AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2017GL073333

Key Points:
- About 55 km^3 of groundwater was lost from the Central Valley during the 2007–2009 and 2012–2016 droughts
- Reduced net inflows, transition from row to tree crops, and higher evapotranspiration lead to most of the groundwater loss in 2012–2016
- Water balance and GRACE estimates of CV groundwater loss agree quite closely during drought (but not during nondrought) periods

Supporting Information:
- Supporting Information S1

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Citation:
Xiao, M., A. Koppa, Z. Mekonnen, B. R. Pagán, S. Zhan, Q. Cao, A. Aierken, H. Lee, and D. P. Lettenmaier (2017), How much groundwater did California's Central Valley lose during the 2012–2016 drought?, *Geophys. Res. Lett.*, *44*, doi:10.1002/2017GL073333.

Received 6 MAR 2017
Accepted 14 APR 2017
Accepted article online 19 APR 2017

How much groundwater did California's Central Valley lose during the 2012–2016 drought?

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Abstract We estimate net groundwater storage change in the Central Valley from April 2002 to September 2016 as the difference between inflows and outflows, precipitation, evapotranspiration, and changes in soil moisture and surface water storage. We also estimate total water storage change attributable to groundwater change using Gravity Recovery and Climate Experiment (GRACE) satellite data, which should be equivalent to our water balance estimates. Over two drought periods within our 14-1/2 years study period (January 2007 to December 2009 and October 2012 to September 2016), we estimate from our water balance that a total of 16.5 km^3 and 40.0 km^3 of groundwater was lost, respectively. Our water balance-based estimate of the overall groundwater loss over the 14-1/2 years is -20.7 km^3, which includes substantial recovery during nondrought periods The estimated rate of groundwater loss is greater during the recent drought (10.0 ± 0.2 versus 5.5 ± 0.3 km^3/yr) than in the 2007–2009 drought, due to lower net inflows, a transition from row crops to trees, and higher crop water use, notwithstanding a reduction in irrigated area. The GRACE estimates of groundwater loss (-5.0 km^3/yr for both water balance and GRACE during 2007–2009, and -11.2 km^3/yr for GRACE versus -10 km^3/yr for water balance during 2012–2016) are quite consistent for the two methods. However, over the entire study period, the GRACE-based groundwater loss estimate is almost triple that from the water balance, mostly because GRACE does not indicate the between-drought groundwater recovery that is inferred from our water balance.

1. Introduction

As one of the most productive agricultural regions in the world and the most populous state in the U.S., water availability is crucial to California. Through 2014 (all years mentioned herein are calendar years unless stated otherwise), the 2012–2016 California drought, by one measure (an integrated soil moisture index), was the most severe of the last 1000 years [*Griffin and Anchukaitis*, 2014]. Exceptionally warm winter (November–March) temperatures across the state (winter 2014–2015 was the warmest of the instrumental record) amplified the effects of low precipitation [*Aghakouchak et al*., 2014]. The 3 year average April 1 snow water equivalent (SWE) for 2012–2014 for the Sierra Nevada Mountains of California was the lowest on record [*Mao et al*., 2015], while 2015 was the lowest single year on record [*Mote et al*., 2016]. Water-year naturalized runoff for both the Sacramento and San Joaquin Rivers was remarkably low during the drought as well [*Shukla et al*., 2015]. *Cooley et al.* [2015] reported that the harvested area in 2014 was the lowest in the past 15 years. Furthermore, the drought resulted in reduced water availability to California's large coastal population centers, although the economic consequences of the mandatory water use reductions that resulted apparently have not been quantified to date.

