

Author response to topical editor comments – “Using satellite-based estimates of evapotranspiration and groundwater changes to determine anthropogenic water fluxes in land surface models”

## Author response to topical editor comments

We thank the topical editor, Professor Wilco Hazeleger, for his comments on our manuscript, “Using satellite-based estimates of evapotranspiration and groundwater changes to determine anthropogenic water fluxes in land surface models”. We detail our responses to his comments below in this font (Arial, font size 12 point, blue text).

“Thank you for your revised manuscript and responses to the reviewers. Both reviewers have reviewed your paper again and are satisfied with your responses. Your paper will be published

The rebuttal provides more detail than the actual revised manuscript. Therefore, I would like to ask you to further revise the manuscript and add more detail to the manuscript itself (in particular the responses to reviewer 1).”

Additional details from the initial response to reviewers’ comments (especially reviewer 1) have been added throughout the manuscript. We have also added three references that show the application of satellite ET products for water rights adjudication and operational water management.

Besides the inclusion of additional details, we have made a very slight revision to Fig. 2 where the picture of the river has been changed. This was done at the request of Prof. M-H. Lo, due to copyright issues with the initial version. No other changes to the model schematic were made.

1 **Using satellite-based estimates of evapotranspiration and**  
2 **groundwater changes to determine anthropogenic water**  
3 **fluxes in land surface models**

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5 **R.G. Anderson<sup>1,\*</sup>, M.-H. Lo<sup>2,\*</sup>, S. Swenson<sup>3</sup>, J.S. Famiglietti<sup>4</sup>, Q. Tang<sup>5</sup>, T. H.**  
6 **Skaggs<sup>1</sup>, Y.-H. Lin<sup>2</sup>, and R.-J. Wu<sup>2</sup>**

7 [1]{USDA, Agricultural Research Service, US Salinity Laboratory, Contaminant Fate and  
8 Transport Unit, Riverside, California, USA}<sup>1</sup>

9 [2]{National Taiwan University, Department of Atmospheric Sciences, Taipei, Taiwan}

10 [3]{National Center for Atmospheric Research, Advanced Study Program, Boulder, Colorado,  
11 USA}

12 [4]{ Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr.,  
13 Pasadena, CA 91109, USA}

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1 [5]{Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of  
2 Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences,  
3 Beijing, China}

4 [\*] These authors contributed equally to this manuscript.

5 Correspondence to: R.G. Anderson (ray.anderson@ars.usda.gov) and M.-H. Lo  
6 (minhuilo@ntu.edu.tw)

7

## 8 **Abstract**

9 Irrigation is a widely used water management practice that is often poorly parameterized in  
10 land surface and climate models. Previous studies have addressed this issue via use of  
11 irrigation area, applied water inventory data, or soil moisture content. These approaches have  
12 a variety of drawbacks including data latency, accurately prescribing irrigation intensity, and a  
13 lack of conservation of water volume for models using a prescribed soil moisture approach.  
14 In this study, we parameterize irrigation fluxes using satellite observations of  
15 evapotranspiration (ET) compared to ET from a suite of land surface models without  
16 irrigation. We then incorporate the irrigation flux into the Community Land Model (CLM),  
17 and use a systematic trial-and-error procedure to determine the ground- and surface-water  
18 withdrawals that are necessary to balance the new irrigation flux. The resulting CLM  
19 simulation with irrigation produces ET that matches the magnitude and seasonality of  
20 observed satellite ET well, with a mean difference of 6.3 mm/month and a correlation of 0.95.  
21 Differences between the new CLM ET values and satellite observed ET values are always less  
22 than 30 mm/month and the differences show no pattern with respect to seasonality. The

1 results reinforce the importance of accurately parameterizing anthropogenic hydrologic fluxes  
2 into land surface and climate models to assess environmental change under current and future  
3 climates and land management regimes.

4

## 5 **1 Introduction**

6 Agricultural irrigation is the dominant anthropogenic use of surface and groundwater  
7 globally (Postel et al., 1996; Siebert et al., 2010; Wisser et al., 2008). Irrigation, and its  
8 associated movement, storage, and depletion of surface and ground waters, can induce major  
9 changes in regional hydrology (Ferguson and Maxwell, 2012; Haddeland et al., 2006; Tang et  
10 al., 2008) and climatology (Kueppers et al., 2007; Lo and Famiglietti, 2013). Irrigation  
11 demand has resulted in groundwater depletion across multiple regions of the world  
12 (Famiglietti, 2014), including the Western United States (Famiglietti et al., 2011; Scanlon et  
13 al., 2012), the Middle East (Voss et al., 2013), and India (Rodell et al., 2009). Globally, this  
14 depletion has a net effect on continental runoff and sea level rise (Van Dijk et al., 2014; Wada  
15 et al., 2010). Given the impact of irrigation on hydrology, climate, and food production, it is  
16 crucial to be able to accurately model irrigation in current land surface models (e.g. Rodell et  
17 al., 2004; Xia et al., 2012a) in order to assess potential land-atmosphere feedback mechanisms  
18 that may impact future water availability for irrigation, municipal, and environmental uses.

