Merging Satellite and Model Information to Improve Snowpack and Water Supply Forecasting CCTC 2013 Paper Number 1569695429

B. Livneh[1], and J.S. Deems[1,2]
[1] CIRES, University of Colorado, Boulder, USA
[2] National Snow and Ice Data Center, Boulder, Colorado, USA

Abstract

Mountain snowpacks provide an important natural reservoir for water resources in western North America. The largely-snowmelt driven Upper Colorado River Basin (UCRB) has projected increases in water demand, such that anticipating changes to meltwater runoff will be essential for water managers. This research evaluates the utility of incorporating satellite measurements into a hydrologic modeling framework to improve forecasts. The Variable Infiltration Capacity (VIC) model was used in this study, together with satellite data, including evapotranspiration, terrestrial water storage data, and a snow albedo product. We explore the temporal dynamics of the basin over a 10-year period of significant climatic variability.

Keywords: hydrologic modeling, streamflow forecasting, water resources, satellite data assimilation.

Résumé

L'accumulation annuelle de neige sur les montagnes constitue un important réservoir naturel de ressources hydriques dans l'ouest de l'Amérique du Nord. Étant donné l'accroissement prévu de la demande en eau dans la région du bassin supérieur du fleuve Colorado (UCRB), largement alimenté par la fonte des neiges, il deviendra essentiel que les gestionnaires des ressources hydriques prévoient des moyens de pallier les modifications du débit de ruissellement de l'eau de fonte. Cette recherche évalue l'utilité d'intégrer des mesures par satellite à un cadre de modélisation hydrologique afin d'améliorer les prévisions. Le modèle de taux maximal d'infiltration variable (VIC) a été utilisé dans cette étude, ainsi que des données obtenues par satellite, entre autres sur l'évapotranspiration, les réserves d'eau terrestre et un produit relatif à l'albédo nival. Nous étudions la dynamique temporelle du bassin sur une période de 10 ans caractérisée par une variabilité climatique substantielle.

Mots-clés: modélisation hydrologique, prévisions de débit, ressources hydriques, assimilation des données obtenues par satellite

1. Introduction

The Colorado River Basin is an essential freshwater resource for the southern Rocky Mountains and U.S. Southwest, providing water supply to 7 states and over 30 million people, and irrigation to roughly 3 million acres of farmland. The majority of water originates in the headwaters region and hence changes to this region will impact downstream water availability. This supply is projected to decrease by 5-20% over the coming decades due to anthropogenic warming and enhanced evapotranspiration ([1]; [2]; [3]; [4]). Recent studies have shown however that dust deposition to snow cover from grazing and agricultural land disturbance that began in the mid 1800s in the Colorado Plateau and Great Basin has been affecting runoff from the Colorado River Basin ([5]; [6]). Dust loading during the period 2005 – 2008 shortened snow cover duration by 25 to 35 days through its reduction of snow albedo (enhancement of absorption of solar radiation). When extended to the entire Upper Colorado River Basin (UCRB) above Lee's Ferry, AZ, this modern dust radiative forcing in snow has shifted peak runoff more than 3 weeks earlier and reduced annual runoff by ~5% through enhanced evapotranspiration ([7]).

Over the past two decades, an increasing number of detailed remote sensing products have come online, providing estimates of hydrometeorological fields that are either impossible, or impractical to measure in-situ. To this end, satellite remote sensing provides a promising alternative to direct observations for hydrologic prediction. One attractive pursuit is closing the terrestrial water budget with remote-sensing and in-situ measurements to improve model estimates (i.e. forecasts) of important hydrologic quantities such as streamflow (e.g. [8], [9]). The equation for the terrestrial water budget can be written as follows:

$$P = Q + ET + TWSC \tag{1}$$

Where: P = incident precipitation;

Q = total river discharge;

ET = Evapotranspiration; i.e. the sum of evaporation, sublimation, and transpiration; and

TWSC = Terrestrial Water Storage Change; including soil moisture and snow water equivalent (SWE).

