output alone. These data represent a unique attempt to characterize consistency and feedback relationships within available remote sensing based hydrological observations and derivable atmospheric variables.

Distinguishing hydrological consistency in remote observations is a critical and needed research objective. Currently, a comprehensive or robust framework for integrating multi-sensor, multi-scale remote observations for hydrological prediction does not exist. While data assimilation approaches show promise, the key issue is not one of simply developing more efficient merging techniques. On one hand, the issue is complicated due to an incomplete understanding of both the role of observational error in modeling and also in accurately estimating the magnitude and variability of this. On the other hand, the predictive skill of hydrologic state ensembles given a variety of error models and remotely sensed information needs to be properly quantified. The initial step in this research direction was taken by Crow et al. (2005).
Hydrological consistency is fundamentally an effort to seek improvement in hydrological prediction, through ensuring concurrence between unique observations of water and energy cycle budget variables. Implementing diverse data and observations into a predictive framework requires the formulation of a holistic modeling philosophy – in contrast to relying solely on single process, single variable oriented approaches. While insight into individual phenomena is no doubt gained through process based approaches, improved understanding lies in integrating diverse components, thereby allowing a more complete understanding of dynamic coupled systems to develop. The analysis presented here offers considerable promise in the ability of remote observations to accurately and consistently monitor variations in the land surface and atmospheric states, and demonstrates a means through which diverse information can be effectively integrated to explore coupled land-atmosphere interactions.

ACKNOWLEDGEMENTS

Research was funded by NASA project grants 1) NNG04GQ32G: A Terrestrial Evaporation Product Using MODIS Data; 2) NAG5-11111 Land Surface Modeling Studies in Support of AQUA AMSR-E Validation; and 3) NAG5-11610: Evaluation of Hydrologic Remote Sensing Observations for Improved Weather Prediction. The NARR derived atmospheric variables HI$_{low}$ and CTP, were kindly produced by Francina Dominguez of the Department of Civil and Environmental Engineering, University of Illinois-Urbana – her effort is greatly appreciated.
REFERENCES


Table 1. Input variables for MODIS based evapotranspiration prediction.

<table>
<thead>
<tr>
<th>Meteorological Variables</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incoming shortwave radiation (W.m(^{-2}))</td>
<td>North American Land Data Assimilation System (NLDAS) interpolated to 0.05 degree, consistent with the satellite based data. Data fields were interpolated using a nearest neighbor scheme, minimizing smoothing and averaging of data.</td>
</tr>
<tr>
<td>Downward longwave radiation (W.m(^{-2}))</td>
<td>Brutsaert (1991; 1999)</td>
</tr>
<tr>
<td>Air temperature (°C)</td>
<td></td>
</tr>
<tr>
<td>Vapour pressure (kPa)</td>
<td></td>
</tr>
<tr>
<td>Wind speed (m.s(^{-1}))</td>
<td></td>
</tr>
<tr>
<td>Wind direction (°)</td>
<td></td>
</tr>
<tr>
<td>Atmospheric Pressure (kPa)</td>
<td></td>
</tr>
<tr>
<td>Aerodynamic Parameters</td>
<td></td>
</tr>
<tr>
<td>Satellite Based Data</td>
<td>MODIS Sensor on board EOS Terra and Aqua</td>
</tr>
<tr>
<td>Nominal Overpass time (local)</td>
<td>11:00 a.m. (Terra) and 2:30 p.m. (Aqua)</td>
</tr>
<tr>
<td>Resolution (m)</td>
<td>0.05 degree Climate Modeling Grid (CMG)</td>
</tr>
<tr>
<td>Land Surface Temperature and Emissivity</td>
<td>MOD11C1 and MYD11C1</td>
</tr>
<tr>
<td>Landcover Type</td>
<td>MOD12C1 Land Cover</td>
</tr>
<tr>
<td>Leaf Area Index (LAI)</td>
<td>VIC Land Surface Model</td>
</tr>
<tr>
<td>Albedo</td>
<td>Based on UMD Land Classification Scheme</td>
</tr>
<tr>
<td>Vegetation Height</td>
<td>Based on UMD Land Classification Scheme</td>
</tr>
<tr>
<td>Vegetation Fraction</td>
<td>Relationship of Xavier and Vettorazzi (2004)</td>
</tr>
</tbody>
</table>
Figure 1. Comparison of the AMSR-E anomaly for identified rain days during August 2004, over the Arizona domain of the NAME campaign. TRMM rainfall amounts (instantaneous rain-rate) are shown for 3, 6, 9 and 12 hours preceding the AMSR-E overpass (~2 a.m.), so as to capture the afternoon convective processes typical of the NAMS. AMSR-E anomaly is the difference between daily values and the monthly average.

Figure 2. Average TRMM precipitation corresponding to ranges of AMSR-E anomaly for a) all TRMM data and b) non-raining cells removed and c) rain cells > 5 mm/hr, together with d) corresponding histograms for the number of cells in each distribution. Errors bars represent ±0.5 standard deviation on the average rainfall.