19 Current land surface models (LSMs), such as the Community Land Model (CLM –  
20 Oleson et al., 2008), that are run without an irrigation parameterization usually have  
21 unrealistically low evapotranspiration in agricultural regions (Lei et al., 2015; Lo et al., 2013;  
22 Lobell et al., 2009; Sorooshian et al., 2011; Ozdogan, 2010). Given that irrigation is

1 predominantly used in semi-arid to arid regions and/or regions where precipitation and  
2 growing seasons are asynchronous, this lack of parameterization can be highly significant for  
3 modeling regional hydrology. Some LSMs and their associated regional climate models  
4 (RCMs) or global climate models (GCMs) prescribe enhanced water availability in  
5 agricultural regions due to irrigation. Representations vary considerably depending on the  
6 simulation; they include (1) prescribing a static soil moisture at field capacity for all irrigated  
7 crops (Kueppers et al., 2007), (2) prescribing a total flux based on a prescribed estimate across  
8 the entire agricultural domain (Lo and Famiglietti, 2013), (3) assigning a fraction of land  
9 surface to be irrigated (Leng et al., 2013 and 2014; Lobell et al., 2009; Tang et al. 2007), and  
10 (4) assigning a seasonally-based soil moisture curve to represent irrigation only during the  
11 active irrigation season (Sooroshian et al., 2011). Each of these approaches has significant  
12 disadvantages. The approaches that assign irrigation based on soil moisture (approaches 1  
13 and 4 above) do not consider basin scale limitations on available irrigation water (particularly  
14 during dry years) and may overestimate the total amount of irrigation water as well as the  
15 differential impacts between dry and wet years. The prescribed/inventory based flux  
16 (approach 2) has the advantage of a mostly conserved water budget, but there are latency  
17 issues for much of the data which are based on potentially outdated or incomplete national  
18 and regional statistics. Assigning a fraction of land area to be irrigated (approach 3) has the  
19 disadvantage of assuming a particular irrigation intensity, and this approach cannot easily  
20 distinguish between full and deficit irrigation. Finally some prescribed flux approaches work  
21 primarily where groundwater is the sole source for applied irrigation and others based on  
22 irrigated area may not account for irrigation intensity. While process differences in  
23 RCMs/GCMs and LSMs can account for variations in the sensitivity of irrigation-climate

1 feedbacks and teleconnections, it should be noted that studies with different irrigation  
2 parameterizations over the same region have had significantly different climatic feedbacks  
3 and downwind impacts (Kueppers et al., 2007; Lo and Famiglietti, 2013; Lo et al., 2013;  
4 Sooroshian et al., 2011).

5         Satellite remote sensing can be used to provide more robust, regional observations of  
6 irrigation water consumption. Evapotranspiration (ET) is routinely monitored over irrigated  
7 agriculture using observations of surface temperature and vegetation greenness (Allen et al.,  
8 2007; Anderson et al., 2007; Tang et al., ~~2009~~-2009a). [The precision and accuracy of](#)  
9 [satellite ET algorithms, particularly those that incorporate land surface temperature data, is](#)  
10 [sufficiently high to quantify water management and water rights transfers \(Cuenca et al.,](#)  
11 [2013; Steele et al. 2015; Tang et al., 2009b\)](#) When combined with satellite gravimetry  
12 (Swenson and Wahr, 2003) and large scale meteorological products (Hart et al., 2009) the  
13 amount of irrigation water coming from surface water supplies (Anderson et al., 2012) and net  
14 groundwater depletion (Famiglietti et al., 2011) can be assessed. Together, these satellite  
15 algorithms can provide a much more detailed and current input dataset for LSMs and  
16 RCMs/GCMs to assess irrigation-climate feedbacks.

17         In this study, we follow on the work of Lo and Famiglietti (2013) by using remote  
18 sensing observations of ET, surface water consumption, and total water storage anomalies to  
19 infer surface and ground water fluxes, instead of using a static surface and ground water  
20 irrigation inventory dataset for parameterization. We use these fluxes to improve and test an  
21 irrigation parameterization in the Community Land Model (Lawrence et al., 2011; Oleson et  
22 al., 2008) in a well instrumented basin with a large amount of irrigated agriculture, the Central

1 Valley of California. We use ET from an ensemble of three satellite products, combined with  
2 gridded precipitation, to determine the seasonality and interannual variability of additional ET  
3 from irrigation. We then use an iterative recharge parameterization, combined with satellite  
4 gravimetry, to determine relative amounts of irrigation applied from groundwater and surface  
5 water. The results show the ability and value of using diagnostic remote sensing observations  
6 and models for improving prognostic algorithms necessary to increase LSM skill in predicting  
7 hydrologic, biogeochemical, and climatic impacts and feedbacks under future greenhouse gas  
8 emission and land used change scenarios.