Estimates of P and Q can generally be made through direct gauge measurement, whereas the latter two terms in Eq. 1 are more difficult and often require remote sensing. The TWSC term, is in fact comprised of two components, soil moisture and snow water equivalent (SWE). In the UCRB, an estimated 2/3 of annual precipitation falls during the cold season, making the SWE component very important for accurate streamflow prediction. An important new product for observing fractional snow covered area and snow detection utilizes the MODIS surface reflectance products (MOD09) for fractional snow cover, plus the grain size and albedo of the fractional snow cover. Referred to as the MODIS Snow Covered Area and Grain Size/Albed; MODSCAG [10]. Figure 1 shows a MODSCAG image of spatially distributed snow cover over the study domain from 8 April, 2010, revealing a high degree of fidelity. During it's development, the relatively coarse (500m) pixel size was evaluated against a much finer resolution (30m) Landsat Thematic Mapper product [11] with root mean squared error (RMSE) of 5 % on average, and less than 13 % for all cases.

The objective of this research is to evaluate the utility of incorporating satellite measurements within a hydrologic modeling framework to improve forecasts. The Variable Infiltration Capacity (VIC) model, [12]) was used in this study, which includes a complete energy-balance snow model [13]. Remote sensing products include MODSCAG (snow covered area and albedo), as well as satellite based ET and TWSC products. The results shall address two primary objectives: (i) to assess spatiotemporal patterns of remotely sensed water budget variables (i.e. ET, TWSC) over the past decade, which to date have not been rigorously tested in such a manner; and (ii) to inform a hydrologic model with these satellite derived quantities to improve hydrologic forecasts.

