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Assessing surface water consumption using remotely-sensed groundwater, evapotranspiration, and precipitation

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[1] Estimates of consumptive use of surface water by agriculture are vital for assessing food security, managing water rights, and evaluating anthropogenic impacts on regional hydrology. However, reliable, current, and public data on consumptive use can be difficult to obtain, particularly in international and less developed basins. We combine remotely-sensed precipitation and satellite observations of evapotranspiration and groundwater depletion to estimate surface water consumption by irrigated agriculture in California's Central Valley for the 2004–09 water years. We validated our technique against measured consumption data determined from streamflow observations and water export data in the Central Valley. Mean satellite-derived surface water consumption was 291.0 ± 32.4 mm/year while measured surface water consumption was 308.1 ± 6.5 mm/year. The results show the potential for remotely-sensed hydrologic data to independently observe irrigated agriculture's surface water consumption in contested or unmonitored basins. Improvements in the precision and spatial resolution of satellite precipitation, evapotranspiration and gravimetric groundwater observations are needed to reduce the uncertainty in this method and to allow its use on smaller basins and at shorter time scales. **Citation:** Anderson, R. G., M.-H. Lo, and J. S. Famiglietti (2012), Assessing surface water consumption using remotely-sensed groundwater, evapotranspiration, and precipitation, *Geophys. Res. Lett.*, *39*, L16401, doi:10.1029/2012GL052400.

1. Introduction

[2] Globally, irrigation accounts for over 70% of anthropogenic withdrawals of surface and groundwater, 90% of consumptive water use and is responsible for ~40% of global food production [*Cai and Rosegrant*, 2002; *Siebert et al.*, 2010]. Major increases in water stress are expected in the future due to patterns of population and economic growth and required increases in food production [*Rijsberman*, 2006]. Furthermore, climate change may reduce water availability in regions that are already water stressed and reliant on irrigation [*Milly et al.*, 2005].

[3] Monitoring consumptive use of surface and groundwater is important for tasks such as assessing food security, enforcing water rights, and improving agricultural water use efficiency [*Akbari et al.*, 2007]. Surface water consumption by irrigated agriculture can have significant impacts on regional climate [*Kueppers et al.*, 2007], ecosystems [*Hollis*, 1990], and human health [*Small et al.*, 2001]. However, current monitoring and reporting of consumptive water use often relies on *in-situ* data, which can be outdated [*Siebert et al.*, 2010], may not exist [*Droogers and Allen*, 2002] or which may not be publicly available due to political incentives to obscure the true amount of water use [*Gleick*, 1993] or a desire to avoid litigation and conflict [*Allen et al.*, 2005].

[4] Recent and prospective advances in remote sensing of evapotranspiration (ET) [*Anderson et al.*, 2011; *Tang et al.*, 2009], precipitation [*Neeck et al.*, 2010], surface water [*Durand et al.*, 2010], soil moisture [*Das et al.*, 2011] and groundwater storage changes [*Famiglietti et al.*, 2011] can enable observations of consumptive surface water entirely from remote sensing. In this study, we present a method to estimate consumptive use of surface water at the basin scale using remotely-sensed and interpolated observations. We test our approach against surface water consumption statistics in the Central Valley, California, USA, a major agricultural region that relies heavily on both surface and groundwater for irrigation, and an area where the conflict between different types of water users is perennial.

2. Method

[5] Our remotely sensed estimate of surface water consumption (Satellite-SW_C) is based on an inversion of the terrestrial water budget. For a control volume that includes the surface and sub-surface in an irrigated agricultural region, the water budget can be written as follows:

$$\frac{dS}{dt} = P + SW_{IN} - SW_{OUT} - ET \tag{1}$$

$$SW_C = SW_{IN} - SW_{OUT} \tag{2}$$

where P is precipitation, ET is evapotranspiration, SW_{IN} is surface water flow into (lost into) the region (including stream flow, run-on and recharge from higher elevations, and anthropogenic imports from other basins), SW_{OUT} is surface water flow out of (gained from) the region (including streamflow, base flow, runoff and exports), $\frac{dS}{dt}$ is the change in terrestrial water storage which integrates surface water storage changes, groundwater withdrawals, percolation and soil moisture changes, and SW_C is surface water