9

## 10 **2 Methods**

### 11 **2.1 Study region**

12 We evaluate our approach in the Central Valley of California, which is a large  
13 (~54,000 km<sup>2</sup>), low elevation (<200 m a.s.l) region (Fig. 1). The Central Valley is a highly-  
14 productive agricultural region, with over 200 cultivated crops and an annual crop value of  
15 more than \$35 billion US Dollars in 2012 (California Department of Food and Agriculture,  
16 2014, USDA National Agricultural Statistics Service, 2014). Relevant aspects of the Central  
17 Valley's geology (Planert and Williams, 1995; Faunt et al., 2009), climatology (Zhong et al.,  
18 2004), hydrology (Scanlon et al., 2012), and anthropogenic inter-basin water transfers (Chung  
19 and Helweg, 1985; Fischhendler and Zilberman, 2005) are extensively reviewed elsewhere.  
20 Average (2004-2009 water years) blue water (surface water plus ground water) consumption  
21 was  $2.03 \pm 0.02 \times 10^{10} \text{ m}^3$  as determined using an inventory method (Anderson et al., 2012).

1 Agriculture in the Central Valley is heavily dependent upon irrigation from both surface and  
2 ground waters, with a large variation in the relative consumption of surface and ground water  
3 due to high inter-annual variation in precipitation and an almost complete lack of precipitation  
4 during the peak summer growing season (Anderson et al., 2012; Scanlon et al. 2012). [In  
5 particular, many farmers have both surface and groundwater irrigation infrastructure and will  
6 pump more groundwater when surface water deliveries are insufficient.](#) In addition to its  
7 agricultural importance, the Central Valley has multiple attributes that are useful for  
8 developing and validating new model processes to better represent anthropogenic impacts on  
9 regional hydrology and climatology. These include (a) well understood hydrogeology,  
10 surface water use, and extensive *in-situ* meteorological observations (Hart et al., 2009; Faunt  
11 et al., 2009; Planert and Williams, 1995); (b) well constrained groundwater systems with little  
12 to no subsurface outflow to the ocean (Faunt et al., 2009); (c) well gauged and modeled  
13 surface water flows into and out of the Valley (Anderson et al., 2012); and (d) anthropogenic  
14 hydrologic processes (irrigation, crop evapotranspiration, and drainage) that have a very  
15 distinct seasonality from the winter precipitation and spring runoff dominated natural  
16 processes that occurred prior to irrigation and agricultural development (Lo and Famiglietti,  
17 2013).

18 Previous remote-sensing based and mechanistic modeling studies have shown sustained  
19 and substantial depletion of groundwater in the Central Valley (Famiglietti et al., 2011; Faunt  
20 et al., 2009), which has accelerated in the most recent drought from 2012 to present (Borsa et  
21 al., 2014; Famiglietti, 2014). [This reliance on remote sensing and modeling is due, in part, to  
22 the historically minimal well reporting requirements from the State of California, resulting in](#)



1 | [a relative paucity of publicly available groundwater extraction data.](#) Recent groundwater  
2 regulation legislation will likely restrict future groundwater pumping differentially across  
3 groundwater basins (Harter and Dahlke, 2014), making alternative irrigation methods and  
4 strategies, such as drip and deficit irrigation, more common and potentially altering the  
5 amount and seasonality of irrigation. The potential for rapid hydrologic changes in the  
6 Central Valley ([such as sudden restrictions on ground water pumping or wholesale](#)  
7 [conversions in irrigation method](#)) is one reason why a potentially dynamic, satellite-based  
8 irrigation parameterization would be useful for land surface modeling.

## 10 | **2.2 Evapotranspiration, precipitation and total water observations**

11 We calculated the monthly mean and standard deviation of evapotranspiration (ET) using an  
12 ensemble of three products. One is a surface energy balance product (Anderson et al., 2012)  
13 based on the SEBAL algorithm (Bastiaanssen et al., 1998) that is applied to the Central Valley  
14 at 250 m resolution using a 250 m vegetation index and 1 km thermal data from the  
15 MODerate resolution Imaging Spectroradiometer (MODIS) in conjunction with gridded  
16 meteorology. The second product (Tang et al., [20092009a](#)) uses the scatter plot relationship  
17 between the vegetation index and surface temperature (VI-Ts) to estimate the Evaporative  
18 Fraction (EF) and ET at 0.05° resolution using MODIS vegetation and thermal data in  
19 conjunction with Geostationary Operational Environmental Satellite (GOES) surface radiation  
20 products. The third product (Jin et al., 2011), uses the Priestley-Taylor equation (Priestley  
21 and Taylor, 1972) with the coefficient term ( $\alpha$ ) optimized using Ameriflux data and net  
22 radiation and ground heat flux parameterized from the MODIS and Clouds and the Earth's

