Dynamics of Terrestrial Water Storage Change from Satellite and Surface Observations and Modeling

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ABSTRACT

Terrestrial water storage (TWS) is a fundamental component of the water cycle. On a regional scale, measurements of terrestrial water storage change (TWSC) are extremely scarce at any time scale. This study investigates the feasibility of estimating monthly-to-seasonal variations of regional TWSC from modeling and a combination of satellite and in situ surface observations based on water balance computations that use ground-based precipitation observations in both cases. The study area is the Klamath and Sacramento River drainage basins in the western United States (total area of about 110 000 km^2). The TWSC from the satellite/surface observation–based estimates is compared with model results and land water storage from the Gravity Recovery and Climate Experiment (GRACE) data. The results show that long-term evapotranspiration estimates and runoff measurements generally balance with observed precipitation, suggesting that the evapotranspiration estimates have relatively small bias for long averaging times. Observations show that storage change in water management reservoirs is about 12% of the seasonal amplitude of the TWSC cycle, but it can be up to 30% at the subbasin scale. Comparing with predevelopment conditions, the satellite/surface observation–based estimates show larger evapotranspiration and smaller runoff than do modeling estimates, suggesting extensive anthropogenic alteration of TWSC in the study area. Comparison of satellite/surface observation–based and GRACE TWSC shows that the seasonal cycle of terrestrial water storage is substantially underestimated by GRACE.

1. Introduction

Terrestrial water storage (TWS) is the water stored on and below the land surface, which includes snow, ice, soil moisture, groundwater, and surface water. It is a fundamental component of the water cycle (Oki and Kanae 2006). However, surface measurements of TWS are essentially nonexistent over large areas. Typical methods to estimate the TWS at basin scales include in situ observations, hydrological modeling, coupled atmospheric and terrestrial water balance, and remote sensing (Troch et al. 2007).

Although some components of TWS can be measured directly, such measurements are generally local, and an observational basis for estimating these components at large scales is lacking. For instance, routine in situ soil moisture measurements are available only at a point scale and only at a few locations globally, mostly in North America and Eurasia (Robock et al. 2000). Microwave satellite sensors provide some spatial context; however, current sensors only provide estimates of surface (upper few centimeters) soil moisture and only in locations where vegetation is sparse (Altese et al. 1996; Jackson 1997; Njoku et al. 2003; Gao et al. 2004). In situ measurements of snow water equivalent (SWE) are extremely limited as well (Cayan 1996; Serreze et al. 1999). Remote sensing measurements of SWE at present are limited to nonforested regions with relatively thin

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and cold snow cover (Ramsay 1998; Hall et al. 2002; Kelly et al. 2003). Groundwater measurements sufficient to characterize large-scale space–time variations in groundwater storage are even more limited (e.g., Hoffmann et al. 2001; Alley et al. 2002). The need for better observations of surface water that is stored in rivers, lakes, and reservoirs is increasingly recognized for water management purposes (Alsdorf et al. 2007). Without more comprehensive in situ measurement networks, water storage studies based upon in situ measurements alone will continue to be few.

The newly available remote sensing measurements from the Gravity Recovery and Climate Experiment (GRACE) provide monthly variations of TWS at the global scale, and they are therefore a first step in understanding regional TWS. However, the GRACE record length is short, and its low spatial resolution ($>10^5$ km^2) poses challenges in the disaggregation of TWS components (Rodell and Famiglietti 1999; Tapley et al. 2004; Wahr et al. 2004).

Estimates based on models or reanalysis (combination of models and observations) are another approach to estimating TWS and/or TWSC (see, e.g., Lettenmaier and Famiglietti 2006; Troch et al. 2007). The most common approach to producing model estimates is via offline simulations (land surface fluxes, including precipitation, surface air temperature, downward solar and longwave radiation, and other variables prescribed). When the model can be shown (or calibrated) to produce reasonable reproductions of the seasonal dynamics of runoff, the argument can be made that reasonable TWS estimates must result at regional scales. This argument has been made elsewhere (e.g., Maurer et al. 2002). In our view, the main limitation in using modeled TWS is in a river basin where water management (e.g., man-made reservoirs and irrigation water withdrawals) substantially affect the land surface hydrological dynamics, as these effects are not represented in most land surface models.

An alternative to using offline land surface simulations is to use model output from coupled model runs, typically those archived by one of several global reanalysis projects (reanalysis amounts to reruns of a numerical weather prediction model with its data assimilation routines but with a "frozen" version of the model and data assimilation algorithms and datasets). This approach to estimating TWS and TWSC has been used by Seneviratne et al. (2004), Hirschi et al. (2006, 2007), and Yeh and Famiglietti (2008). One advantage of the use of reanalysis is that consistent estimates of atmospheric variables—such as atmospheric water vapor convergence—are produced along with land surface variables, which offer alternative strategies for estimating TWSC (Oki et al. 1995). The National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR; Kalnay et al. 1996) and 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40; Uppala et al. 2005) datasets are the most widely used. The use of reanalysis for estimation of TWS and TWSC is not without complications. However, the most substantial issue is that the data assimilation process results in an imbalance in the surface water budget (due to the so-called analysis increment), and this can result in drift in TWS estimates (Seneviratne et al. 2004). Another issue is the effect of changes in the observation network and data sources, which are the basis for the data assimilation (e.g., Bengtsson et al. 2004). Lastly, although the effects of water management are arguably included to some extent in the TWS estimates as a result of the assimilation process, the land surface schemes used in the coupled modeling systems on which the reanalyses are based do not represent these effects, and there is some effective (but unknown) blending effect due to this inconsistency.

An alternative to the earlier mentioned methods of estimating TWS is to use terrestrial water budget estimates, which infer changes in TWS as the difference between precipitation (P), evapotranspiration (ET), and runoff (R). Although seemingly straightforward, this approach is complicated by the fact that although direct observations of P and R are available, ET is not. Regional ET may be derived from satellite observations and surface measurements using the terrestrial water budget equation; however, in this case TWSC is required (e.g., Rodell et al. 2004; Ramillien et al. 2006). One solution is to obtain an ET estimate using satellite-based observations. Such ET products are not from direct retrievals, but rather they come from simplified models in which some terms can be related to satellite measurements (e.g., net radiation, surface temperature, and vegetation properties). Satellite-based ET products provide actual land surface evapotranspiration measurements, whereas ET estimates from hydrological models usually provide potential ET or actual ET without consideration of water management. Nonetheless, Tang et al. (2009a) showed that under some conditions (notably, regions where there is strong contrast in vegetation properties and surface temperature, such as the boundary between irrigated and nonirrigated areas), satellite-based ET algorithms can provide usable regional ET estimates at a daily time interval. The ET estimates that are produced, along with observed precipitation and streamflow, provide an alternative basis for estimating TWS that is based on satellite and surface observations. Here, we pursue such a strategy to investigate temporal TWS variations over the western United States.