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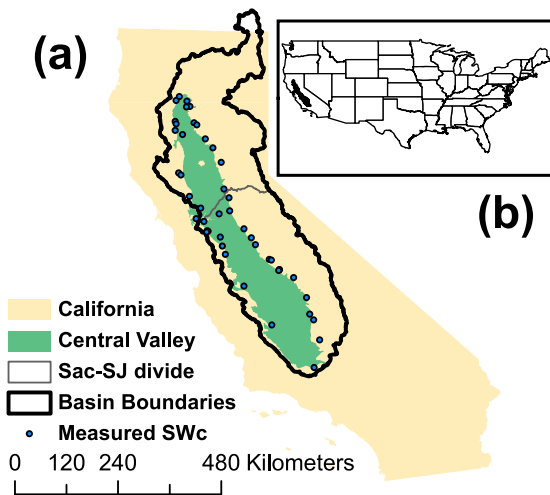
Figure 1. (a) Map of the Central Valley and the Sacramento (Sac) -San Joaquin (SJ) Basins in relation to California. Points on map indicate surface stations or gauging points used to calculate measured Surface Water Consumption (SW_C); see Table S1 of the auxiliary material for full site details. (b) The Central Valley in relation to the United States.

consumption. dS/dt can be partitioned into groundwater $\left(dGW/dt\right)$, soil moisture $\left(dSM/dt\right)$, and surface water $\left(dSW/dt\right)$ storage changes, as shown in equation (3):

$$dS/dt = dGW/dt + dSM/dt + dSW/dt \qquad (3)$$

Surface water and soil moisture can be measured [*Piles et al.*, 2011] or modeled [*Rodell et al.*, 2004a] to remove its signal from dS/dt to obtain dGW/dt [*Rodell et al.*, 2009]. Rearranging equation (1) and substituting in equations (2) and (3), we can now calculate SW_C as shown in equation (4):

$$SW_C = ET - P + dGW/dt + dSM/dt + dSW/dt \qquad (4)$$

With equation (4), regional surface water consumption can be inferred solely from remote sensing observations as ET, P, dGW/dt, dSM/dt, and dSW/dt, can be independently observed, modeled, or estimated at regional scales. We calculate SW_C uncertainty by combining the relative and absolute errors in the individual hydrologic components following *Rodell et al.* [2004b].

3. Study Region and Data

[6] We tested the remotely-sensed surface water consumption method in the Central Valley of California (Figure 1). The Central Valley is one of the most economically productive agricultural regions in the world, with over 250 types of crops and $28 billion/year in direct value, and the valley accounts for ~15% of irrigated agricultural land in the United States [*Faunt*, 2009]. The Valley extends over 650 km in length and is composed of three basins, the Sacramento and San Joaquin basins and the normally closed Tulare Lake basin. The Valley's agriculture relies heavily on

surface and groundwater irrigation, with increasing reliance on precipitation in the wetter Sacramento basin. Groundwater extraction increases during drought periods to compensate for reductions in available surface water, but publicly available groundwater observations are relatively sparse [*Faunt*, 2009; *Famiglietti et al.*, 2011]. We conducted the study during from the 2004–05 to 2008–09 water years (October–September), which overlapped both the observations of dS/dt and ET and calculated SW_C at monthly and annual time scales.

[7] Monthly, 4 km resolution precipitation data come from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), which interpolates gauge data using topographic information and inverse distance weighting [http://prism.oregonstate.edu]. Following *Jeton et al.* [2005] and *Daly* [2006], we set the annual P uncertainty at 10% and monthly P uncertainty at 15%. We used the monthly, mean of two ET products, based on satellite data from the MODerate resolution Imaging Spectroradiometer (MODIS), in our water balance. One is a daily, 0.05° ET energy balance algorithm [*Tang et al.*, 2009]. The other product is the 250 m Surface Energy Balance ALgorithm (SEBAL) run using 250 m and 1 km observations with automatic pixel selection, dynamic wind meteorology and gridded radiation data, and thermal disaggregation [*Bastiaanssen et al.*, 2005; *Gao et al.*, 2011; *Hart et al.*, 2009; *Merlin et al.*, 2010].