The use of groundwater in the Central Valley (CV) is widespread and makes up part of surface water shortages during droughts as well as (to a somewhat lesser extent) during nondrought years [*Bertoldi et al*., 1991]. During the period 2003–2010, *Famiglietti et al.* [2011] estimated total consumptive use of groundwater in the CV at ~20 km^3, based on a combination of water balance modeling and Gravity Recovery and Climate Experiment (GRACE) satellite data. They showed that the CV has experienced increased groundwater depletion since about 2000. Nonetheless, aggregated groundwater use is not well monitored, and groundwater storage (GWS) is difficult to assess [*Famiglietti et al*., 2011]. Additionally, while [*Famiglietti et al*., 2011] and others (e.g., [*Scanlon et al*., 2012]) have used GRACE data to attempt to document groundwater storage changes in California and elsewhere, the effective footprint of GRACE is on the order of 250,000–500,000 km^2, which greatly exceeds the area of the CV (~52,000 km^2) and even of the entire Sacramento-San Joaquin River basin

(~154,000 km^2). This makes the interpretation of GRACE-based estimates of groundwater depletion specific to the CV tenuous (see e.g., *Scanlon et al.*, 2012 and section 3 herein). Furthermore, while several studies of the CV agree that its groundwater storage has declined since the mid-2000s [*Famiglietti et al.*, 2011; *Scanlon et al.*, 2012; *Famiglietti*, 2014; *Chen et al.*, 2016], none have examined the role of the 2012–2016 drought on groundwater storage.

Here we estimate groundwater storage changes in the CV as well as the Sacramento-San Joaquin-Tulare (SSJT) River basins over the period April 2002 to September 2016 using a water balance approach, with a focus on groundwater depletions. We use in situ observations to the greatest extent possible, and we use multiple estimates where feasible to provide a basis for uncertainty estimation. We also compare our water balance-based estimates with a GRACE-based estimate.

2. Data and Methods

Figure 1 shows our study domain, which consists of the CV as well as the entire SSJT. We used a water-balance approach on a monthly time step as follows:

$$\Delta\mathrm{GW} = P + Q_{\mathrm{in}} - \Delta\mathrm{SM} - \Delta\mathrm{SWE} - Q_{\mathrm{out}} - \mathrm{ET} - \Delta S$$

where P, Q_{in}, and Q_{out} represent precipitation over the basin and surface flow in and out (whether as streamflow or in canals), respectively. ΔSM is soil moisture change, ΔSWE is snow water equivalent change, ET is evapotranspiration, and ΔS is surface water storage (primarily in reservoirs) change. Storage terms are defined as the storage on the first day of each month (hence, storage change is storage on the first day of the current month minus storage on the first day of the previous month), and fluxes are averaged over the month.

2.1. Precipitation (*P*)

We used gridded P data from the University of California Los Angeles (UCLA)/University of Washington (UW) drought monitor [*Mao et al.*, 2015; *Xiao et al.*, 2016], PRISM (PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu), DayMet [*Thornton et al.*, 1997], and nClimGRID [*Vose et al.*, 2014] at the monthly aggregation level. We used multiple data sets to provide an estimate of uncertainty, recognizing that there are commonalities in the station data that underlie the different P data sets. We aggregated all data sets from their native spatial resolutions to 1/16-degree spatial resolution using the nearest neighbor interpolation technique and then estimated spatial means over the CV and SSJT.

2.2. Evapotranspiration (ET)

We extracted ET from three land surface models (LSMs): Variable Infiltration Capacity Model [VIC; *Liang and Lettenmaier* [1994]], Noah-MP [*Niu et al.*, 2011; *Chen et al.*, 2014; *Barlage et al.*, 2015], and a grid-based version of the National Weather Service Sacramento Soil Moisture Accounting Model (SAC; [*Burnash et al.*, 1973]). We forced all models with P, temperature, downward solar and longwave radiation, humidity, and wind from the UCLA/UW Drought Monitoring System at a daily or shorter time step. We found that variations among ET estimates from the three models were attributable primarily to differences in model physics rather than modest differences in the precipitation data sets; hence, the model runs that produced the ET estimates all used the UCLA/UW drought monitor forcing data set. Our initial results showed increases (in the ensemble mean) in groundwater storage over both the 2002–2016 and pre-2002 periods for the portion of the SSJT basin outside the CV, which seemed implausible. We traced this to the fact that while the LSMs all balance water internally by construct, their runoff does not necessarily match observations. This is resolvable by adjusting, or calibrating, model parameters such as soil depths, which affect evapotranspiration. This process is somewhat painful and time consuming, especially given that we used three LSMs, so we instead rescaled the precipitation data such that not only were soil moisture and SWE in approximate balance over our simulation period but groundwater storage was as well over the nondrought period January 1991 to December 2000 (see Figure S1 in the supporting information). While this precipitation adjustment (by a uniform factor of 0.9) affects the seasonal cycle of both SWE and soil moisture, it has little effect on our results for CV, where SWE is always nearly zero, and soil moisture variations are dominated by the irrigated portions. It does, however, reduce ET in such a way that on average over our ensemble members (VIC, SAC, and Noah-MP), modeled runoff is approximately equal to observations, and hence, the water balance is preserved over that portion