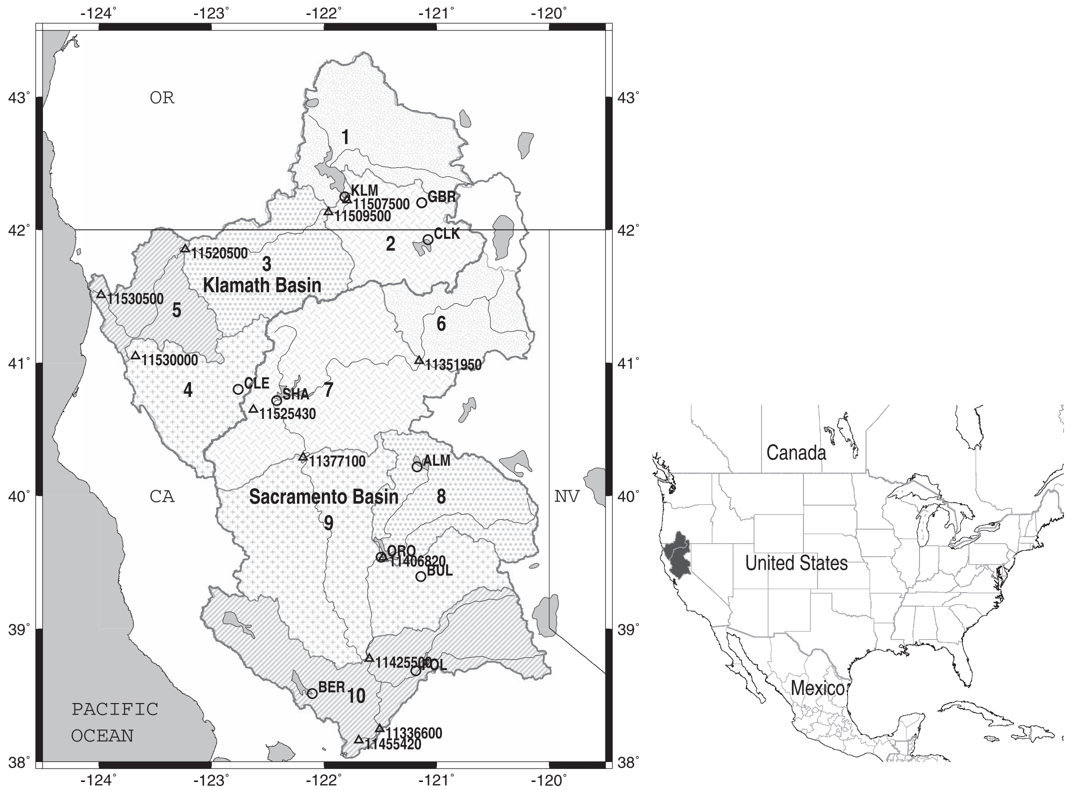

FIG. 1. Location of the USGS streamflow gauge sites (triangles) and water management reservoirs (circles) in the Klamath and Sacramento River basins. The two main basins are divided into a total of 10 subbasins, with subbasins 1–5 in the Klamath basin, and 6–10 in the Sacramento basin.

Our main goal is to evaluate regional-scale TWS estimates produced using a macroscale hydrological model compared with estimates produced by the satellite/surface observation–based (SatObs) strategy outlined earlier. We compute five years (2001–05) of daily TWS variations using the two methods in which the model-based approach is based on the Variable Infiltration Capacity (VIC) model (Liang et al. 1994). For both estimates, precipitation is gridded from surface observations. In the satellite/surface observation–based method, ET is estimated using the satellite-based estimation method of Nishida et al. (2003) as implemented by Tang et al. (2009a); runoff is taken from stream gauges. We also compare estimates derived from both methods with TWS estimated from GRACE remote sensing data (Wahr et al. 1998).

2. Study area and data

The study area consists of the Klamath (drainage area 4.04×10^4 km^2) and Sacramento (6.93×10^4 km^2) river basins. Each basin (Fig. 1) is divided into five subbasins for purposes of water budget computations. Twelve daily USGS stream gauges record the surface water flow out of and into (in the case of nonheadwater) each of the subbasins.

National Climatic Data Center (NCDC) cooperative observer stations within and adjacent to the study area were used to construct $1/8°$ gridded precipitation, and daily maximum and minimum temperature from 2001 to 2005 using methods described in Maurer et al. (2002). The gridding method for precipitation and temperature performs an adjustment so that each month's mean matches that of the Precipitation-elevation Regressions on Independent Slopes Model (PRISM), as described in Daly et al. (1994, 2002), to adjust for the effects of orography. PRISM has been widely used in hydrological and meteorological studies (see, e.g., Maurer et al. 2002; Xie et al. 2007); it defines a monthly precipitation climatology through locally established empirical relationships between precipitation and elevation. Near-surface wind speed was taken from the NCEP–NCAR reanalysis.

The Nishida et al. (2003) method of ET estimation is based entirely on satellite data. As applied by Tang et al. (2009a), downward solar radiation is taken from the National Oceanic and Atmospheric Administration (NOAA)/National Environmental Satellite, Data, and Information Service (NESDIS) Surface Radiation Budget

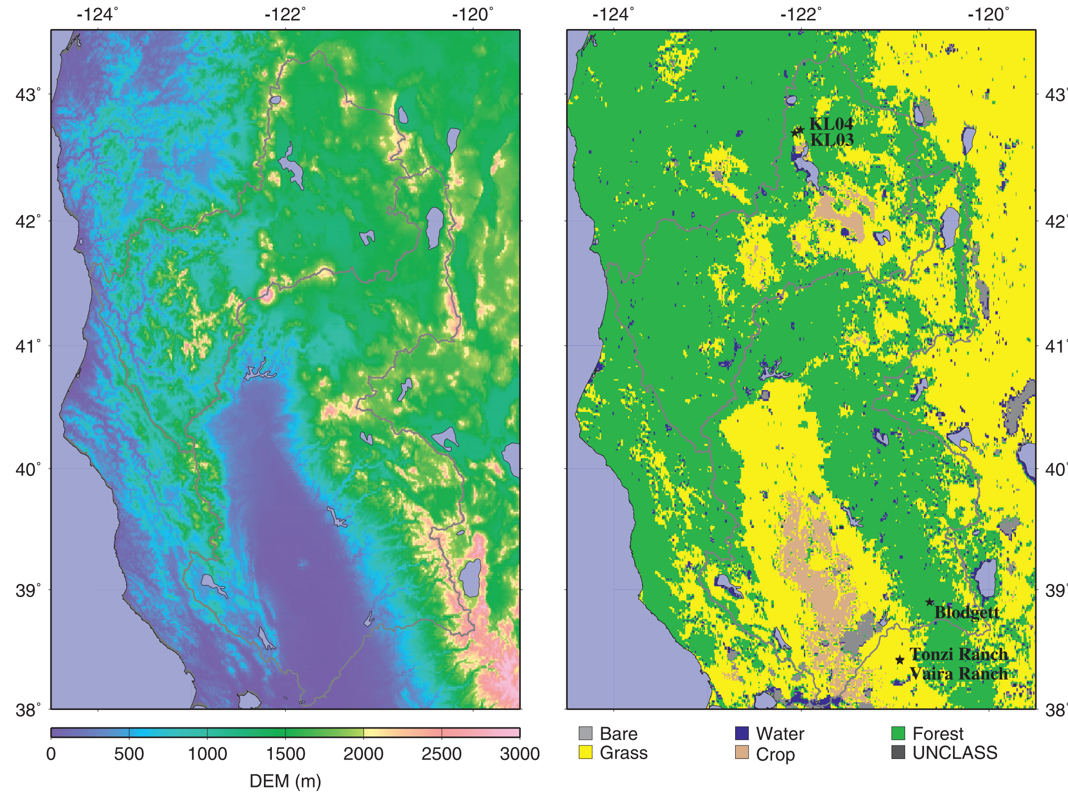

FIG. 2. DEM, land cover classification from MODIS, and the tower flux site locations (stars) that were used to test the ET method.