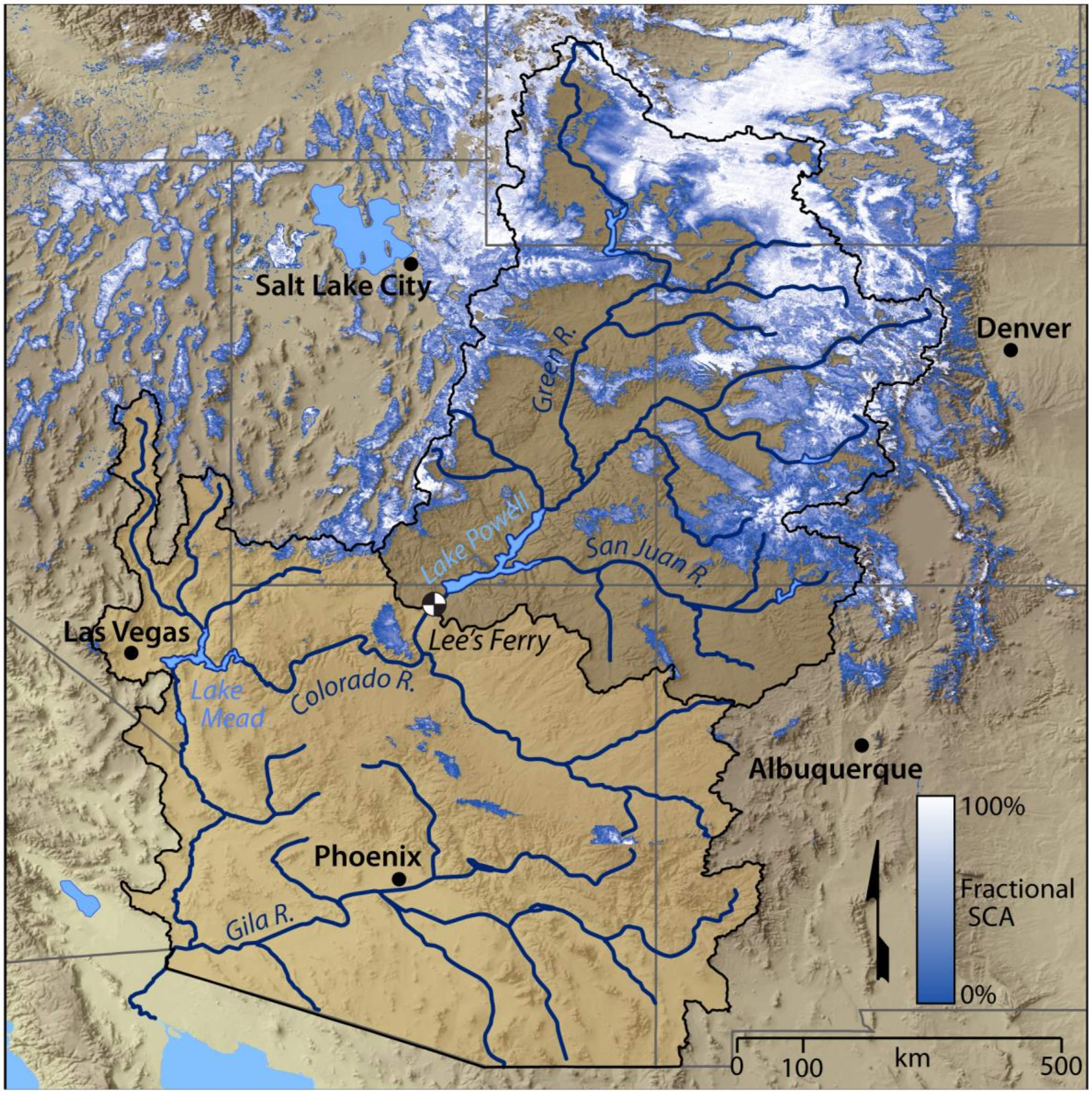

Figure 1. MODSCAG image of fractional snow covered area over the Colorado River Basin on 8, April, 2010; the upper basin (UCRB) is shaded in dark brown.

2. Methods and Experimental Development

In this section we describe the hydrologic model and data that were used to investigate hydrologic sensitivities in the UCRB. The final part of the section describes the rationale behind the experimental set-up and provides additional quantitative considerations for conducting an analysis over large scales.

2.1 Hydrologic model and driving data

Hydrologic states and fluxes were simulated via the VIC model [12], which is a grid-based hydrologic model that balances surface energy and water budgets at typical spatial resolutions ranging from a few km to hundreds of km. VIC considers sub-grid variability of vegetation and runoff generation, while also accounting for sub-grid topography through elevation-bands. Land-cover input data include static vegetation aggregated from a 1-km database of University of Maryland classes [14], and soils information aggregated from a 1-km-resolution dataset produced by the Pennsylvania State University [15]. The VIC model version used here, v.4.1.2c, was implemented at a spatial resolution (i.e. horizontal resolution) of 1/8° (~12 km).

The meteorological data used in this study were derived by [16] at a 1/16° (~6 km) resolution for the period 1915 – 2011. Precipitation and daily minimum and maximum temperatures were obtained for the NOAA Cooperative Observer (Co-op) stations shown in Figure 2. Precipitation and temperature were gridded directly from station data. Wind data were linearly interpolated from a larger (1.9° latitude-longitude) NCEP–NCAR reanalysis grid. Lastly, precipitation values were scaled on a monthly basis, to match the long-term parameter-elevation regressions on independent slopes model (PRISM – [17]). The 4km PRISM product that was used represents a statistically adjusted dataset that captures local precipitation variability due to complex terrain.