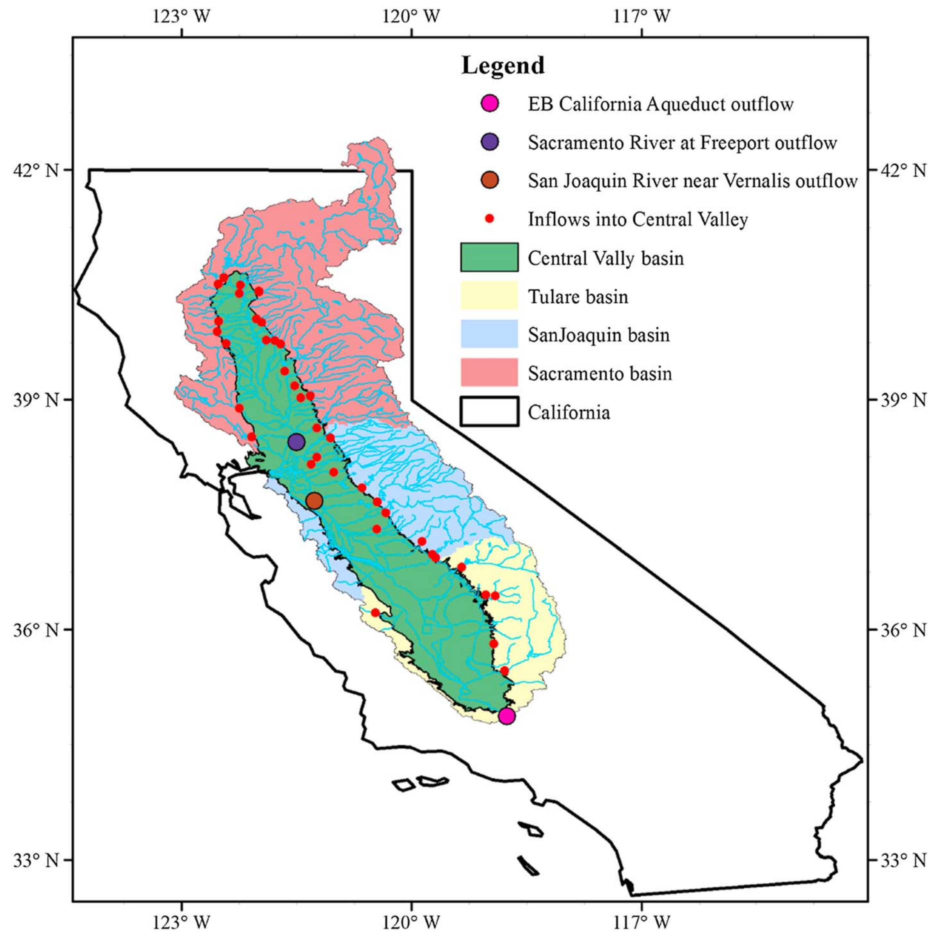

Figure 1. Study domain.

of the SSJT outside the CV. Essentially, the adjustment of precipitation serves as a surrogate for calibration of the LSMs.