[8] Monthly groundwater change $\left(dGW/dt\right)$ was estimated from GRACE gravity coefficients from Release-04, computed at the Center for Space Research at the University of Texas at Austin and further processed by *Famiglietti et al.* [2011]. Monthly GRACE terrestrial water storage anomaly uncertainties are on the order of 45 mm/month [*Swenson and Wahr*, 2002], and, over the longer period of *Famiglietti et al.*'s [2011] study, the dGW/dt error diminishes to an estimate of 3.9 mm/year, which is 20% of the 20.4 mm/year groundwater change. We set dGW/dt uncertainty at 20% of the magnitude of dGW/dt. While the GRACE dGW/dt estimate covers the entire Sacramento-San Joaquin Basin, we assume that all dGW/dt occurs in the Central Valley (control volume) due to geology and land use patterns of the basin [*Famiglietti et al.*, 2011]. Soil moisture changes $\left(dSM/dt\right)$ for the Central Valley were obtained from an ensemble of three models [*Ek et al.*, 2003; *Koster and Suarez*, 1992; *Liang et al.*, 1994] from NASA's Global Land Data Assimilation System [*Rodell et al.*, 2004a]. We assumed that monthly changes in surface water were negligible $\left(dSW/dt = 0\right)$ since there are no major surface reservoirs or snow within the Central Valley. We chose to decompose GRACE dGW/dt this way because GRACE cannot resolve dS/dt at the Central Valley's scale (5.2×10^4 km^2), thus requiring the assumption that all dGW/dt occurs in the Central Valley instead of being distributed throughout the larger Sacramento-San Joaquin Basin (1.5×10^5 km^2) and adding dSM/dt for only the Central Valley to close the water budget.
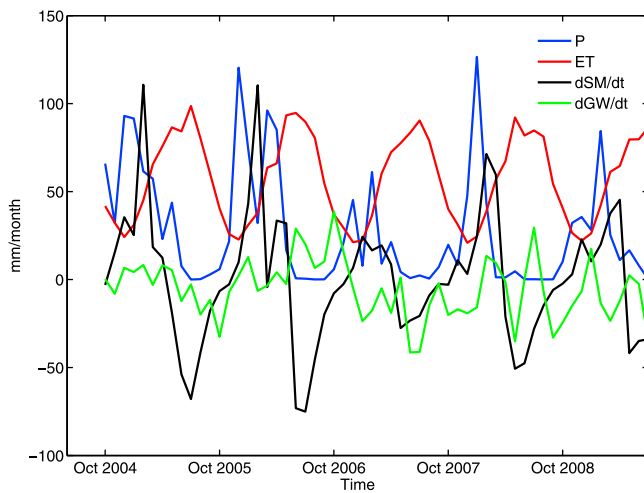
Figure 2. Monthly precipitation (P), evapotranspiration (ET), groundwater change $\left(\frac{dGW}{dt}\right)$, and soil moisture $\left(\frac{dSM}{dt}\right)$ from July 2004–June 2009 (mm/month).

[9] We used measured surface water flows in (SW_{IN}) and out (SW_{OUT}) of the Central Valley to validate our satellite SW_C estimate as defined in equation (2) (Table S1 of the auxiliary material).[1] Streamflow data into the Central Valley come from USGS and California Data Exchange Center gauges. Monthly water exports out of the Central Valley come from the California State Water Project (SWP) (http://www.water.ca.gov/swp/operationscontrol/annual.cfm). Streamflow out of the Central Valley, through the hydrologically complex California Delta, is provided by DWR's DAYFLOW program (http://www.water.ca.gov/dayflow/). Measured surface

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[1]Auxiliary materials are available in the HTML. doi:10.1029/2012GL052400.

water flows are also computed independently for the Sacramento and San Joaquin portions of the Central Valley.