(SRB) products derived from the Geostationary Operational Environmental Satellites (GOESs; Pinker and Laszlo 1992; Menzel and Purdom 1994), and Moderate Resolution Imaging Spectroradiometer (MODIS)-based vegetation index (VI; MOD13Q1), surface temperature and emissivitiy (MOD11A1), and albedo (MCD43A3) products are used as well. Land cover is obtained from the International Geosphere-Biosphere Programme (IGBP) land cover dataset archived as MOD12Q1 (Belward et al. 1999). The digital elevation model (DEM) and classified land cover for bare soil, forest, grassland, and cropland are shown in Fig. 2. The Nishida et al. (2003) method is based on the combination of satellite VI and radiative surface temperature (T_s). It assumes that bare soil and sparse vegetation (with lower VI values) are warmer than dense vegetation (with higher VI values) as the surface becomes drier, and it is based on the concept of a diversity of VI–T_s combinations over an area (Nishida et al. 2003).

Tang et al. (2009a) showed that the method worked well in comparison with observations in the Klamath River basin, with instantaneous evapotranspiration biases less than 10% and daily evapotranspiration biases less than 15%. In this paper, the domain is much larger than in Tang et al. (2009a). Variations of the VI–T_s method have been widely used (e.g., Carlson et al. 1995; Gillies et al. 1997; Jiang and Islam 2001; Nishida et al. 2003; Tang et al. 2009a).

The requirement for diversity in VI–T_s pairs restricts applicability of the Nishida et al. method when vegetation cover is relatively homogeneous, as in the forested portions of the study area (Fig. 2). However, this issue is resolvable over our study domain, by appropriate definition of subdomains, so as to include a diversity of forested, agricultural, and sparsely vegetated areas (Roerink et al. 2000; Courault et al. 2005). The method was tested at two tower flux sites (KL03 and KL04) over a cropland portion of the domain by Tang et al. (2009a) and at three flux tower sites within the region by Tang et al. (2007b; see Fig. 2). The results of these comparisons show that the ET estimation approach agrees favorably with ground observations in the cropland areas, and that although there are substantial discrepancies in instantaneous estimation of ET at towers in savanna and forest ecosystems, the long-term biases can be significantly reduced for long (e.g., seasonal) averaging times. We apply the method over subbasins, as shown in Fig. 1, which allows us to evaluate the method using the long-term subbasin water balance terms: precipitation, ET, and runoff.

The GRACE data used in this study are described by Chambers (2006) and were extracted from the National

TABLE 1. Subbasin, USGS streamflow gauges, and annual mean runoff from 2001 to 2005. The simulated NR is from VIC model simulation.

Subbasin	River basin	Upriver station	Downriver station	Area (km^2)	Observed runoff ($mm\ yr^{-1}$)	Simulated NR ($mm\ yr^{-1}$)
1[a]	Klamath	—	11507500	9852	116	157
2[b]	Klamath	11507500	11509500	7736	−42	50
3	Klamath	11509500	11520500	9414	157	240
4[c]	Klamath	—	11530000, 11525430	7389	686	667
5	Klamath	11520500, 11530000	11530500	5960	1089	892
6	Sacramento	—	11351945	6816	16	178
7[d]	Sacramento	11351950, 11525430	11377100	16 655	520	585
8[e]	Sacramento	—	ORO	9371	409	685
9[f]	Sacramento	11377100, ORO	11425500	21 759	187	445
10[g]	Sacramento	11425500	11455420, 11336600	14 661	145	337

[a] Local water diversions at ''A'' Canal and Keno Canal are accounted for here.
[b] Local water diversions at ''A'' Canal and Keno Canal are taken into account.
[c] Interbasin water transfer (11525430) to subbasin 7 at the Sacramento basin.
[d] Interbasin water transfer (11525430) from subbasin 4.
[e] Oroville Dam creates Lake Oroville and provides water for central and Southern California.
[f] Flow over Fremont weir is taken into account when flooding.
[g] Delta Cross Channel (11336600) transfers freshwater from the Sacramento River across the delta.

Aeronautics and Space Administration (NASA) Web site (available online at http://grace.jpl.nasa.gov). We used the monthly mass grids of the GRACE land water solutions for the period from August 2002 to December 2005 (two months—June 2003 and January 2004—are missing). The GRACE land water solutions consist of the total land water mass.

3. Methodology

The terrestrial water balance for a prescribed area and period can be written as

$$\Delta S = P - \mathrm{ET} - R, \tag{1}$$

where ΔS is TWSC (mm), P is the precipitation (mm), ET is the evapotranspiration (mm), and R is the total runoff (mm). Here, P and ET are spatially varying quantities; therefore, they must be integrated both spatially and over time, whereas R is generally defined as a flux through a stream channel system. For this reason, the equation is most easily applied over river basins, where R can be taken from (or related to) streamflow observations.

a. *Satellite/surface observation–based TWSC*

The satellite/surface observation–based estimates use the same gridded precipitation data that are used to force the VIC model for the model-based TWS estimates. Daily ET estimation is as in Tang et al. (2009a), which uses remote sensing estimates of surface radiation, temperature, vegetation, and land cover properties to estimate latent heat flux as a residual in a surface energy balance.

Daily runoff for each subbasin was computed using stream gauge data from the U.S. Geological Survey (USGS) and California Data Exchange Center (CDEC), which are summarized in Table 1. The areas of the subbasins range from approximately 6000 to 22 000 km^2. The annual mean net runoff from 2001 to 2005 for the subbasins ranges from −42 (negative values imply net water consumption in the basin) to 1089 mm. The spatial distribution of runoff production within the subbasins was estimated by rescaling the modeled gridded runoff distribution to match gauged streamflow in each subbasin.

The satellite/surface observation–based TWSC accounts for human alterations of the hydrological cycle—for example, the effects of dams, diversions and water withdrawals. Subtracting water management reservoir storage changes from satellite/surface observation–based TWSC should provide an estimate of the effect of water resources management on TWSC. Table 2 shows the water management reservoirs that we consider. The four largest water management reservoirs in the Klamath basin have a total water storage capacity of 4.4 billion cubic meters (BCMs). The six largest water management reservoirs in the Sacramento basin have a storage capacity of 16 BCM, which is about 95% of the total water management reservoir storage capacity in the basin.

b. *Model-based TWS*

The VIC macroscale hydrological model (Liang et al. 1994; Nijssen et al. 1997) was used to calculate the model-based TWS. The VIC model has been calibrated in a number of previous efforts using observed streamflow across much of the continental United States. It has

TABLE 2. Water management reservoirs (see Fig. 1) considered in this study.