Irrigation substantially affects evapotranspiration in some parts of our domain (especially the CV). Therefore, over the irrigated portions of the CV (determined according to [*Melton et al*., 2015]), we computed reference ET (ET_0) using the Penman-Monteith equation [*Monteith*, 1965] as implemented by *Allen et al.* [1998] and subsequently adjusted using crop factors for CV reported by the California Department of Water Resources [*Department of Water Resources*, 1986] and [*Brush et al*., 2004]. We determined crop types and changes therein over our study period using data from *Han et al.* [2012] (see supporting information for details). We updated the irrigated region post-2011 to reflect the change in irrigated area during the drought following *Melton et al.* [2015]. For the irrigated areas, ET_0 replaced model ET. In addition to model ET, we initially considered the satellite-based ET data set of *Tang et al.* [2009] used by *Famiglietti et al.* [2011]. However, we found that the satellite-based ET estimates exceeded precipitation on annual average over the portion of the SSJT outside the CV. Irrigation is small in this part of the basin; hence, ET exceeding precipitation on long-term average there is physically implausible. For this reason, we rejected this ET data set as physically implausible.

2.3. Soil Moisture

We took soil moisture variations over the nonirrigated portions of the domain from the three LSMs. We found that the equivalent flux associated with differences in soil moisture from the beginning to end of our period of analysis was small relative to variations in *P* and ET from the different sources we considered, and therefore, we used ΔSM from Noah-MP (which had SM variations that were intermediate between the other two models) in all of our computations. For irrigated portions of the basin, we assumed that soil moisture was close to field capacity and did not change from year to year. For those areas that were taken out of production during the 2012–2016 drought (see above), we assumed that at the time the land was taken out of production, SM was at field capacity, and that by September 2016, it had declined to the unirrigated value. In general, even the contribution of SM change over the irrigated area taken out of production was small relative to other fluxes; hence, alternative assumptions make relatively little difference to our results.

2.4. Snow Water Equivalent (SWE)

We took first of month SWE from Noah-MP. Over the CV, SWE is nearly always zero, hence was neglected. Over the SSJT outside of CV, it can be substantial. However, at the beginning of the water year (1 October), SWE is nearly zero each year across the SSJT. For this reason, we used only the Noah-MP SWE.

2.5. Inflow and Outflow

The SSJT basin has no natural or artificial inflow coming into the basin from external sources. In other words, all the water flowing in the rivers and canals originates from within the basin for water balance purposes. But for CV, several rivers and canals deliver water into the basin from outside. We identified a total of 35 gauged (albeit not continuously) inflow locations from United States Geological Survey (USGS) and California Department of Water Resources (CDWR) records (see Table S4 in the supporting information). Of the 35 stations, 19 had monthly flow data available for our study period (2002–2016) from CDWR. These 19 stations make up about 90% of the estimated long-term mean of the 35 stations, based on our analysis of longer term (and sometimes fragmentary) USGS and CDWR flow records.

We used three different methods to estimate the total inflow into CV based on the available data during 2002–2016. The first method utilizes a factor to adjust for the unaccounted flows, i.e., the 16 stations without complete data and smaller ungauged flows. Based on the percentage contribution of the 16 stations (~10%) and area of the ungauged smaller flows (~10%), we developed an adjustment factor which we applied to the 19-station total as an estimate of the total flow into the CV. The second method involved estimating flow for each of the 16 stations using linear regression on nearby observed stations. After constructing the correlation matrix among the 19 stations with data and the 16 stations without data, we identified the mostly highly correlated station pairs. The station with highest correlation coefficient was then used to extend the flow record through water year 2016 for each of the 16 stations. Our third method used inflows from a USGS study [*Faunt et al*., 2009] which developed estimates of CV inflows at 43 locations. We used the sum of the 43 USGS inflows to bias correct (using probability mapping) our 19-station totals.

The Q_{out} from both the CV and SSJT basins is defined as the sum of Delta outflow at Chipps Island and the East Bound California Aqueduct (USGS Station #10260776). We used the Delta outflow estimate by CDWR from Dayflow (http://www.water.ca.gov/dayflow/). Details of Dayflow are provided in the supporting information.