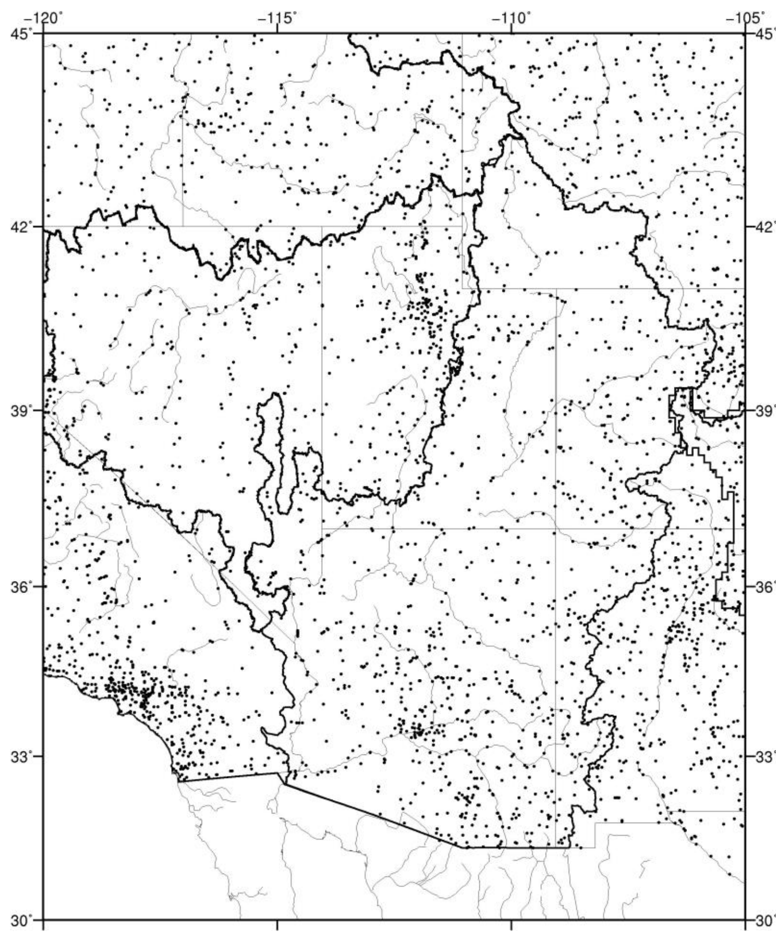

Figure 2. Depiction of spatial distribution of NOAA Cooperative Observer (Co-op) stations used to drive the VIC model with daily minimum and maximum temperatures and precipitation.

2.2 Auxiliary Remote Sensing Data

To obtain a spatial estimate of ET, we rely exclusively on satellite data. Combining data from MODIS and Geostationary Operational Environmental Satellites (GOES) an estimate of ET was produced by [18], based on vegetation index (VI) and surface temperature (Ts) data are from MODIS and radiation data from GOES. The major 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, 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. Further algorithm details are included in [18], who conclude that ET estimates matched will those from a much higher resolution Landsat-based method, [19] with consistently high correlations (R^2>0.85) at flux tower sites across the United States.

Monthly variations of TWSC were estimated using the Gravity Recovery and Climate Experiment (GRACE) product. Given the coarse nature of this product, which monitors changes in the Earth's gravitational field measured by a pair of satellites, the spatial TWSC estimates are only valid over areas on the order of 10^5 km^2 or larger.

2.3 Experimental Development

A preliminary investigation into the relative magnitudes of the components in Eq. 1 reveals the importance of each term. Figure 3 shows the mean seasonal cycle for these component based on a retrospective VIC simulation (1920-2003). The exchanges between stored moisture (TWSC) and streamflow -- i.e. negative TWSC values – are most notably driven by SWE during spring and by releases of soil moisture during summer. ET shows a clear seasonal pattern, peaking in July, with a roughly monotonic decline towards a December minima.

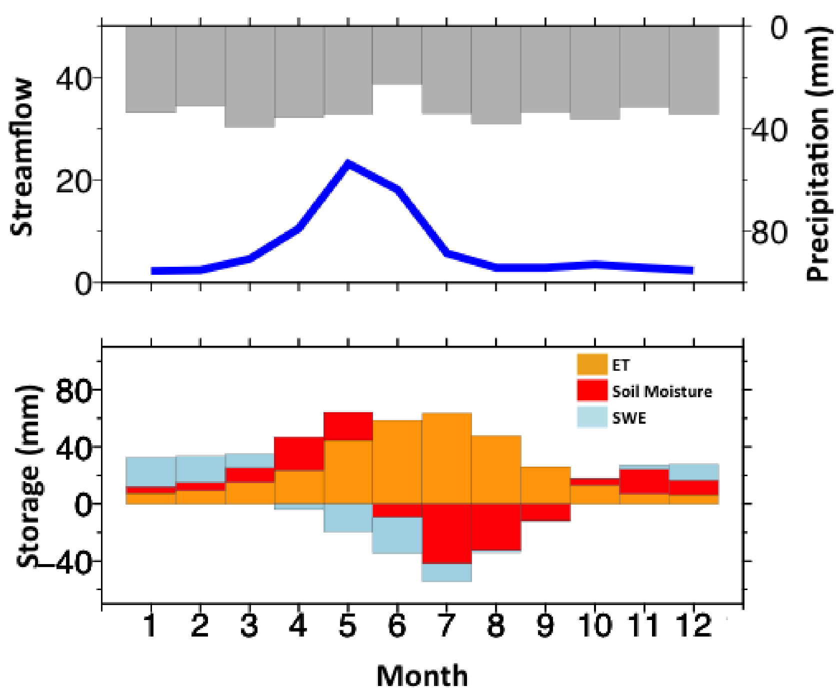

Figure 3. Simulated monthly water budget terms from the VIC model averaged over the UCRB 1920-2003; driven by the precipitation values depicted in the upper panel.

A further consideration for making accurate spatial hydrological assessments in the snowmelt-driven UCRB, is the role of snow-cover on land-atmosphere energy exchanges. Seasonal snow cover insulates the soil from the atmosphere and creating a sink for latent heat during snowmelt [20], while coupled land-atmosphere modelling studies (e.g. [21]) have found that snow covered area plays a major role in atmospheric feedbacks.