CDEC station	Latitude (°N)	Longitude (°W)	Storage capacity (BCM)	Subbasin	Remarks
KLM	42.250	121.815	0.60	1	Upper Klamath Lake
CLK	41.927	121.075	0.65	2	Clear Lake, Klamath River
GBR	42.205	121.130	0.12	2	Gerber
CLE	40.801	122.762	3.02	4	Trinity Lake
SHA	40.718	122.420	5.61	7	Shasta Dam
ORO	39.540	121.493	4.36	8	Oroville Dam
ALM	40.218	121.173	1.61	8	Lake Almanor
BUL	39.393	121.140	1.20	9	New Bullards Bar
FOL	38.683	121.183	1.20	10	Folsom Lake
BER	38.513	122.104	1.98	10	Berryessa

a long history of use for evaluating the land surface water budget in studies, such as Abdulla et al. (1996; Arkansas–Red River basin); Maurer et al. (2001, 2002; Mississippi River basin and continental United States, respectively); and Nijssen et al. (1997, 2001; Columbia and Delaware River basins and global land areas, respectively). The VIC model has been used to simulate land surface fluxes and states in many different applications, including cold land processes (Cherkauer and Lettenmaier 1999), continental water and energy balances (Maurer et al. 2001, 2002), Arctic hydrology (Su et al. 2006), and monsoon teleconnections (Zhu and Lettenmaier 2007).

In this study, the model was applied at a 1/8° spatial resolution. Model parameters were calibrated to naturalized streamflow (i.e., streamflow records adjusted for water management effects). Land cover, soils, and topographic data were taken from Maurer et al. (2002), and they are similar to those used in the North American Land Data Assimilation System (NLDAS; Mitchell et al. 2004). The model was initialized by a long model spin-up period starting in 1950 using the forcing data from Maurer et al. (2002).

A separate (postprocessor) routing model is used by VIC to simulate streamflow (Lohmann et al. 1996, 1998). The routing model assumes that water can leave a model grid cell through one river in the direction of one of its eight neighboring grid cells. It is then added to the water in the river routing scheme. Both parts of the routing scheme (within the grid cell and river routing) are represented as simple linear transfer functions (Lohmann et al. 1996) and can be derived independently of the VIC land surface scheme using measured streamflow and precipitation data. The model assumes runoff transport processes are linear and time invariant. The linear transfer function models lump the horizontal flow properties, which are assumed not to be a function of the soil moisture content.

The VIC model and the routing scheme together represent a parameterization that arguably has about the necessary degree of sophistication for the representation of the land surface water balance (Schultz et al. 1995). The parameters for the routing model are from the Nijssen et al. (1997) study, which quoted velocity values of 0.5–2.0 for the Columbia basin. Gridded daily precipitation, daily maximum and minimum temperature, and wind speed used to force the model are described in section 2; other model forcings—downward solar and longwave radiation, and humidity—were derived from daily temperature or temperature range data as described in Maurer et al. (2002). Land cover, soils, and topographic data were taken from Maurer et al. (2002). Standard versions of the VIC model simulate naturalized runoff (NR); that is, the effects of dams, diversions and water withdrawals are not accounted for in the scheme. The modeled ET and runoff, together with the precipitation climatology, were used to calculate modeled TWS change of each grid cell and subbasin. As noted earlier, as a first step, precipitation was adjusted to match PRISM in the monthly-mean sense. Modeled runoff was calibrated to match observed naturalized runoff. In the long-term mean, therefore, model ET should be approximately correct by difference.

4. Results and analysis

Figure 3 compares VIC-simulated streamflow and estimated monthly NR at the stations where NR data are available (generally, these data are estimated by water management agencies using observed USGS stream gauge data, adjusted by observed water management reservoir storage changes upstream and estimates of net diversions above the gauge). The comparison period is the same as the study period (2001–05) for most of the stations. NR for Upper Klamath Lake (KLM) was unavailable after 1999, and therefore the period from 1989 to 1999 was used in this case. The VIC-simulated streamflow agrees well with the NR in most cases, with Nash–Sutcliffe efficiencies (Nash and Sutcliffe 1970) exceeding 0.65 on a monthly basis for most of the stations. An exception is the KLM station at which the Nash–Sutcliffe efficiency coefficient is

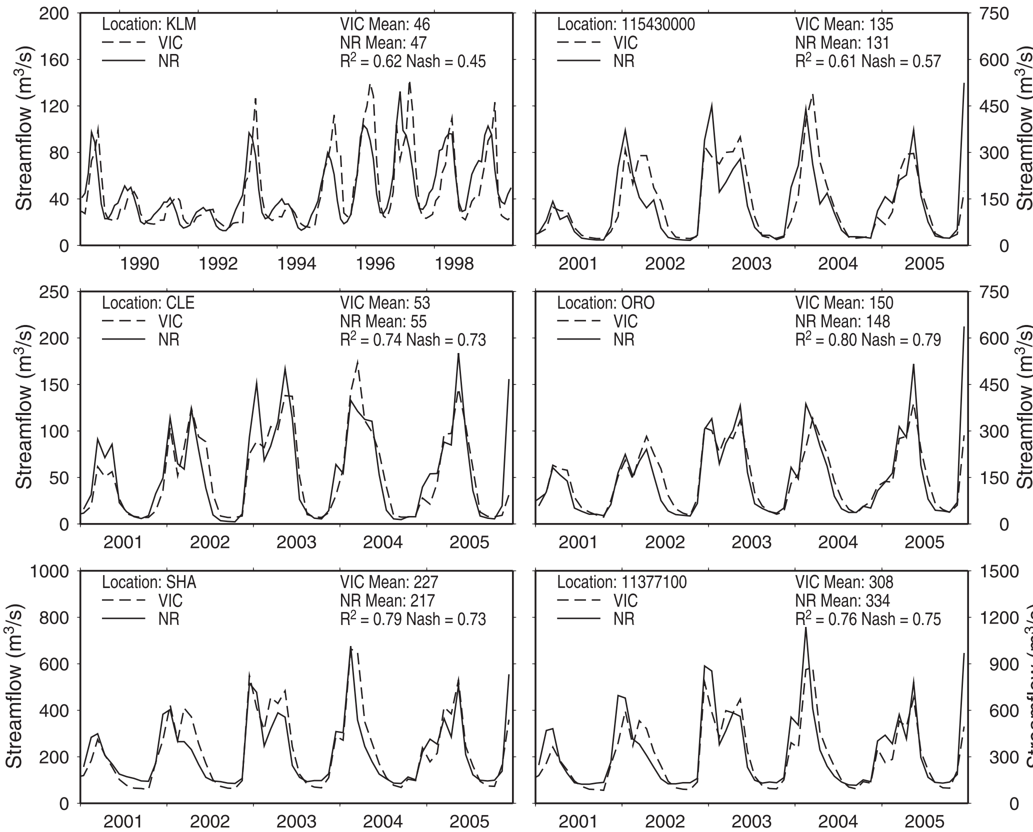

FIG. 3. Satellite/surface observation–based and VIC modeled monthly naturalized runoff.