1 Radiant Energy System (CERES) instruments to estimate ET at 1 km resolution. All three  
2 products were clearly able to distinguish peak summertime ET in the Central Valley, which is  
3 asynchronous with largely winter precipitation and which is a characteristic sign of irrigation.  
4 Other ET products (e.g. Miralles et al., 2011; Mu et al., 2011; Jung et al., 2010) were not used  
5 as they were either too coarse in resolution ( $>0.25^\circ \times 0.25^\circ$  cell size) or were unable to detect  
6 irrigation in the Central Valley.

7 Monthly precipitation (approximately 4 km spatial resolution) was obtained using the  
8 Parameter-elevation Regressions on Independent Slopes Model (PRISM), which interpolates  
9 station precipitation data, accounting for orography (Daly, 1994; Daly et al., 2008).  
10 Observations of total water changes were obtained from Gravity Recovery And Climate  
11 Experiment (GRACE) mission (Tapley et al., 2004) for the entire Sacramento and San  
12 Joaquin River Basins (including the usually endoheric Tulare Lake Basin). Using the  
13 methodology of Famiglietti et al. (2011), groundwater changes were obtained by removing  
14 snow, soil moisture, and surface reservoir storage variations from the total water storage  
15 anomalies from GRACE. Groundwater changes in the combined basins were assumed to  
16 have occurred entirely within the Central Valley where major agricultural and municipal wells  
17 exist rather than in the non-irrigated, sparsely-populated, mountainous regions surrounding  
18 the Valley.

19

## 20 **2.3 Land surface models**

21 For intercomparison with satellite observed fluxes and determination of additional water

1 application in CLM, we use an ensemble (9 members) of three North American Land Data  
2 Assimilation System (NLDAS-2 - Mitchell et al., 2004; Xia et al., 2012b), four Global Land  
3 Data Assimilation System (GLDAS-1 - Rodell et al., 2004) outputs, and two CLM  
4 simulations. For NLDAS-2 and GLDAS-1, we used the Noah, Mosaic, VIC, or CLM models  
5 from each system with the primary NLDAS-2 and GLDAS-1 forcings. Along with the  
6 NLDAS/GLDAS outputs, we also include outputs from different versions of the CLM  
7 (including CLM3.5 and CLM4) with the GLDAS-1 atmospheric forcings. [Our intention with](#)  
8 [including this number of permutations of LSMs and LSM forcings was to increase our](#)  
9 [confidence in the mean and uncertainty of non-irrigated ET.](#) In addition, we evaluated the  
10 CMIP5 control outputs (Taylor et al., 2012) to assess the larger performance of climate  
11 models in assessing latent heat fluxes across agricultural regions. Details about the CMIP5  
12 models and simulations are provided in supplemental section S1. For our study, CLM is run  
13 at 0.125° by 0.125° grid cells with 30 minute temporal resolution.

14 The water budget for the soil layer and groundwater in CLM can be written as:

$$\Delta SM = P - ET - Q_S - q_{recharge} \quad (1)$$

$$\Delta GW = q_{recharge} - Q_d \quad (2)$$

15 where  $\Delta SM$  is soil moisture change,  $P$  is precipitation,  $ET$  is evapotranspiration,  $Q_S$  is surface  
16 runoff,  $q_{recharge}$  is groundwater recharge,  $\Delta GW$  is groundwater storage changes, and  $Q_d$  is  
17 groundwater discharge. However, equations 1 and 2 only reflect the natural hydrology and  
18 neglect the substantial contribution of irrigation in major agricultural regions as previously  
19 discussed. A more reasonable equation should include the aforementioned irrigation water  
20 from surface (river) water ( $SW_{WD}$ ) and from groundwater withdrawal ( $GW_{WD}$ ) as shown in

1 Figure 2 and equations 3 and 4. We will incorporate the estimated irrigation water use into  
2 the CLM version 4 and the withdrawn water in the irrigation process will be treated as an  
3 extra water input (effective precipitation).

$$\Delta SM = P - ET - Q_s - q_{recharge} + GW_{WD} + SW_{WD} \quad (3)$$

$$\Delta GW = q_{recharge} - Q_d - GW_{WD} \quad (4)$$

4

## 5 **2.4 CLM groundwater and surface water application parameterization**

6 We use the difference ( $\Delta ET$ ) between remote sensing observed ET ( $ET_{obs}$ ) and the original  
7 model parameterized ET ( $ET_{om}$ ) to estimate total applied surface and groundwater as shown  
8 in equation 5.