To quantitatively understand the role of snow cover and other hydrologic terms on land-atmosphere energy exchanges, it is useful to consider the land-surface energy budget:

$$Q_{net} = Q_{SW} + Q_{LW} + Q_h + Q_l + Q_g + Q_a + \Delta H/\Delta t \qquad (2)$$

where Q_{net} is the net energy available to heat or cool the land surface; over snow this energy is used to melt or refreeze the snowpack;

Q_{SW} is the net shortwave radiation at the land surface, considering emission absorption and reflection;

Q_{LW} is the net longwave radiation at the surface;

Q_h is the surface sensible heat flux;

Q_l is the surface latent heat flux;

Q_g is the ground heat flux;

Q_a is the energy advected to the land surface from external sources (e.g. rain); and

$\Delta H/\Delta t$ is the change in internal energy of the surface soil; during snow conditions this is the energy change within the snowpack.

Among the terms in Eq. 2, the solar radiation term Q_{SW} is typically the dominant driver for seasonal snowmelt and ET processes. Further, the amount of absorbed radiation is inversely related to the albedo of the land surface, α_{LAND}, e.g. $Q_{SW} = Q_{SWdownward}(1 - \alpha_{LAND})$. If we consider that the albedo of a snow-coverd serface, α_{SNOW}, can be over 4 times greater than that of a snow free surface, then it becomes apparent how important estimating the spatial extent of snow cover becomes in resolving land surface budgets of moisture and energy (Equations 1 and 2, respectively).

3. Preliminary Results

The analysis begins with an examination of the interannual variability of water budget terms, in an effort to reconcile their respective sensitivities and magnitudes. The focus then proceeds to contrasting the remote sensing estimtes with simulated outputs (i.e. from VIC) and concludes by testing a simple data assimilation strategy.

3.1 Interannual variability of water budget components

The seasonal variability of water budget terms obtained exclusively from remote sensing are shown in Figure 4. The importance of annual precipitation cannot be understated when examining the relative sensitivities of each term. In the driest year of the study (2002) the evaporative faction is larger than other years, due to the non-linear nature of the ET mechanisms, namely an abundance of solar energy (Q_{SW}) with fewer precipitation events, and a more complete drying of the soil. Conversely, the wettest year (2005) has nearly the smallest evaporative fraction.

Oscillations in TWSC are pronounced in certain years, reflecting the potentially opposing seasonal influences of soil moisture and SWE changes. Overall, increases in storage are seen during the winter, while stored moisture is released during summer; consistent with the model estimates in Figure 3.

It follows intuitively that the largest discharge magnitudes occurred in the wettest year (2005). However, the second largest discharge results in 2006 (3rd wettest), which was a year that had reported severe dust-on-snow events, driven by airborne dust from the upwind desert southwestern U.S. (mostly northern Arizona). This interesting finding provides insights into the role of dust on streamflow generation, which has been shown to cause more efficient melt of the snowpack [7], due to a darkening of the snow surface and increased absorption of solar radiation (Q_{SW}). Incorporating the MODSCAG product into the model estimates of snowmelt will further help to quantify the role of dust in snow disappearance.

3.2 Simulated Water Budget

One notable shortcoming of relying exclusively on independent remote sensing estimates is the implicit lack of water budget closure (i.e. inconsistency). This will conceivably result in an error, or residual term in Eq. 1. Since the VIC model closes the energy and water budgets by construct, it provides a useful tool to ensure a physically consistent estimate of respective budget components. To this effect, Figure 5 shows model estimates of key water budget terms over the seasonal cycle.

Although the largest spatial extent of snow coverage occurs in March, the deepest snow depths are simulated in May, which is consistent with in-situ observations from the SNOTEL network. The spatial SWE pattern largely follows the pattern of maximum precipitation (upper right panel in Figure 5), however, the additional dimension in this pattern is elevation (not shown), which is typically positively correlated with precipitation. Furthermore, elevation is accompanied by colder air temperatures needed for sustained snowpacks. The relatively high precipitation but low elevation in the southwestern portion of the basin demonstrates this additional relationship.