0.45. It should be noted that the drainage area controlled by this station is only 9% of the total area of the study area. Figure 3 shows that the VIC simulations capture the seasonal variations in NR, which suggests that they should also be capable of capturing seasonal TWSC variations—assuming accurate precipitation.

Figure 4 shows the modeled monthly TWSC for 2001–05. TWSC is positive throughout most of the study area from November to February, which reflects the effects of the winter rainy season and snowpack accumulation in winter. The largest positive TWSC is for high-elevation areas (see Fig. 2) and for downstream portions of the Klamath basin where precipitation has the highest winter-dominant (November–January) seasonality. The persistence of positive TWSC recedes over low-elevation areas beginning in February. Small positive TWSC persists over the high-elevation area in March. TWSC over most of the study area is negative from May to August, which corresponds to snowmelt and high ET in summer. The largest negative TWSC is found in high-elevation areas.

Figure 5 shows monthly TWSC from satellite/surface observation–based estimates for 2001–05. Similar to modeled TWSC, TWSC is positive from November to February and negative from May to August, corresponding with snowpack accumulation in winter and depletion in summer. Positive TWSC in high-elevation areas persists longer into March and April than in the model-based estimates. The largest negative TWSC is in high-elevation areas. Large negative TWSC occurs over forest and cropland in the southern portion of the Sacramento basin (subbasin 9, see Fig. 2). This suggests that satellite/surface observation–based ET is larger than modeled ET in summer, for which the VIC model simulates the natural situation well. Tang et al. (2009b) found that the VIC-modeled ET in managed river basins was typically smaller than the remotely sensed ET—particularly over irrigation areas—and these differences are consistent with groundwater withdrawal observations in the Klamath River basin (Risley et al. 2006). The model does not take into account the effects of water management reservoirs, interbasin water diversions, and irrigation water withdrawals, which may introduce discrepancies between modeled and satellite/surface observation–based TWSC. A typical example is subbasin 8 (see Fig. 1; Table 1), where the satellite/surface observation–based TWSC is more positive in winter and more negative in summer than the model-based estimate. This is

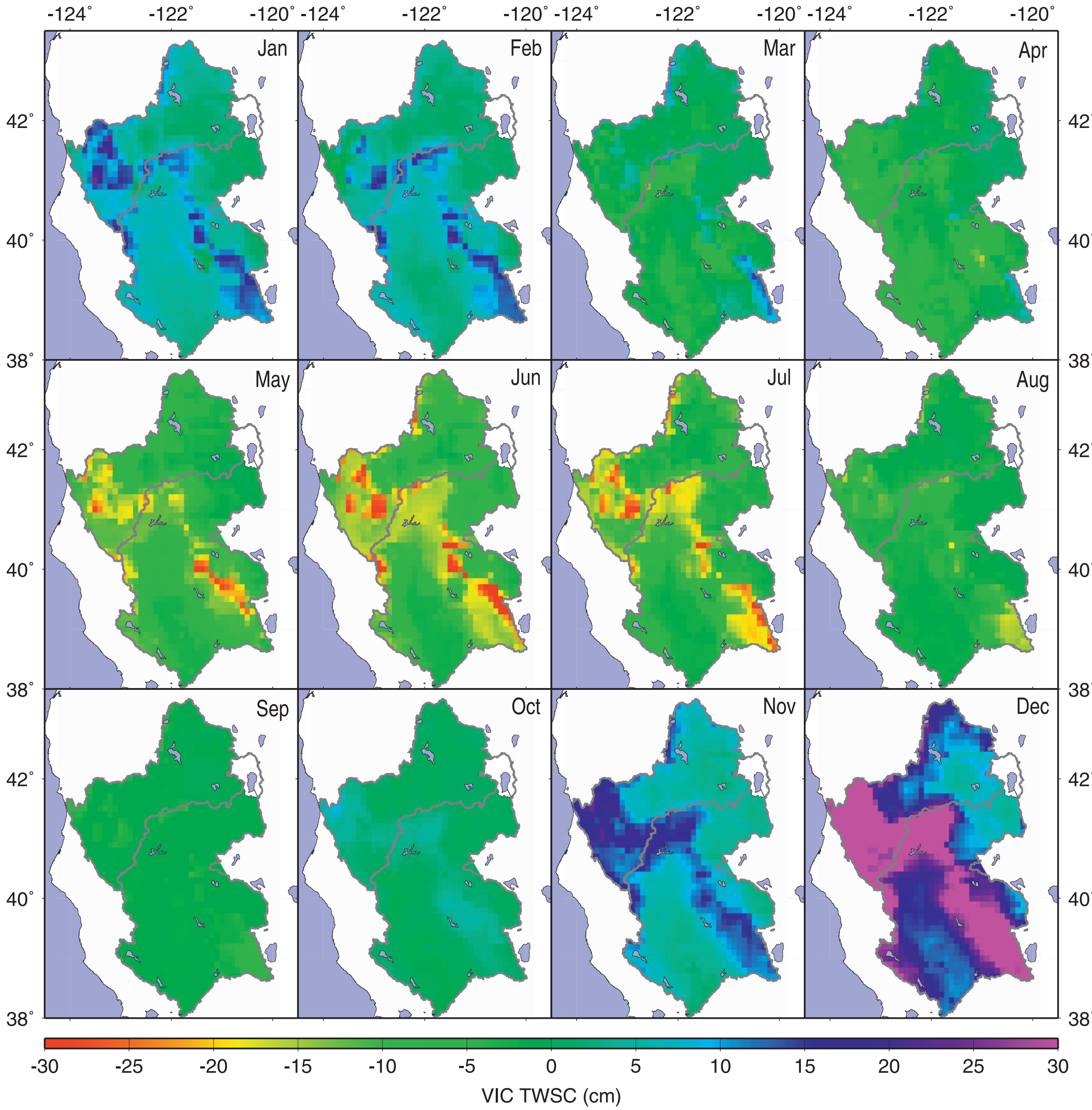

FIG. 4. Modeled monthly TWSC for 2001–05.

almost certainly caused by water management reservoir operations, which store water in winter and release water for irrigation in summer. The negative TWSC in the southern portion of the Sacramento basin may also in part be a result of irrigation withdrawals.

Figure 6 shows observed precipitation as well as modeled and satellite/surface observation–based monthly ET and runoff over the Klamath and Sacramento basins for 2001–05. The VIC model is driven by observed precipitation, hence the precipitation used to force the VIC model and the precipitation used for the satellite observation–based TWS are identical. For both basins, modeled ET is smaller than satellite/surface observation–based ET in summer. The modeled runoff is larger than observed in most months in the winter and spring, suggesting the extent to which human influences have altered the natural hydrological processes through diversions and impoundments in the two basins. The observed runoff is about 85% of the modeled natural runoff for the Klamath basin and about 55% of the modeled runoff for the