$$\Delta ET = ET_{obs} - ET_{om} = SW_{WD} + GW_{WD} \quad (5)$$

9  $\Delta ET$  in equation 5 is determined as an inter-annual (2004-09) mean difference between  
10 satellite observed and modeled ET. Water is applied evenly in CLM4 throughout the primary  
11 growing and irrigation season (May-October). We can partition the total withdrawn irrigation  
12 water into  $SW_{WD}$  and  $GW_{WD}$  by requiring that equations 3 and 4 are both satisfied by the  
13 CLM4 simulation. A systematic, trial-and-error procedure is used to determine the necessary  
14 partitioning using groundwater recharge since it is a common variable to both equations. For  
15 each trial, a value of  $q_{recharge}$  is guessed.  $GW_{WD}$  is then determined from re-arranging  
16 equation 4, with  $\Delta GW$  and  $Q_d$  being set to average values derived from processed GRACE  
17  $\Delta GW$  and the baseline simulations for the study period (2004-2009), respectively.  $SW_{WD}$  is  
18 then found as a residual from equation 5, and CLM4 is run. The model run generates a

1 simulated recharge (equation 3). If the trial (or “parameterized”) recharge value and the  
2 simulated recharge value agree, then equations 3 and 4 are satisfied and the partitioning is  
3 accepted. Equation 5 notes that all abstracted water eventually contributes to ET. While this  
4 assumption may be violated at a field scale, it likely holds at a regional scale in the Central  
5 Valley where extensive conjunctive use and reuse of water occurs (Canessa et al., 2011).

6 To find the correct recharge and withdrawal partitioning, we ran a series of trials in which the  
7 parameterized recharge was increased in 5 mm/year increments, from 20 mm/year (the first  
8 point in the left in Figure 5 and the minimum value of recharge necessary to generate the  
9 baseline  $Q_d$  of 20 mm/year) to 115 mm/year. With the average  $\Delta GW$  and  $Q_d$  (section 3.1),  
10 this corresponds to a  $GW_{WD}$  range of 60 to 155 mm/year. The procedure assumes only  
11 minimal differences exist in  $Q_d$  computed for the baseline and trial simulations, an  
12 assumption that we verified by inspecting irrigation simulation outputs. Since the Central  
13 Valley aquifer system is a combination of unconfined and confined aquifers, we assume that  
14 groundwater withdrawals are equally distributed between both types of aquifers (Fig 2).  
15 Because the CLM lacks a confined aquifer component, confined withdrawal is taken from a  
16 hypothetical water store, which is constrained together with the unconfined aquifer using  
17 equation 4 and GRACE estimated groundwater. Unconfined withdrawals were taken from the  
18 saturated zone of the soil.

19

### 20 **3 Results and Discussion**

### 1 **3.1 Existing model parameterizations and satellite observed hydrologic** 2 **fluxes**

3 Monthly satellite observed and simulated evapotranspiration (ET) for the Central Valley  
4 showed strong and differing seasonality (Fig. 3a). Satellite observed monthly ET ranged from  
5 13 mm (December 2009) to 106 mm (July 2005). Seasonal maxima and minima of ET  
6 coincided with seasonal maxima and minima of regional solar radiation and temperatures that  
7 control potential ET (solar radiation and temperature data not shown). Over the entire 2004-  
8 2009 study period, mean ( $\pm$  one standard deviation) satellite observed ET was  $54.6 \pm 12.8$   
9 mm/month (655 mm/year). GLDAS-1, NLDAS-2, and CLM simulated ET was substantially  
10 lower than satellite observed ET (Fig. 3a), with mean simulated ET of  $23.3 \pm 5.0$  mm/month  
11 (280 mm/year). Simulated ET ranged from 19 mm/month (September 2008) to 69 mm/month  
12 (April 2006). GLDAS-1/NLDAS-2/CLM simulated seasonal maxima and minima of ET  
13 coincided with maximal and minimal natural soil moisture availability following the end of  
14 the winter rainy season and at the end of the dry summer season (Fig. 3c). On an average  
15 seasonal basis, satellite observed ET showed the greatest difference from simulated ET in  
16 July, when satellite ET was 79 mm/month larger. In winter (November-February), observed  
17 ET exceeded simulated ET by less than 10 mm/month (Fig. 3c).