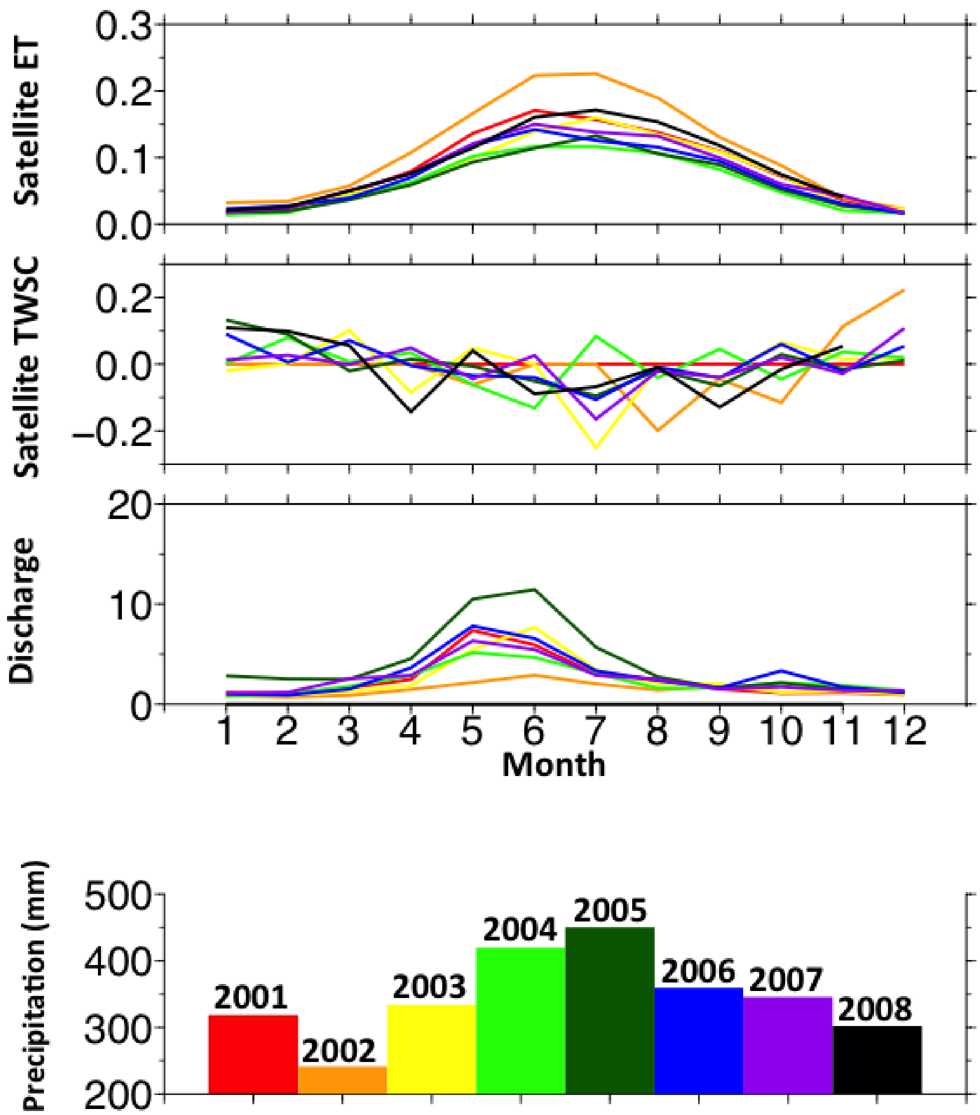

Figure 4. Average monthly water budget components over the UCRB derived exclusively from remote sensing estimates; ET and TWSC are normalized by annual precipitation to highlight sensitivities to annual variability; time series are colored by year, corresponding to annual precipitation of that year provided in the bottom panel.

3.3 Data Assimilation

This section examines the utility of combining selected remote sensing estimates within the model structure to improve forecasts. The processing of the MODSCAG data is currently underway. Therefore this final section is a work in progress.