2.6. Reservoir Storage

According to CDWR (http://cdec.water.ca.gov/reservoir.html), as of 2015 there were 93 dams and reservoirs with storage capacities greater than 0.1×10^6 m^3 in the SSJT. The total storage capacity of these reservoirs according to CDWR is about 36.5 km^3 (http://cdec.water.ca.gov/misc/resinfo.html). Monthly time series storage data for the largest 22 reservoirs, which have aggregate storage greater or equal to 250×10^6 m^3 (totaling about 85% of total reservoir storage), were available. We acquired these data from USGS and CDWR through the California Data Exchange Center (CDEC) directly for the period 1980–2016 (http://cdec.water.ca.gov/misc/monthly_res.html and http://waterdata.usgs.gov/nwis/uv/?referred_module=sw). We aggregated the smaller dams into one equivalent reservoir with storage capacity of 5.3 km^3. We constructed a time series of storage for this single equivalent reservoir for the period 2002–2016, from available storage time series of small dams within the SSJT that were available from USGS, based on an assumption of similar seasonal storage variations of all small reservoirs. Only one of the 22 large dams is within the CV (Camanche Reservoir; capacity 0.5 km^3). We included storage variations of this reservoir in our estimates for CV and for the others in our estimates for the portion of SSJT outside of CV, although they had little effect on our results.

2.7. GRACE-Based Estimate of Groundwater Storage Change

We used GRACE Release 05 (RL05) data from the Center for Space Research (CSR, University of Texas at Austin), with adjustments for mass change over the CV associated with soil moisture variations explained in section 2.3. We added missing degree 1 spherical harmonic coefficients (geocentric offset) in RL05 data using values calculated based on ocean and atmospheric models and GRACE coefficients for degrees 2 and higher following *Swenson et al.* [2008]. The degree 2 coefficients were then replaced with the solutions from satellite laser ranging [*Cheng et al.*, 2011]. We applied the decorrelation filter [*Duan et al.*, 2009] and Gaussian smoothing with a 300 km radius [*Guo et al.*, 2010]. We reduced the leakage error caused by this low-pass filtering by performing locally constrained forward modeling [*Chen et al.*, 2016; *Long et al.*, 2016], which is an iterative correction process that adjusts the filtered signal to match the reference. This is an advance relative to previous attempts to use GRACE data to estimate groundwater variations in CV and/or SSJT and avoids the need for rescaling to compensate for GRACE leakage effects using results from land surface models (see *Scanlon et al.*, 2012). The locally constrained forward modeling proceeds by first obtaining the filtered groundwater storage anomalies by subtracting the filtered soil moisture (from the Noah-MP model, which typically had interseasonal soil moisture variations that were intermediate among the three LSMs) from the filtered GRACE total water storage anomalies [*Scanlon et al.*, 2012]. Then, we implemented constrained forward modeling over the SSJT Basin to reduce the leakage effects based on the assumption that the groundwater signal is mainly confined to the CV. This approach, described in detail by *Long et al.* [2016], uses the filtered groundwater storage signal as a reference rather than LSM output. We subtracted monthly changes in the other storage components (soil moisture, SWE, and reservoir storage) from the GRACE-based monthly total water storage change estimates to produce our GRACE-based estimate of groundwater storage change. The sources of our soil moisture, SWE, and reservoir storage estimates are described in sections 2.3, 2.4, and 2.6, respectively.