18 While the seasonality of satellite observed and simulated ET was different, the annual patterns  
19 of ET matched annual precipitation well, although satellite observed ET had considerably  
20 lower interannual variation than simulated ET (Fig. 3). Annual precipitation ranged from 202  
21 mm/year (2007 calendar year) to 416 mm/year (2005 calendar year). Mean ( $\pm$  one standard  
22 deviation) calendar year precipitation for 2004-2009 was  $315.8 \pm 84.8$  mm/year. Annual

1 changes in groundwater vary considerably from year to year, with a maximum increase of 120  
2 mm/year in 2006 and a maximum decrease of 220 mm/year in 2007 (Fig. 4). Mean  
3 groundwater decrease across the entire study period is approximately 60 mm/year. Annual  
4 precipitation and groundwater change are well correlated ( $r=0.78$ ), with the largest  
5 groundwater decrease occurring in one of the driest years in California history (2007) and the  
6 largest increase in 2006 following a succession of wet years. Mean annual satellite observed  
7 ET showed less variation than precipitation, ranging from 624 mm/year in 2009 to 690  
8 mm/year in 2005. Since precipitation in the surface water source regions for the Central  
9 Valley (Sierra Nevada Mountains) is very well correlated with precipitation in the Valley  
10 (Daly, 1994; Daly et al., 2008), variations in precipitation are also assumed to be variations in  
11 surface water availability. Together, this lower variation in ET in spite of higher variation in  
12 precipitation and surface water availability and the inverse relationship between groundwater  
13 level change and precipitation is consistent with the relatively steady water demand from  
14 Californian agricultural crops, many of which are perennial crops with large, multi-year  
15 investments (Ayars, 2013; Blank, 2000), and the long-standing practice of increasing  
16 groundwater use to compensate for deficits in surface supplies and precipitation (Howitt,  
17 1991).

18

### 19 **3.2. Application of Groundwater and Surface Water in CLM and impact on CLM-** 20 **simulated ET**

21 The mean amount of additional water that is consumed or transpired under irrigation in the  
22 Central Valley is 376 mm/year (satellite observed ET minus mean GLDAS-1/NLDAS-2/CLM

1 ensemble simulated ET). The parameterized recharge estimates plotted against CLM  
2 simulated recharge are shown in Figure 5. Simulated recharge ( $q_{recharge}$ ) showed a more  
3 dampened response to a wide range of parameterized recharges, with simulated recharge  
4 ranging from 47 to 66 mm/year across the parameterized recharge space (20-115 mm/year).  
5 The parameterized and simulated recharge comes to convergence at approximately 55  
6 mm/year (Fig. 5), which is the value we used to partition applied surface water and  
7 groundwater. Using equation 4, we calculated mean applied groundwater ( $GW_{WD}$ ) as 95  
8 mm/year over the 2004-2009 study period. Mean applied surface water ( $SW_{WD}$ ) was 281  
9 mm/year.

10 The model optimized  $SW_{WD}$  compares well with previous remote sensing and high resolution  
11 inventory estimates of surface water consumption in the Central Valley. For the 2004-08  
12 water years, Anderson et al. (2012) found a mean ( $\pm$  uncertainty) surface water consumption  
13 of  $291 \pm 32$  mm/year using remote sensing and  $308 \pm 7$  mm/year using an inventory approach  
14 calculated from dam releases into the Central Valley, canal exports to coastal basins to the  
15 south, and outflow through the California Delta. The close comparison of these values to  
16  $SW_{WD}$  gives us further confidence in our optimization method and its underlying assumptions.

17 Figure 6 shows the impact of the irrigation water parameterization on CLM simulated ET  
18 compared to observational data. With the new parameterization, monthly CLM simulated ET  
19 ranged from a minimum of 10 mm (December 2008) to a maximum of 96 mm (June 2006),  
20 with a mean of 48.3 mm. The differences between CLM simulated ET and satellite observed  
21 ET (CLM minus satellite) ranged from -30 mm/month to 11 mm/month with a mean  
22 difference of -6.3 mm/month. There was low correlation between seasonality (month) and the



1 discrepancy between satellite observed and non-irrigated simulated ET ( $r < 0.5$ ) as assessed  
2 with a geometric mean regression. Conversely, the relationship between satellite observed  
3 monthly ET and CLM simulated ET was excellent ( $r = 0.95$ , slope = 0.94, intercept = -3.1  
4 mm/month).

5 With respect to other hydrologic fluxes, simulated groundwater base flow ( $Q_d$ ) changed little  
6 with irrigation over the 2004-09 study period (27 mm/year in experimental run versus 18  
7 mm/year in control – data not shown). Surface runoff ( $Q_s$ ) changed more considerably (68  
8 mm/year in experimental run versus 38 mm/year in control, which is an expected consequence  
9 due to the wet soil from irrigation leading to higher surface runoff. The small change in  $Q_d$   
10 despite additional irrigation concurs with GRACE-derived groundwater changes, simulated  
11 reductions in groundwater in CLM, and previous hydrogeologic observations that many rivers  
12 and streams in the Central Valley are now losing streams due to long-term groundwater  
13 depletion, [with some wells in the Southern Central Valley being over 1000 m deep](#) (Planert  
14 and Williams, 1995). The larger increase in  $Q_s$  may reflect on the ground spatial differences  
15 in cropping patterns and water management within the Central Valley. For example, the  
16 northern part of the Central Valley (Sacramento Valley) has extensive rice production that  
17 results in multiple flooding and drainage events in the course of a production season (Hill et  
18 al., 2006). Much of this water is reused further downstream (south). Other cropping systems,  
19 particularly those in parts of the southern Central Valley (San Joaquin Valley) affected by  
20 drainage issues, use tail water recovery systems as required by state and local regulations  
21 which minimize surface runoff from irrigation (Schwankl et al. 2007).