4. Results

[10] Figure 2 shows monthly hydrologic fluxes for the entire Central Valley. Groundwater consumption $\left(\frac{dGW}{dt} < 0\right)$ increased substantially following the drought beginning in the winter of 2006–07 with peak consumption of ~40 mm/month in the summer of 2007. Annual $\frac{dGW}{dt}$ was most negative in 2008–09 towards the end of drought (−145 mm) while 2005–06 was the only year with net recharge (32 mm). Precipitation (P) showed strong interannual variability, with monthly maximum P ranging from ~120 mm in January 2005 and 2007 to 61 mm in January 2006. Yearly P clearly indicated drought, dropping from 454 mm in 2005–06 to 186 mm in 2006–07 and less than 260 mm in 2007–09 (Table 1). Conversely, ET showed less interannual variation, with an annual minimum of ~25 mm/month and maximum of ~95 mm/month (Figure 2). Annual ET ranged from 663–725 mm/year over 2004–2009 with the minimum coming at the end of the study period, three years into drought. Soil moisture changes, $\frac{dSM}{dt}$, exhibited expected seasonality changes with seasonal maxima following peak winter precipitation and minima following peak summer ET. $\frac{dSM}{dt}$ showed relatively little annual change, with the greatest depletion of moisture occurring with onset of drought in 2006–07. Annual uncertainty for ET was the largest component of uncertainty in the entire hydrologic budget and was 49–76 mm/year.

[11] Annual surface water consumption (SW_C) data are shown in Figure 3. Over the entire multi-year study period, the mean satellite and measured SW_C were close at 291 and 308 mm/year, respectively. However, on an annual basis, there is greater discrepancy between satellite and measured SW_C. Measured SW_C ranges from 374 mm/year in 2004–05

Table 1. Water Year Statistics[a]

Water Year	P	ET	$\frac{dGW}{dt}$	$\frac{dSM}{dt}$	Satellite SW_C
2004–05	479 ± 48	725 ± 76	−24 ± 5	14 ± 3	237 ± 90
2005–06	454 ± 45	700 ± 48	32 ± 7	2 ± 3	282 ± 66
2006–07	186 ± 19	669 ± 71	−113 ± 22	−18 ± 3	351 ± 76
2007–08	253 ± 25	674 ± 49	−95 ± 19	−1 ± 3	324 ± 59
2008–09	254 ± 25	663 ± 59	−145 ± 28	−1 ± 3	262 ± 70
Mean for 2004–2009	325 ± 15	686 ± 27	−69 ± 6	−1 ± 2	291 ± 32

	P		ET		Measured SW_C		
Water Year	SJ	Sac	SJ	Sac	SJ	Sac	SJ + Sac
2004–05	388 ± 39	674 ± 67	709 ± 87	760 ± 52	338 ± 17	452 ± 23	375 ± 19
2005–06	315 ± 31	752 ± 75	690 ± 62	723 ± 18	339 ± 17	91 ± 4	261 ± 13
2006–07	129 ± 13	310 ± 31	649 ± 76	710 ± 59	177 ± 9	708 ± 35	345 ± 17
2007–08	181 ± 18	409 ± 41	663 ± 53	697 ± 41	167 ± 8	493 ± 25	271 ± 14
2008–09	177 ± 18	422 ± 42	637 ± 72	718 ± 30	195 ± 10	491 ± 25	289 ± 14
Mean for 2004–2009	238 ± 11	514 ± 23	670 ± 31	722 ± 18	243 ± 5	447 ± 10	308 ± 7