3. Results

Figure 2 shows the April 2002 to September 2016 time series of cumulative (monthly) water balance changes, corresponding to ΔGW in equation (1), for CV (similar results for non-CV are shown in Supporting Information Figure S2). We estimated the uncertainty bounds for (partial) 2016 from linear regression extension as Daymet, PRISM, and NCDC precipitation data sets were not available for 2016. We fit linear regressions and estimated trends in the inferred ΔGW over the drought periods January 2007 to December 2009 and October 2012 to September 2016. Over CV, the inferred ΔGW is -20.7 km^3 over the entire period April 2002 to September 2016 averaged over all data sources (approximately the midpoint of the range shown in Figure 2). The rates of decline in ΔGW over the two drought periods are higher than the long-term average, and the recent drought (2012–2016) has a higher rate of decline (10.0 $\pm$ 0.2 km^3/yr) than the earlier (2007–2009) drought (5.5 $\pm$ 0.3 km^3/yr). Over the non-CV region, ΔGW is also negative (-13.3 km^3; see Figure S2), however not so much as in CV which is expected due to much greater consumptive water use in the CV. Our estimated decreasing trend from April 2006 to March 2010 in CV is -4.1 ± 0.2 km^3/yr compared with -6.0 km^3/yr from *Famiglietti et al.* [2011], who based their analysis on GRACE (see below). For April 2006 to September 2009, our rate of decrease in ΔGW trend is -4.2 ± 0.3 km^3/yr compared with -7.8 km^3/yr in *Scanlon et al.* [2012], who also based their analysis on GRACE.

Figure 3 shows our inferred ΔGW using GRACE data processed as described in section 2.7. Our best-estimate rate of change in ΔGW from GRACE is -64.6 km^3 over the period April 2002 to September 2016, as compared with -20.7 km^3 from our water balance. For the drought periods January 2007 to December 2009 and October 2012 to September 2016, we estimate ΔGW trends of -5.5 km^3/yr from GRACE (as compared with -5.5 km^3/yr from our water balance approach) and -11.2 km^3/yr (compared with -10.0 km^3/yr from our water balance approach). In short, our water balance estimates of groundwater loss during drought periods are quite close to those inferred from GRACE; however, our water balance estimates show substantial groundwater recovery during nondrought periods that is not inferred from GRACE. Estimated errors for the GRACE estimates are about $\pm$1.4 km^3/yr for 2007–2010 and $\pm$1.3 km^3/yr for 2012–2016, where the uncertainty bounds are one-σ fitting errors (and do not include other error sources, notably those associated with leakage and other scale effects associated with the small size of the CV relative to the GRACE footprint). The estimated confidence bounds for the water balance estimates ($\pm$0.2 to $\pm$0.3 km^3/yr for the drought periods) are smaller than for GRACE; however, they likewise are regression errors that cannot represent all sources of uncertainty and therefore almost certainly are underestimates. For the period April 2006 to September 2009 noted by *Scanlon et al.* [2012], we estimate ΔGW of -7.9 ± 1.3 km^3/yr as compared with their -7.8 km^3/yr, although we note that both estimates are from GRACE and therefore are subject to common errors (furthermore,

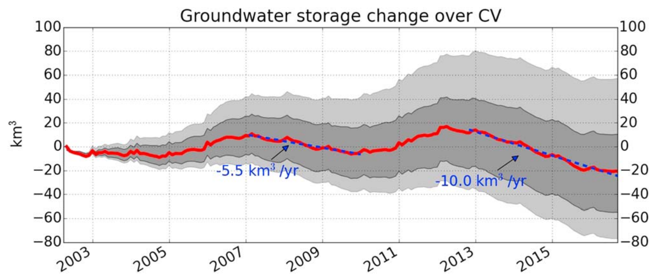

Figure 2. Monthly groundwater storage time series plots for CV over April 2002 to September 2016. In each subplot, light grey shading shows the range of all ensembles and dark gray shows the inner quartiles. The red line is the individual ensemble member closest to the ensemble mean. The two blue lines are linear regressions for the drought periods in January 2007 to December 2009 and October 2012 to September 2016.

this period overlaps substantially with our first drought period, for which, as noted above, our water balance and GRACE estimates match closely). Our GRACE-based ΔGW estimate of −7.2 ± 1.0 km^3/yr from April 2006 to March 2010 compares with −6.0 km^3/yr from [*Famiglietti et al.* [2011].