22

### 1 **3.3 Impact of parameterizations of irrigated agriculture in land surface** 2 **modeling**

3 The significant underestimation of peak growing season ET in irrigated agricultural regions is not  
4 confined to the NLDAS/GLDAS and default CLM models. Figure 7 shows the mean climatology  
5 of ET for the control runs of the CMIP5 models over the Central Valley compared to satellite  
6 observed ET. The mean ( $\pm$  one standard deviation) ET is  $45.9 \pm 15.8$  mm/month. While the peak  
7 ET of the mean of the CMIP5 ensemble is higher (68 vs. 48 mm/month) and later (May vs. April)  
8 than the NLDAS/GLDAS/CLM ensemble, the CMIP5 ET still is more than 100 mm/year lower  
9 than satellite observed ET (550 vs. 655 mm/year) and exhibits minima and maxima characteristic  
10 of the natural hydrologic cycle. Furthermore, some of the improved closure between CMIP5 and  
11 satellite observed ET compared to NLDAS/GLDAS/CLM could be due to substantially higher  
12 CMIP5 modeled ET during the winter. Despite the relatively large uncertainty of the CMIP5  
13 models over the Central Valley, the satellite observed ET for over half of the year is significantly  
14 outside of the CMIP5 envelope.

15 Compared with previous parameterizations of irrigation water in the Central Valley our remote-  
16 sensing based approach resulted in a lower consumed amount of water than the soil moisture-  
17 based parameterizations (Kueppers et al., 2007; Sorooshian et al., 2011) and a slightly higher  
18 amount of consumed water than a global inventory (Siebert et al., 2010), based approach (Lo and  
19 Famiglietti, 2013). For the summer months of May-August, a high soil moisture parameterization  
20 at field capacity (Kueppers et al., 2007) resulted in an annual summer irrigation water  
21 consumption of 612 mm/summer whereas a variable soil moisture parameterization (Sorooshian et  
22 al., 2011) resulted in a summer irrigation water consumption of 430 mm/summer. These values

1 do not include potential water consumption from the shoulder irrigation months of April,  
2 September, and October. The inventory data of Siebert et al. (2010) used in the Lo and  
3 Famiglietti (2013) parameterization was only about 25 mm lower (350 mm/year versus 376  
4 mm/year) than our remote sensing parameterization, but the amount of consumed water from  
5 groundwater (140 mm/year) was substantially higher than our applied groundwater (95 mm/year).  
6 Furthermore, our satellite-ET derived estimate is also likely to be a lower envelope estimate of  
7 applied water due to the slight increase in surface runoff observed in CLM. The overestimation of  
8 ET and latent heat fluxes with the soil moisture parameterization suggests challenges in using this  
9 type of parameterization; however, soil moisture parameterization may become significantly more  
10 feasible with precise and accurate regional and global soil moisture observations from upcoming  
11 missions such as the Soil Moisture Active Passive, whose outputs are specifically designed to  
12 improve inputs to numerical weather prediction and land surface models (Entekhabi et al., 2010).  
13 Currently, both inventory and remote sensing based approaches have sufficiently low spatial  
14 and temporal resolution so that irrigation water parameterization is typically done on inter-  
15 annual time scales for large basins. This temporal resolution for water parameterization  
16 works well for accurately modeling the hydrology of the Central Valley, likely due to the  
17 lower amount of inter-annual variation in ET and the use of groundwater to compensate for  
18 surface water deficits. However, it is unclear how well this approach will work in irrigated  
19 regions where ET may be more variable due to a lack of supplemental reservoirs and thus a  
20 necessary fallowing of land during dry periods. Current and future missions (GPM, SMAP,  
21 SWOT, GRACE-Follow On/GRACE II) have the potential to sufficiently improve the  
22 resolution of satellite hydrologic products to enable annual quantification of surface and

1 ground water application at higher spatial resolution (Biancamaria et al., 2010; Entekhabi et  
2 al., 2010, Smith et al., 2007; Zheng et al., 2015). These higher resolution parameterizations  
3 may enable better quantification of hydrologic impacts of changing management and cropping  
4 patterns, including shifts in irrigation regimes and changes between annual and perennial  
5 crops. Parameterizations from inventory methods may improve if public monitoring and  
6 reports requirements become more widespread (similar to those for Arizona's Active  
7 Management Areas – see Jacobs and Holway, 2004).