[a]All fluxes are in mm/year. Mean fluxes are averaged over the study period. SJ and Sac refer to San Joaquin/Tulare Lake and Sacramento basins, respectively. All values rounded to nearest mm. $\frac{dGW}{dt}$ and $\frac{dSM}{dt}$ are not shown for SJ and Sac due to spatial resolution limitations.
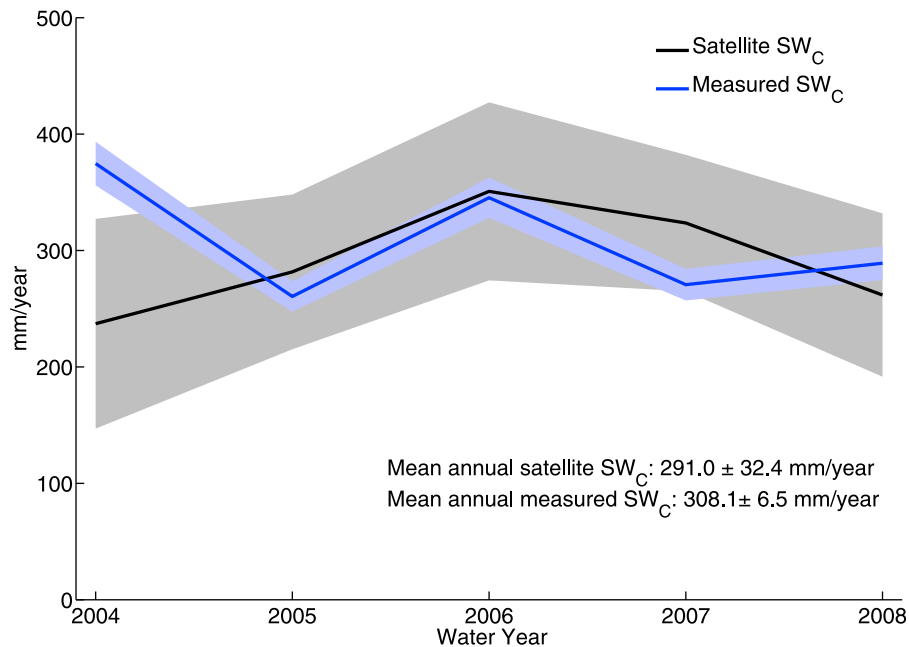
Figure 3. Annual surface water consumption in the Central Valley for the 2004–2009 water years (mm/year). Gray shading indicates uncertainty in the satellite estimate of surface water consumption while blue shading shows uncertainty in the measured surface water consumption.

and then oscillates with a minimum of 261 mm/year in 2005–06. Satellite SW_C increases from 237 mm/year in 2005–06 to 351 mm/year in 2006–07 and then decreases with ongoing drought. 2004–05 was the only year in which measured and satellite SW_C were significantly different. Outside of 2004–05, annual satellite and measured SW_C were within 55 mm/year of each other.

[12] In addition to our water budget for the entire Central Valley, we calculated separate water budgets for the Sacramento and San Joaquin/Tulare Lake portions of the Valley (Figure 1 and Table 1). Annual P and ET were consistently larger in the Sacramento Valley, but uncertainty in ET was greater in the San Joaquin Valley. SW_C exhibited far greater variability in the Sacramento Valley than the San Joaquin Valley. Unlike the San Joaquin/Tulare Lake Valley, SW_C increased in the Sacramento Valley during the 2007–09 drought, probably due to less effective precipitation and the ability to draw on senior water rights to use surface water. Annual water year precipitation and measured SW_C are negatively correlated in the Sacramento Valley (r = −0.87) and positively correlated in the San Joaquin Valley (r = 0.95).

5. Discussion

[13] Our satellite-based method to estimate SW_C in agricultural regions shows good multi-annual agreement with measured SW_C. On an annual basis, however, there is some inter-annual variation between measured and satellite SW_C. One explanation for this discrepancy is lags in the Central Valley's hydrology that propagate from one water year (WY) to another. For example, the 2004–06 was quite wet and the end of the pluvial period (2005–06) saw the highest and lowest measured SW_C in the San Joaquin and Sacramento Valleys, respectively (Table 1 and Figure 2). Since these WYs were wet, farmers in some regions (particularly the San Joaquin Valley) had ample local supplies,

more effective precipitation, and full deliveries from large scale projects to use first, thus reducing or eliminating the need to draw on ground water while farmers in the Sacramento Valley had excess water that drained out through the Delta to San Francisco Bay. The availability of surface water and manifests itself in a large (up to 40 mm/month) increase in dGW/dt in the last part of the 2005–06 WY (Figure 1). Following the failure of winter rains, farmers begin drawing on groundwater in the 2006–07 WY when drought persists. These dynamics indicate substantial intra-basin lags that need to be considered when evaluating satellite-based SW_C at annual or monthly timescales. The SW_C method vividly illustrates the importance of GRACE in estimating regional hydrologic fluxes. If we had estimated surface water consumption solely as the difference of ET, P and modeled dSM/dt, our mean estimate of surface water consumption for 2004–09 would be 360 mm/year for the Central Valley, a substantially greater deviation from the measured SW_C (308 mm/year) than our approach which integrates GRACE (291 mm/year).