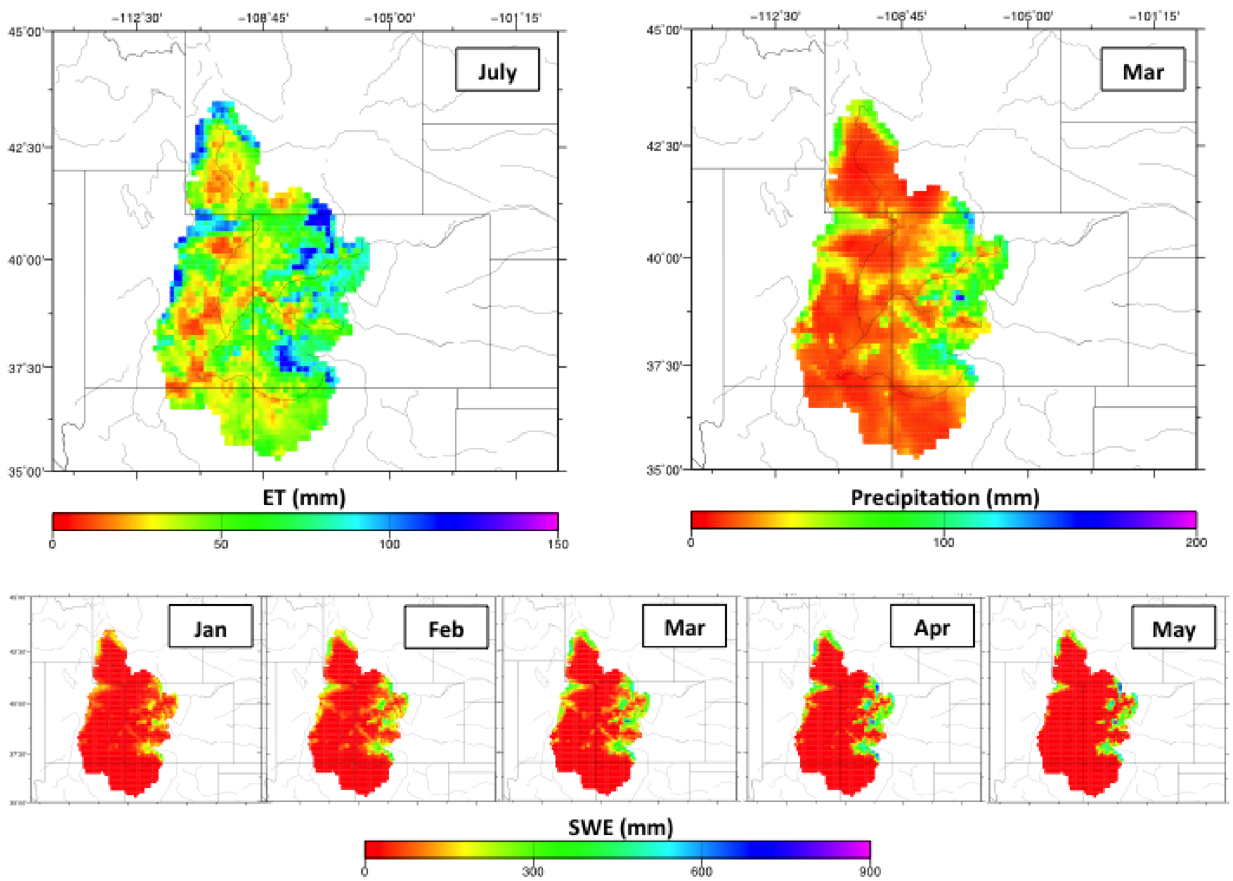

Figure 5. Spatial maps of key simulated water budget components; top two panels show ET and precipitation during their peak months, while the lower five panels track the evolution of snowpack as expressed by SWE.

4. Conclusion

We have presented estimates of the terrestrial water budget over a large river basin using both remote sensing and hydrologic model outputs. Despite notable differences between the two estimates, much remains to be gleaned from the spatial information provided by each. Despite the broad information content of remote sensing, the key obstacle in hydrologic prediction is a lack of water budget closure, which may be addressed by applying a hydrologic model to constrain each respective component to ensure closure. Future work should be directed towards further refining the assimilation approach to develop numerical techniques for redistributing the residual term in the remote sensing water budget estimate, to ideally allow for a near real-time estimates, as satellite retrievals come available.

5. References

[1] Christensen, N. S., Wood, A. W., Lettenmaier, D. P., and Palmer, R. N., "Effects of climate change on the hydrology and water resources of the Colorado River Basin", *Journal of Hydroclimatology*, 62, 2004, pp 337-363.

[2] Christensen, N. S., and Lettenmaier, D. P., "A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin", *Hydrology and Earth System Sciences*, 11, 2007,1417-1434.

[3] McCabe, G. J., and Wolock, D. M., "Warming may create substantial water supply shortages in the Colorado River basin", *Geophysical Research Letters*, 2007, doi: 10.1029/2007GL031764.