4. Interpretation

As compared with previous (extrapolated) GRACE-based estimates, our estimate of the rate of long-term groundwater loss in the CV is about 40 km^3 smaller over the 14-1/2 year GRACE period. For both the 2007–2009 drought and the 2012–2016 droughts, our water balance-based estimate is about the same as the GRACE-based estimates. We investigated the various terms in the water balance during the two drought periods (see Supplement). The balance (inferred ΔGW) over CV is dominated by surface inflows, surface outflows, precipitation, and evapotranspiration. Precipitation variations over the four data sets we used (Figure S3) are generally modest (maximum variation about 2 km^3/yr) over the CV, and the differences between estimates tend to be consistent over time (i.e., the highest estimate is the highest for both drought periods). Surface outflows are well gauged, and the errors are thought to be small relative to errors in inflows, which are not entirely gauged; some inflows were estimated from other gauged inflows (see section 2.5 and supporting information). Hence, variations in the three estimates we used are larger than for the outflows, with typical ranges of 4 km^3/yr, although these are generally consistent from year to year, and the variations tend to be smaller during the drought periods. ET is a combination of model-based estimates for the unirrigated area and PM ET_0 (rescaled based on CADWR information specific to CV) for the irrigated area. Because we used a single estimate (rescaled PM ET_0) for the irrigated areas, the range in our ET estimates, which reflects variations in the unirrigated portion of the CV, underestimates the actual uncertainty. Comparing the relevant figures in the supporting information for the recent drought as compared with the 2007–2009 drought, precipitation was slightly lower, and ET was higher (despite reduction in the irrigated area by about 7%). Inflows were slightly lower, but outflows were lower as well, the result of which was that net inflows (inflows − outflows) were lower by about 3 km^3 in 2012–2016 compared with 2007–2009. The balance of all of the terms, as indicated above, was negative during the 2012–2016 drought, i.e., our ΔGW estimate for the 2012–2016 versus 2007–2009 drought is more negative (by 4.5 km^3/yr, which is due to the combination of lower net inflows and higher ET in the recent drought). There is some uncertainty in the reduction of irrigated area during the recent drought; we took our estimated 7% from *Melton et al.* [2015]. Figure S11 shows that ET over the irrigated region during the recent drought computed on a per unit area basis was considerably higher than for the 2007–2009 drought period (by about 106 mm/yr, as compared with the 2002–2011 average of 708 mm/yr). To investigate the causes of increased 2012–2016 ET, we analyzed individual irrigated grid cells with no cropping pattern change over our study period, located at about the midpoint (north-south) of the CV. Figure S13 shows the interannual variability in ET for the two fixed agricultural crop types we used (each of which is a composite of a number of different crops). The increase in ET during the recent drought for the single grid cell was about 8% of the study period

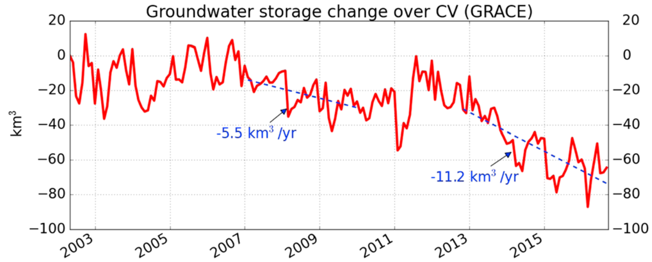

Figure 3. Groundwater anomaly time series estimate from GRACE satellite data; blue lines are linear regressions for the same drought periods as in Figure 2.

average. The drought period net radiation was quite similar (varies by ~1%) compared to the long-term mean; the increase in ET is attributable mostly to warmer summer temperatures (about 0.5 degrees for the growing season) and higher vapor pressure deficit (VPD). Therefore, the aggregate ~15% increase in ET during 2012–2016 is attributable to the combined effect of the transition from row crops to trees and the combined effects of warmer temperature and higher VPD. We note that our estimates make use of crop coefficients (from CA DWR), and the inferred effect of the transition from row crops to trees is strongly dependent on the DWR estimates of differences in crop coefficients, which incorporate uncharacterized uncertainty.