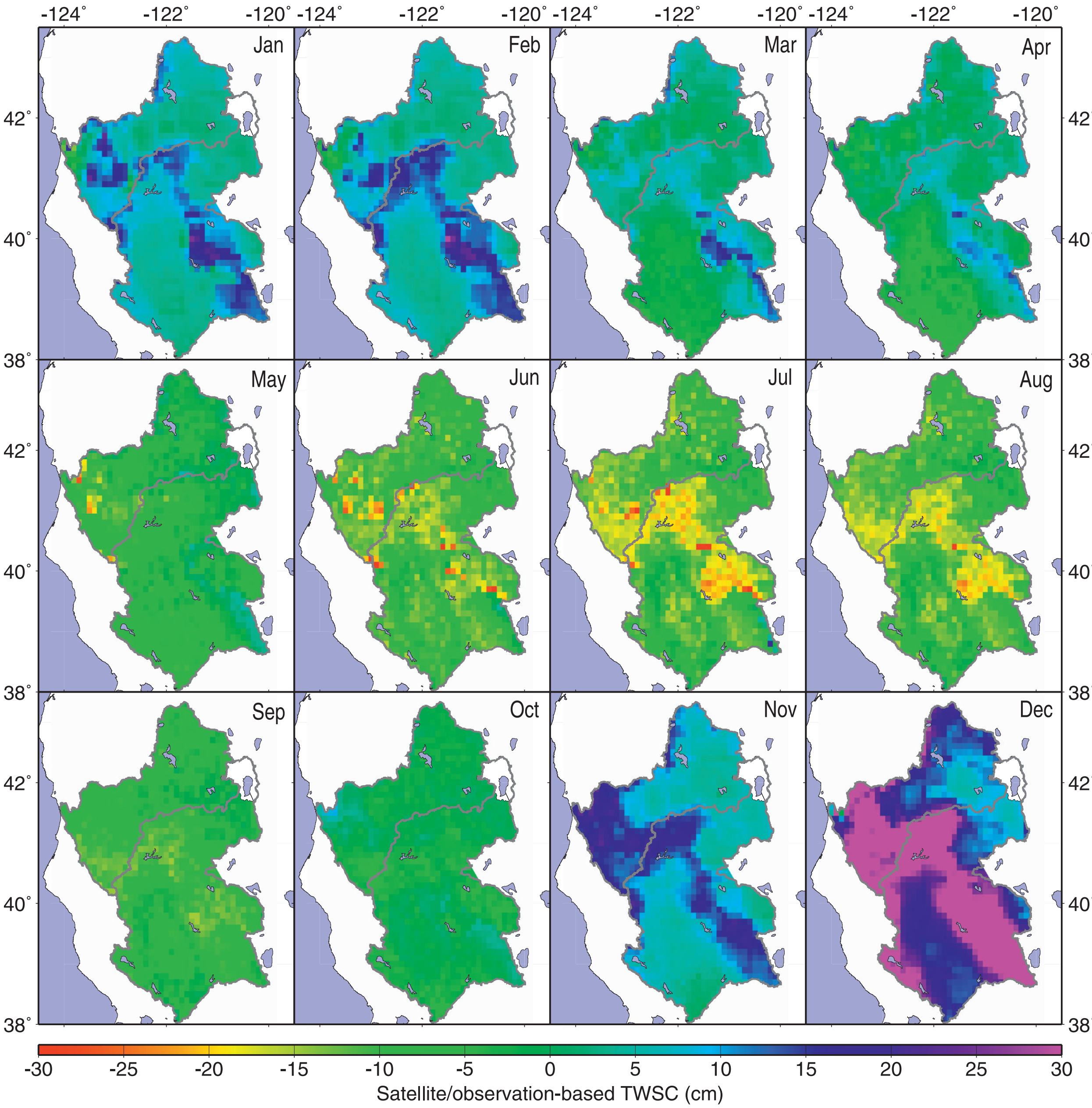

FIG. 5. Monthly satellite/surface observation–based TWSC for 2001–05.

Sacramento basin. These anthropogenic alterations should also have affected regional TWSC. In the study area, human alterations seem to have increased the seasonal TWS variations by storing water in the rainy (low elevation) and snow accumulation (high elevation) periods and by consuming water in the dry and/or snow depletion period. Others have reported that the TWS from several models (including ERA-40) show considerable underestimation of interannual TWS variability (Hirschi et al. 2006, 2007), which may partly be a result of the lack of representation of human influences. Haddeland et al. (2006) describe algorithms that predict the effects of water management reservoir operation and irrigation water withdrawals. Although not implemented here, these algorithms could be used to explore the discrepancies between naturalized runoff and observed streamflow, and thus quantify the effect of water resources management on TWSC components.

Figure 7 shows daily modeled and satellite/surface observation–based TWS and water management reservoir water storage variations from 2001 to 2005 in the subbasins of the Klamath. The TWS on the first day of

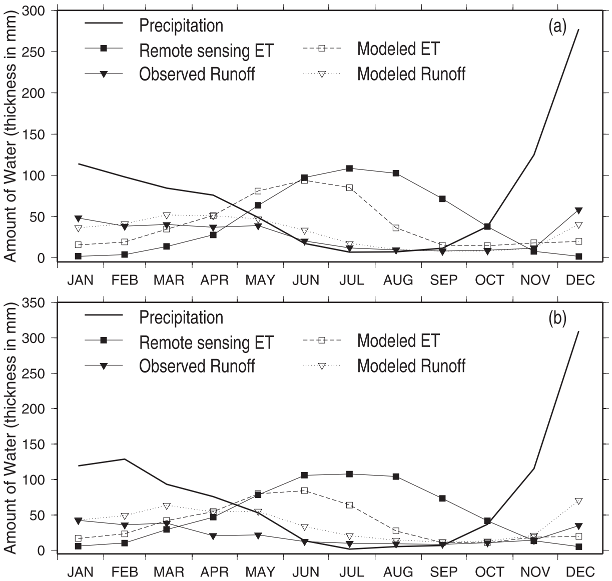

FIG. 6. Observed precipitation as well as modeled and satellite/surface observation–based monthly ET and runoff over (a) Klamath and (b) Sacramento basins for 2001–05.

2001 is arbitrarily set to zero for reference purposes. The satellite-based ET estimates combined with observed runoff generally balance with observed P quite well. This suggests that the bias of the ET estimates is small for long averaging times. The first two years—2001 and 2002—are drought years. The satellite/surface observation–based TWS declines during the drought years and gradually recovers after the drought. For subbasin 2, observed R is negative, indicating that subbasin 2 is a net water consumption zone; that is, the annual discharge at the upstream stations is less than at the downstream station. This is caused by large water withdrawals from the river for irrigation. Net water consumption zones are also found in other intensively cultivated river basins in arid areas (Tang et al. 2007a, 2008). Comparing with the modeled results, the satellite/surface observation–based estimates show larger ET and smaller R for the subbasins. This is likely the effect of water management reservoirs and irrigation water withdrawals, which the model does not represent.

The difference between observed streamflow and modeled naturalized flow is considerable for most of the subbasins. The TWS variations agree well in subbasin 4, where the difference between modeled and observed R is smallest. The amplitude of water management reservoir seasonal water storage variations is about 20% of the satellite/surface observation–based TWS variation in subbasin 4. Although the water management reservoir water storage is not the major contributor of TWS, annual water management reservoir storage variations are consistent with TWS variations in the subbasins. For example, water management reservoir storage decreased from 2001 to 2005 in subbasin 2, corresponding with a decrease in TWS during the same period. Higher water management reservoir storage in 2003 and 2004 corresponds with higher satellite/surface observation–based TWS in subbasin 4.