[4] Barnett, T. P., and Pierce, D. W., "Sustainable water deliveries from the Colorado River in a changing climate", *Proceedings of the National Academy of Sciences*, 106(18), 2009, pp. 7334-7338, doi: 10.1073/pnas.0812762106.

[5] Painter, T. H., Barrett, A. P., Landry, C. C., Neff, J. C., Cassidy, M. P., Lawrence, C. R., McBride, K. E., and Farmer, G. L., "Impact of disturbed desert soils on duration of mountain snow cover", G*eophysical Research Letters*, 34, 2007, doi: 10.1029/2007GL030284.

[6] Neff, J. C., Ballantyne, A. P., Farmer, G. L., Mahowald, N. M., Conroy, J. L., Landry, C. C., Overpeck, J. T., Painter, T. H., Lawrence, C. R., and Reynolds, R. L., "Increasing eolian dust deposition in the western United States linked to human activity", *Nature Geosciences*, 2008, doi: 10.1038/ngeo133.

[7] Painter, T. H., J. S. Deems, J. Belnap, A. F. Hamlet, C. C. Landry, and B. Udall, "Response of Colorado River runoff to dust radiative forcing in snow", *Proceedings of the National Academy of Sciences*, 107(40), 2010, pp. 17125-30, doi:10.1073/pnas.0913139107.

[8] Livneh, B. and D.P. Lettenmaier, **"**Multi-criteria parameter estimation for the unified land model", *Hydrol. Earth Syst. Sci.*, 16, 2012, pp. 3029-3048, doi:10.5194/hess-16-3029-2012.

[9] Pan M., A. K. Sahoo, T. J. Troy, R. Vinukollu, J. Sheffield and E. F. Wood, "Multi-source estimation of long-term Terrestrial Water Budget for major global river basins", *Journal of Climate*, 2012, DOI: 10.1175/JCLI-D-11-00300.1.

[10] Painter, T. H. and A. Bryant, "Radiative forcing of dust in mountain snow from MODIS surface reflectance data", *in preparation*., 2009.

[11] Chander, G., & Markham, B., "Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges", *IEEE Transactions on Geoscience and Remote Sensing*, 2003.

[12] Liang, X., Lettenmaier, D. P., Wood, E. F., and Burges, S. J., “A simple hydrologically based model of land-surface water and energy fluxes for general-circulation models”, *Journal of Geophysical Research-Atmospheres*, 99(D7), 1994, pp. 14415-14428.

[13] Andreadis, K., P. Storck, and D.P. Lettenmaier, “Modeling snow accumulation and ablation processes in forested environments”, *Water Resour. Res.*, 45, 2009, W05429, doi:10.1029/2008WR007042.

[14] Hansen, M. C., R. S. DeFries, J. R. G. Townshend, and R. Sohlberg, “Global land cover classification at 1 km spatial resolution using a classification tree approach”, *Int. J. Remote Sens.,* 21, 2000, pp. 1331–1364.

[15] Miller, D. A., and R. A. White, “A conterminous United States multilayer soil characteristics dataset for regional climate and hydrology modeling”, 1998, *Earth Interactions,* 2. [Available online at http://EarthInteractions.org.]

[16] Livneh B., E.A. Rosenberg, C. Lin, V. Mishra, K.M. Andreadis, E.P. Maurer, and D.P. Lettenmaier, “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 review), 2013.

[17] Daly, C., R.P. Neilson, and D.L. Phillips., “A statistical-topographic model for mapping climatological precipitation over mountainous terrain”, *Journal of Applied Meteorology*, 33, 1994, pp. 140-158.

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

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

[20] Zhang, T., “Influence of the seasonal snow cover on the ground thermal regime: an overview”, *Rev. Geophys.,* 43(1), 2005, doi:10.1029/2004RG000157.

[21] Qu X, and A. Hall, “Assessing snow albedo feedback in simulated climate change”, *J. Clim.* 19, 2006, pp. 2617-2630.

6. Biography

Dr. Ben Livneh earned two Engineering degrees at the University of Western Ontario in Civil Engineering. He subsequently earned his Ph.D. at the University of Washington with an emphasis on Hydrology. Currently, he is a visiting Postdoctoral Fellow at the Cooperative Institute for Research in Environmental Sciences (CIRES), in Boulder, Colorado, focusing on distributed hydrologic prediction with Dr. Jeffery Deems.