Both our water balance-based and GRACE-based ΔGW estimates are subject to errors, not all of which can be estimated explicitly. As noted above, CV is much smaller in area than the effective footprint of GRACE, which results in considerable unquantified uncertainty in our GRACE-based estimates. While it is comforting that our GRACE-based estimates of ΔGW for the earlier 2007–2009 drought are comparable with previously published estimates, all GRACE-based estimates of CV ΔGW are subject to the scale mismatch problem noted above. On the other hand, the water balance method inherits uncertainty from a variety of sources in each of the individual terms, not all of which is well quantified. Arguably, the major errors that are not well represented by our multiple data sources are the crop water use portion of ET and surface inflows from ungauged sources. We note also the important (but uncertain) effect of reduction in irrigated area during the recent drought. There also is uncertainty (which we did not attempt to represent) in the magnitude and timing of transitions from annual to perennial crops in the CV; while a rapid transition is known to have occurred, the transition time may have been longer than we assumed. The timing of this transition would affect variations in our estimates of ΔGW for 2007–2009 versus 2012–2016 as we allocated all of the transition to the post-2011 period.

An obvious question is the reason for differences between our water balance and GRACE estimates for inter-drought periods. One possible reason is the GRACE scale mismatch noted above; our GRACE estimates essentially attribute all of the groundwater change to the effective GRACE footprint to the CV. Clearly, this may not be the case, but substantial groundwater loss outside the CV during non-drought periods does not seem likely either. Other possible sources of the differences are our estimates of net outflow (from Dayflow) which is a large term in the water balance, or errors in the inflows (some of which are ungauged), although it is not clear why either would have systematic differences in moderate to high flow years.

5. Summary and Conclusions

Our water balance estimates indicate that ΔGW was negative over the two major drought periods within the 14-1/2 year time period of our study, but there was substantial recovery not only in high inflow years (e.g., 2006 and 2010) but during much of the interdrought periods, so the inferred groundwater loss over the entire period was much smaller than the sum of losses during the two drought periods. GRACE results are somewhat more noisy but show negative ΔGW over most of the period aside from short periods of increases (much shorter than for the water balance estimates) at roughly the same times as the water balance model. Over the entire period, our water balance estimate is that over 20 km^3 of groundwater has been lost from the CV; the GRACE-based estimate is almost triple this amount.

During the two prominent drought periods during our study period, 2007–2009 and 2012–2016, the net rate of groundwater extraction increased substantially; essentially all of the total groundwater loss in the 14-1/2 year period occurred during the 7 years of two severe droughts (in fact, during most of the rest of the period, groundwater storage recovered, although not enough to fully offset the drought losses). ΔGW during both droughts clearly is related to reduced net inflow to CV during the drought periods. During the recent drought, ΔGW was more negative, which is attributable in part to smaller net inflows but also to a combination of a transition from row to tree crops, along with warmer growing season temperatures and larger VPD. Larger groundwater loss during the recent drought occurred despite reductions in irrigated area.

Finally, while GRACE provides useful confirmation of the water balance estimates, it does not provide insights into the causes of differences. Furthermore, the relatively small area of CV is challenging for the GRACE-based analysis. While the GRACE and water balance estimates show similar patterns (e.g., amplified ΔGW in the recent, as compared with the earlier drought), unquantified (and perhaps unquantifiable) uncertainties may be responsible for some of those differences.

Acknowledgments
The authors acknowledge funding from NOAA's Climate Program Office to UCLA under grant NA14OAR4310293 and to the University of Houston from NASA under GRACE and SERVIR grants NNX12AJ95G and NNX16AN35G, respectively. We appreciate the assistance of Professor Qiuhong Tang and Ms. Lei Huang for the Chinese Academy of Sciences Institute of Geographic Sciences and Natural Resources Research, who provided us with access to an extended version of the satellite-derived ET data used in *Famiglietti et al.* [2011] and in an earlier version of this paper. We thank Peter H. Gleick and an anonymous reviewer for comments that helped improve the paper. The monthly data used in this study is archived at https://ucla.box.com/v/data-grl-ca-groundwaterloss; contact muxiao@ucla.edu for access to the data.

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