Figure 8 shows daily modeled satellite/surface observation–based TWS and water management reservoir water storage variations from 2001 to 2005 in the subbasins of the Sacramento basin. Here, P, ET, and R from different observations balance well during the study period for these subbasins. In the upstream subbasins (subbasins 6–8), the decrease in TWS during late summer and increase in TWS during early winter are sharp, implying large summer ET and the effects of the water management reservoirs, which store water in winter and release water for irrigation in summer. The amplitude of water management reservoir water storage variation is about 30% of the satellite/surface observation–based TWS variation in subbasin 8, which includes Oroville Dam (ORO), a major facility of the California State Water Project (SWP). Water management reservoir storages in 2003–05 are larger than in 2001, corresponding with larger TWS in these years. The satellite/surface observation–based TWS without water management reservoirs shows better agreement with the VIC model simulations. In the downstream subbasins (subbasins 9 and 10 in the Sacramento Valley), satellite/surface observation–based TWS agrees well with modeled TWS. There are considerable differences between satellite/surface observation–based and modeled ET during summer in the downstream subbasins. However, the water released from the upstream water management reservoirs replenishes the soil moisture in the Sacramento Valley during summer, so water deficiencies (large negative TWS) are not present in the Sacramento Valley during summer.

Figure 9 shows the TWS variations and mean monthly TWS variations from model simulations, satellite/surface observation–based water balance, and GRACE measurements averaged over the Klamath and Sacramento basins (note that because of the relatively coarse GRACE spatial resolution, comparisons are performed at the basin scale, rather than at subbasin level). The satellite/surface observation–based TWS declines during the drought years (2001 and 2002) and gradually recovers after the drought. GRACE TWS variations have a seasonal cycle amplitude that is much smaller than either the satellite/surface observation–based TWS (28%) or the VIC-simulated TWS (35%). The temporal pattern of GRACE TWS variations matches the satellite/surface observation–based TWS well with the correlation coefficient of 0.81. The linear

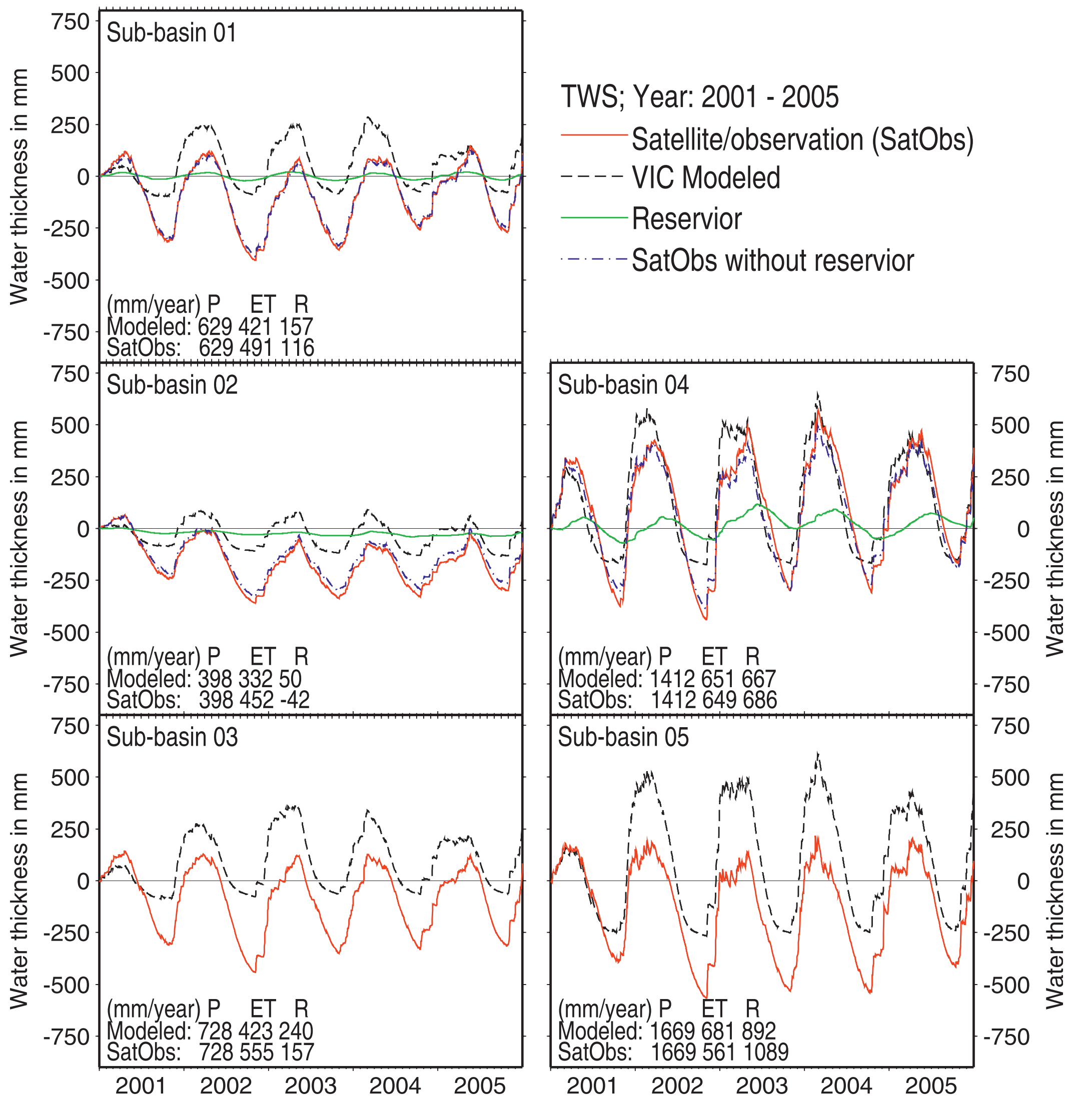

FIG. 7. Daily satellite/surface observation–based TWS, modeled TWS, and water management reservoir water storage variations from 2001 to 2005 in the subbasins of the Klamath basin.

relationship between GRACE and satellite/surface observation–based TWS is SatObs = GRACE × 3.0 + 70. The relationship is used to scale the GRACE TWS. The scaled GRACE TWS agrees well with the satellite/surface observation–based TWS with Nash–Sutcliffe efficiency coefficient (Nash and Sutcliffe 1970) of 0.77 for monthly TWS and of 0.94 for mean monthly TWS from August 2002 to December 2005. The comparisons with VIC simulation (not shown) indicate that the GRACE seasonal cycle amplitude appears to be biased downward at the larger scale of the Columbia River basin and Sacramento–San Joaquin River basins as well. The major contributors to the GRACE error budget are measurement noise, spatial leakage error, and atmospheric and ocean dealiasing (AOD) model error (Seo et al. 2006). The downward biases are likely caused by leakage error that is concentrated in regions of high-water-storage variability and AOD model error, which arises from the imperfect correction for atmosphere and ocean mass redistribution applied during GRACE processing (Seo et al. 2006). Figure 9 also shows the water management reservoir water storage change, the amplitude of which is 12% of the satellite/surface observation–based TWSC. This suggests the extent to which water resources management may be affecting seasonal TWSC.