[14] Improved precision and resolution of satellite inputs are needed to estimate SW_C over smaller regions and at monthly time scales. Satellite ET products have advanced considerably with multiple algorithms and satellite platforms available [*Anderson et al.*, 2011]. Irrigated agriculture is one of the most studied applications for satellite ET and is one of the best land cover types for accurate estimation, as irrigated regions tend to have strong gradients in vegetation cover and surface temperature within a region. Nevertheless, individual products and algorithms, including those used in this study, show divergence; annual uncertainty of ~15% or more can occur.

[15] Satellite based precipitation products have historically had large uncertainty, particularly for drier, continental

regions as well as medium and high latitude regions not covered by the Tropical Rainfall Measurement Mission (TRMM); over the Sacramento-San Joaquin Basin, standard deviations of TRMM products range from 50–80% of the mean of the products during the rainy December–February period [*Tian and Peters-Lidard*, 2010]. At present, satellite derived precipitation is not precise enough to quantify SW$_C$ in the Central Valley. The planned Global Precipitation Mission promises greater spatial coverage and higher sensitivity to light precipitation events than TRMM and could have the precision necessary to quantify SW$_C$ in (semi) arid regions [*Neeck et al.*, 2010].

[16] Perhaps the greatest potential for improvement lies in satellite gravimetry. Currently GRACE can only estimate terrestrial water storage anomalies $\left(\frac{dS}{dt}\right)$ at 1.5×10^5 km^2 or larger scales [*Rodell and Famiglietti*, 1999]. Additional data and assumptions on soil moisture, surface water variations, snow water equivalent, and location of groundwater pumping are needed to convert $\frac{dS}{dt}$ into $\frac{dGW}{dt}$ at the scale of the Central Valley [*Famiglietti et al.*, 2011]. We note, however, that while we assumed that surface water storage change was negligible $\left(\frac{dSW}{dt} = 0\right)$, surface water changes can be explicitly parameterized or included with the gravimetric storage observations depending on the characteristics of the study region. Future satellite missions to observe soil moisture $\left(\frac{dSM}{dt}\right)$ and surface water $\left(\frac{dSW}{dt}\right)$ [*Das et al.*, 2011; *Durand et al.*, 2010] could enable direct observation of $\frac{dGW}{dt}$ and/or $\frac{dGW}{dt} + \frac{dSW}{dt}$ from $\frac{dS}{dt}$. Future gravimetric missions (GRACE – Follow On and GRACE-II) could have a spatial gravimetric resolution that is more than a magnitude of order higher than GRACE, which would enable direct measurement of $\frac{dS}{dt}$ at scales significantly smaller than the Central Valley [*Wiese et al.*, 2009].

[17] The framework here is designed to be sufficiently flexible depending upon the availability and quality of satellite $\frac{dS}{dt}$, $\frac{dSM}{dt}$, and $\frac{dSW}{dt}$ observations as well as the relative importance of each of these terms for the study region. While this framework would most frequently be applied to semi-arid regions, this method can also be used to assess changes in surface water resources in more humid regions where SW$_C$ would often be negative as defined in equations (1), (2), and (4). The change in surface water consumption (or production) over time $\left(\frac{dSW_C}{dt}\right)$ can serve as a meaningful indicator of anthropogenic or natural impacts on regional hydrology.

[18] Integrating remote sensing data is needed to observe surface water consumption for agricultural, ecological, and hydrologic purposes. For basins in developing countries and international basins, remotely-sensed observations provide independent measures where publicly-available in-situ data are often non-existent. Even developed countries often have only direct measurements of applied surface water; runoff, and percolation are poorly measured. Furthermore, the quality of in-situ observations is likely to decrease as the resources needed to maintain monitoring networks continues to decrease in many countries. As satellite-based hydrologic data continues to mature and improve in temporal and spatial resolution, flexible frameworks such as the one presented here to estimate surface water consumption are essential for quantifying the impact of irrigated agriculture on food production, water resources, and ecosystems.

References

Akbari, M., N. Toomanian, P. Droogers, W. Bastiaanssen, and A. Gieske (2007), Monitoring irrigation performance in Esfahan, Iran, using NOAA satellite imagery, *Agric. Water Manage.*, *88*(1–3), 99–109, doi:10.1016/j.agwat.2006.10.019.

Allen, R. G., A. J. Clemmens, C. M. Burt, K. Solomon, and T. O'Halloran (2005), Prediction accuracy for projectwide evapotranspiration using crop coefficients and reference evapotranspiration, *J. Irrig. Drain. Eng.*, *131*(1), 24–36, doi:10.1061/(ASCE)0733-9437(2005)131:1(24).