Figure 3. From left to right: Comparison of the AMSR-E anomaly for identified rain days with; 6 a.m. Humidity Index (HI$_{low}$) of the previous day; HI$_{low}$ for 6 a.m. sounding following the AMSR-E overpass; Convective Triggering Potential (CTP) of the previous day (6 a.m.) and; combined map of MODIS based sensible heat flux for Terra and Aqua. AMSR-E anomaly is the difference between daily values and the monthly average.

Figure 4. Hydrological consistency between AMSR-E, MODIS sensible heat and TRMM precipitation results for periods not covered in Fig. 1 and Fig. 3.

Figure 5. From left to right: AMSR-E anomaly for select rain days together with Humidity Index (6 a.m. same day) discriminated for HI$_{low}$$<15^\circ$ (white circles) and $15^\circ$$<HI_{low}$$<20^\circ$ (red circles). TRMM observed precipitation events occurring 9, 12, 15 and 18 hours after the 2 a.m. AMSR-E overpass are shown to assess whether positive or negative feedback can be characterized from knowledge of land surface and atmospheric states.
Figure 6. Time series of 10cm soil moisture (top) and ET (bottom) averaged over the entire Arizona region. Lines show NLDAS driven VIC simulations (black), TRMM driven VIC simulations (red), and expected values of assimilations with TMI brightness temperature and MODIS evapotranspiration (blue). The uncertainty in the expected values is given by spatially averaged standard deviation band (grey area).

Figure 7. Left column from top down: Total rainfall amount (mm) in August 2004 from: NLDAS database; TRMM retrieval; and the data assimilation. Right column from top down: Average top 10cm soil moisture (%) during August 15-20 2004 for; NLDAS driven VIC simulation; TRMM driven VIC simulation and data assimilation.

Figure 8. Average noon time latent heat flux (W/m2) estimate from: NLDAS driven VIC simulation (top left); TRMM driven VIC simulation (top right); data assimilation (bottom left); and MODIS retrieval (bottom right) during August 15-20 2004.
Table 1. Input variables for MODIS based evapotranspiration prediction.

<table>
<thead>
<tr>
<th><strong>Meteorological Variables</strong></th>
<th><strong>Data Source</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Incoming shortwave radiation (W.m(^{-2}))</td>
<td>North American Land Data Assimilation System (NLDAS) interpolated to 0.05 degree, consistent with the satellite based data. Data fields were interpolated using a nearest neighbor scheme, minimizing smoothing and averaging of data.</td>
</tr>
<tr>
<td>Downward longwave radiation (W.m(^{-2}))</td>
<td>Brutsaert (1991; 1999)</td>
</tr>
<tr>
<td>Air temperature (°C)</td>
<td></td>
</tr>
<tr>
<td>Vapour pressure (kPa)</td>
<td></td>
</tr>
<tr>
<td>Wind speed (m.s(^{-1}))</td>
<td></td>
</tr>
<tr>
<td>Wind direction (°)</td>
<td></td>
</tr>
<tr>
<td>Atmospheric Pressure (kPa)</td>
<td></td>
</tr>
<tr>
<td>Aerodynamic Parameters</td>
<td></td>
</tr>
</tbody>
</table>

**Satellite Based Data**

| Nominal Overpass time (local)                                 | MODIS Sensor on board EOS Terra and Aqua |
| Resolution (m)                                                | 11:00 a.m. (Terra) and 2:30 p.m. (Aqua)   |

| Land Surface Temperature and Emissivity                       | MOD11C1 and MYD11C1 |
| Landcover Type                                                | MOD12C1 Land Cover |
| Leaf Area Index (LAI)                                         | VIC Land Surface Model |
| Albedo                                                        | Based on UMD Land Classification Scheme |
| Vegetation Height                                             | Based on UMD Land Classification Scheme |
| Vegetation Fraction                                           | Relationship of Xavier and Vettorazzi (2004) |
Figure 1

AMSRAnomaly
TRMM -3hrs
TRMM -6hrs
TRMM -9hrs
TRMM -12hrs

Aug 3
Aug 5
Aug 7
Aug 12
Aug 14
Aug 16

AMSRAnomaly
TRMM Rain Rate (mm/hr)

-5 -20 0 > 5

Kilometers

AMSRAnomaly
TRMM Rain Rate (mm/hr)

-5 -20 0 > 5

Kilometers
Figure 2
Figure 3

[Images of spatial data maps for different days showing various meteorological parameters such as AMSR-Anomaly, Humidity Index, CTP, and Sensible Heat. Each day (Aug 2, Aug 5, Aug 7, Aug 12, Aug 14, Aug 16) has corresponding maps for the previous day and current day, with color scales indicating values for AMSR-Anomaly, Humidity Index (°C), Conv Trig Potential (J/Kg), and Sensible Heat (W/m²).]
Figure 5
Figure 6
Figure 7

AMSR-Anomaly  Humidity Index  TRMM 18Z  TRMM 21Z  TRMM 00Z  TRMM 03Z

Aug 2  Aug 5  Aug 7  Aug 14  Aug 16
Figure 8

- NLDAS ET
- TRMM ET
- Assimilated ET
- MODIS ET

Latent Heat (W/m²)

Legend: 0 - 250 W/m²