5. Discussion and conclusions

We have estimated temporal variations of TWS from model simulations and water budget computations using

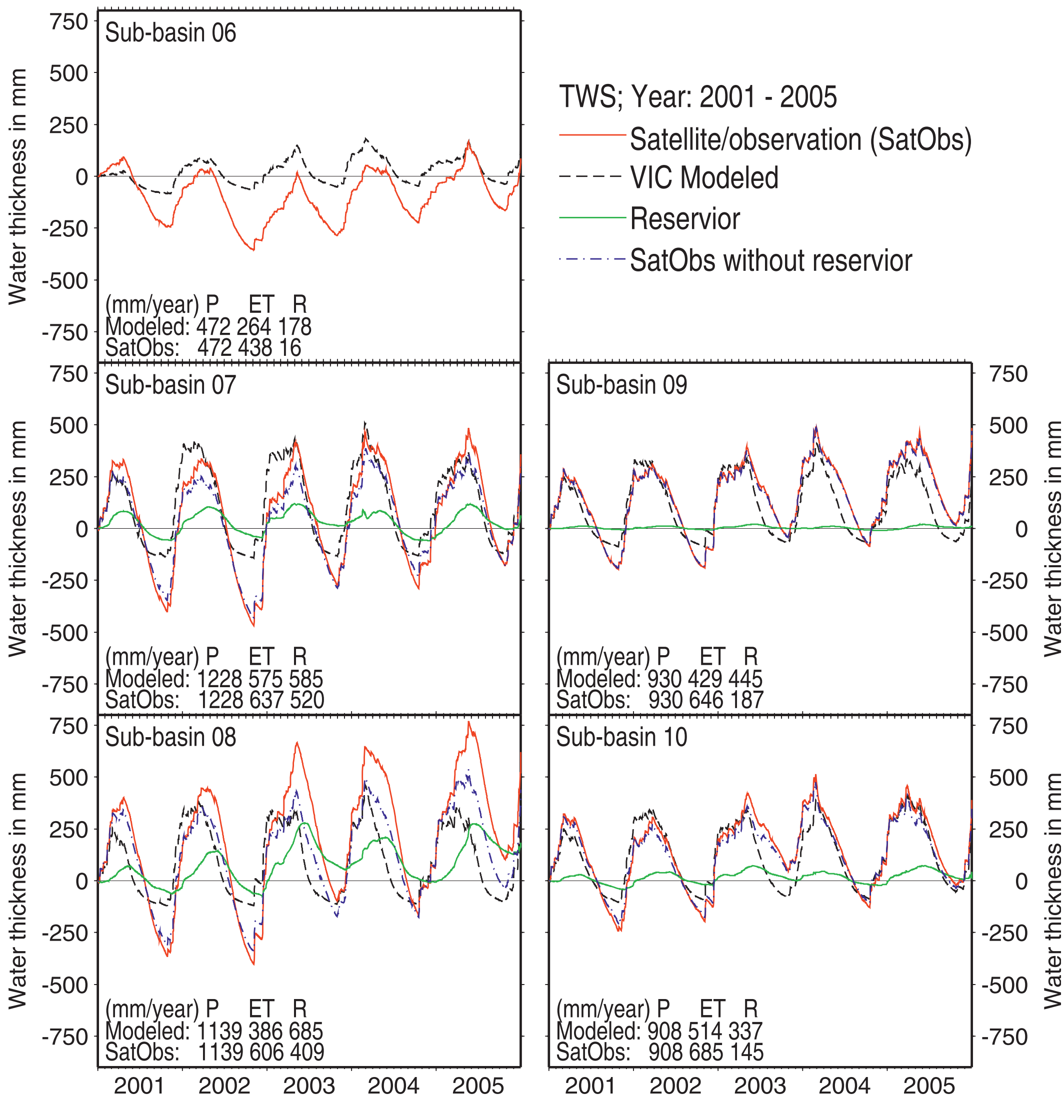

FIG. 8. Same as Fig. 7 but for the Sacramento basin.

surface precipitation observations, satellite-based ET estimation, and gauge runoff measurements for major subbasins of the Klamath and Sacramento Rivers. The results show that the precipitation, ET, and runoff from these two methods balance reasonably well during the study period. The satellite/surface observation–based TWS declines during the drought years (2001 and 2002) and gradually recovers after the drought, whereas the model simulations do not capture the interannual TWS variation. The snowpack accumulation in winter and depletion in summer is captured by both modeled and satellite/surface observation–based regional terrestrial water storage change. The model gives the naturalized TWSC, whereas the satellite/surface observation–based estimates give the actual TWSC. Comparing to modeled results, the satellite/surface observation–based estimates show larger ET and smaller *R*, indicating that human influences have extensively altered the natural hydrological processes and seasonal TWSC in the study area. Human alterations appear to increase the seasonal TWS variation by storing water in the rainy season and snow persistence period, and consuming water in the dry season and snow depletion period. Water management reservoir storage change is 12% of the satellite/surface observation–based TWS seasonal cycle by amplitude for the aggregate of the Klamath and Sacramento basins. Water management reservoir storage change accounts for up to 30% of the TWS mean seasonal amplitude at the subbasin scale.

Comparing TWS variations from model simulations, satellite/surface observation–based water balance, and

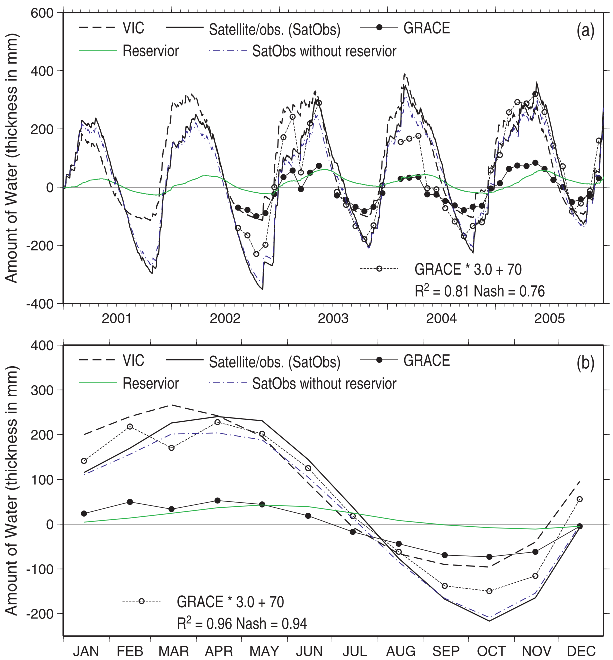

FIG. 9. (a) TWS variations and (b) mean monthly TWS variations averaged over the Klamath and Sacramento basins from model simulation, satellite/surface observation–based water balance, GRACE (August 2002–December 2005), and contributions from water storage change in water management reservoir.

GRACE measurements shows that GRACE substantially underestimates the amplitude of the seasonal cycle in the Klamath and Sacramento basins.

A near-real-time satellite-based ET estimation system has recently been implemented for northern California and southern Oregon by Tang et al. (2009a), hence, allowing the computation of TWSC on a near-real-time basis for that region. To the extents that near-real-time estimates of precipitation and runoff are available, the approach could be extended over much of the continental United States.

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