Anderson, M. C., et al. (2011), Mapping daily evapotranspiration at field to continental scales using geostationary and polar orbiting satellite imagery, *Hydrol. Earth Syst. Sci.*, *15*(1), 223–239, doi:10.5194/hess-15-223-2011.

Bastiaanssen, W. G. M., E. J. M. Noordman, H. Pelgrum, G. Davids, B. P. Thoreson, and R. G. Allen (2005), SEBAL model with remotely sensed data to improve water-resources management under actual field conditions, *J. Irrig. Drain. Eng.*, *131*(1), 85–93, doi:10.1061/(ASCE)0733-9437(2005)131:1(85).

Cai, X., and M. Rosegrant (2002), Global water demand and supply projections, *Water Int.*, *27*(2), 159–169, doi:10.1080/02508060208686989.

Daly, C. (2006), Guidelines for assessing the suitability of spatial climate data sets, *Int. J. Climatol.*, *26*(6), 707–721, doi:10.1002/joc.1322.

Das, N. N., D. Entekhabi, and E. G. Njoku (2011), An algorithm for merging SMAP radiometer and radar data for high-resolution soil-moisture retrieval, *IEEE Trans. Geosci. Remote Sens.*, *49*(5), 1504–1512, doi:10.1109/TGRS.2010.2089526.

Droogers, P., and R. G. Allen (2002), Estimating reference evapotranspiration under inaccurate data conditions, *Irrig. Drain. Syst.*, *16*(1), 33–45.

Durand, M., L.-L. Fu, D. P. Lettenmaier, D. E. Als, E. Rodriguez, and D. Esteban-Fernandez (2010), The surface water and ocean topography mission: Observing terrestrial surface water and oceanic submesoscale eddies, *Proc. IEEE*, *98*(5), 766–779, doi:10.1109/JPROC.2010.2043031.

Ek, M. B., K. E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, G. Gayno, and J. D. Tarpley (2003), Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta model, *J. Geophys. Res.*, *108*(D22), 8851, doi:10.1029/2002JD003296.

Famiglietti, J. S., M. Lo, S. L. Ho, J. Bethune, K. J. Anderson, T. H. Syed, S. C. Swenson, C. R. de Linage, and M. Rodell (2011), Satellites measure recent rates of groundwater depletion in California's Central Valley, *Geophys. Res. Lett.*, *38*, L03403, doi:10.1029/2010GL046442.

Faunt, C. (2009), Groundwater availability of the Central Valley Aquifer, California, *U.S. Geol. Surv. Prof. Pap.*, *1766*, 225 pp.

Gao, Z. Q., C. S. Liu, W. Gao, and N.-B. Chang (2011), A coupled remote sensing and the Surface Energy Balance with Topography Algorithm (SEBTA) to estimate actual evapotranspiration over heterogeneous terrain, *Hydrol. Earth Syst. Sci.*, *15*(1), 119–139, doi:10.5194/hess-15-119-2011.

Gleick, P. H. (1993), Water and conflict: Fresh water resources and international security, *Int. Secur.*, *18*(1), 79–112, doi:10.2307/2539033.

Hart, Q. J., M. Brugnach, B. Temesgen, C. Rueda, S. L. Ustin, and K. Frame (2009), Daily reference evapotranspiration for California using satellite imagery and weather station measurement interpolation, *Civ. Eng. Environ. Syst.*, *26*(1), 19–33, doi:10.1080/10286600802003500.

Hollis, G. E. (1990), Environmental impacts of development on wetlands in arid and semi-arid lands, *Hydrol. Sci. J.*, *35*, 411–428, doi:10.1080/02626669009492443.

Jeton, A. E., S. A. Watkins, J. Thomas, and J. Hunnington (2005), Evaluation of precipitation estimates from PRISM for the 1961–90 and 1971–2000 data sets, Nevada, *U.S. Geol. Surv. Sci. Invest. Rep.*, *2005–5291*.

Koster, R. D., and M. J. Suarez (1992), Modeling the land surface boundary in climate models as a composite of independent vegetation stands, *J. Geophys. Res.*, *97*(D3), 2697–2715, doi:10.1029/91JD01696.

Kueppers, L. M., M. A. Snyder, and L. C. Sloan (2007), Irrigation cooling effect: Regional climate forcing by land-use change, *Geophys. Res. Lett.*, *34*, L03703, doi:10.1029/2006GL028679.

Liang, X., D. P. Lettenmaier, E. F. Wood, and S. J. Burges (1994), A simple hydrologically based model of land surface water and energy fluxes for general circulation models, *J. Geophys. Res.*, *99*(D7), 14,415–14,428, doi:10.1029/94JD00483.

Merlin, O., B. Duchemin, O. Hagolle, F. Jacob, B. Coudert, G. Chehbouni, G. Dedieu, J. Garatuza, and Y. Kerr (2010), Disaggregation of MODIS surface temperature over an agricultural area using a time series of Formosat-2 images, *Remote Sens. Environ.*, *114*(11), 2500–2512, doi:10.1016/j.rse.2010.05.025.

Milly, P. C. D., K. A. Dunne, and A. V. Vecchia (2005), Global pattern of trends in streamflow and water availability in a changing climate, *Nature*, *438*(7066), 347–350, doi:10.1038/nature04312.

Neeck, S. P., R. K. Kakar, A. A. Azarbarzin, and A. Y. Hou (2010), *Global Precipitation Measurement (GPM) Implementation*, Int. Soc. for Opt. and Photon., Toulouse, France.

Piles, M., A. Camps, M. Vall-llossera, I. Corbella, C. Rudiger, Y. H. Kerr, and J. Walker (2011), Downscaling SMOS-derived soil moisture using MODIS visible/infrared data, *IEEE Trans. Geosci. Remote Sens.*, *49*(9), 3156–3166, doi:10.1109/TGRS.2011.2120615.

Rijsberman, F. R. (2006), Water scarcity: Fact or fiction?, *Agric. Water Manage.*, *80*(1–3), 5–22, doi:10.1016/j.agwat.2005.07.001.

Rodell, M., and J. S. Famiglietti (1999), Detectability of variations in continental water storage from satellite observations of the time-variable gravity field, *Water Resour. Res.*, *35*(9), 2705–2723, doi:10.1029/1999WR900141.

Rodell, M., et al. (2004a), The global land data assimilation system, *Bull. Am. Meteorol. Soc.*, *85*(3), 381–394, doi:10.1175/BAMS-85-3-381.

Rodell, M., J. S. Famiglietti, J. Chen, S. I. Seneviratne, P. Viterbo, S. Holl, and C. R. Wilson (2004b), Basin scale estimates of evapotranspiration using GRACE and other observations, *Geophys. Res. Lett.*, *31*, L20504, doi:10.1029/2004GL020873.

Rodell, M., I. Velicogna, and J. S. Famiglietti (2009), Satellite-based estimates of groundwater depletion in India, *Nature*, *460*(7258), 999–1002, doi:10.1038/nature08238.

Siebert, S., J. Burke, J. M. Faures, K. Frenken, J. Hoogeveen, P. Döll, and F. T. Portmann (2010), Groundwater use for irrigation: A global inventory, *Hydrol. Earth Syst. Sci.*, *14*(10), 1863–1880, doi:10.5194/hess-14-1863-2010.

Small, I., J. van der Meer, and R. E. G. Upshur (2001), Acting on an environmental health disaster: The case of the Aral Sea, *Environ. Health Perspect.*, *109*, 547–549, doi:10.1289/ehp.01109547.

Swenson, S., and J. Wahr (2002), Methods for inferring regional surface-mass anomalies from Gravity Recovery and Climate Experiment (GRACE) measurements of time-variable gravity, *J. Geophys. Res.*, *107*(B9), 2193, doi:10.1029/2001JB000576.

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

Tian, Y., and C. D. Peters-Lidard (2010), A global map of uncertainties in satellite-based precipitation measurements, *Geophys. Res. Lett.*, *37*, L24407, doi:10.1029/2010GL046008.

Wiese, D. N., W. M. Folkner, and R. S. Nerem (2009), Alternative mission architectures for a gravity recovery satellite mission, *J. Geod.*, *83*(6), 569–581, doi:10.1007/s00190-008-0274-1.