8

#### 9 **4 Summary and Conclusion**

10 We used satellite-based estimates of evapotranspiration (ET) and groundwater change  
11 combined with precipitation data to constrain and parameterize the additional water applied to  
12 a major irrigated agricultural region (Central Valley, California, USA) for simulation of land  
13 surface fluxes using the Community Land Model (CLM) version 4. We evaluated the baseline  
14 amount of consumed water using a suite of nine land surface models/forcing data sets and  
15 estimating the additional water consumed as a residual of current satellite observations. We  
16 used an iterative solution of parameterizing and then simulating groundwater recharge to  
17 partition the total water withdrawals among ground and surface water. The additional water  
18 parameterization resulted in CLM tracking the total amount and seasonality of ET closely.  
19 The remote sensing parameterization of irrigation water consumption results in a smaller total  
20 amount of water being consumed than in previous soil moisture-based parameterizations.  
21 The results emphasize the need for irrigation parameterization in land and climate models to  
22 accurately assess land-atmosphere energy and mass fluxes in regions with major

1 anthropogenic modifications. Given the potential for intense irrigation to modify regional  
2 climate (Kueppers et al., 2007) and to enhance convection precipitation in downwind regions  
3 (Lo and Famiglietti, 2013), it is important that the additional water consumption from  
4 irrigation is properly represented to better model the local and more distant impacts of  
5 anthropogenic land surface modification. [Particular emphasis should be placed on evaluating](#)  
6 [irrigation impacts in less developed regions with fewer surface data constraints and different](#)  
7 [cultivation and irrigation practices than the Central Valley.](#) An improved parameterization  
8 will also be useful for assessing regional climatic impacts of possible future changes in  
9 irrigated agricultural regions due to increased logistical, political, and/or economic restrictions  
10 on groundwater pumping or changes in surface water use.

11

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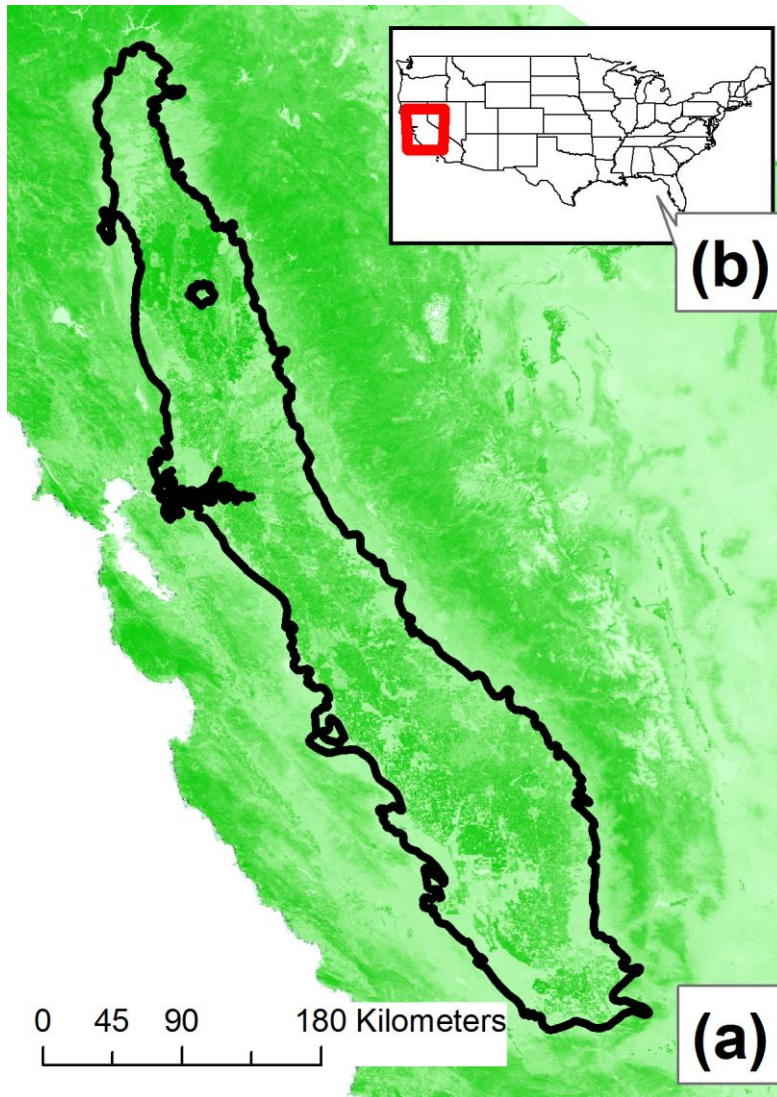
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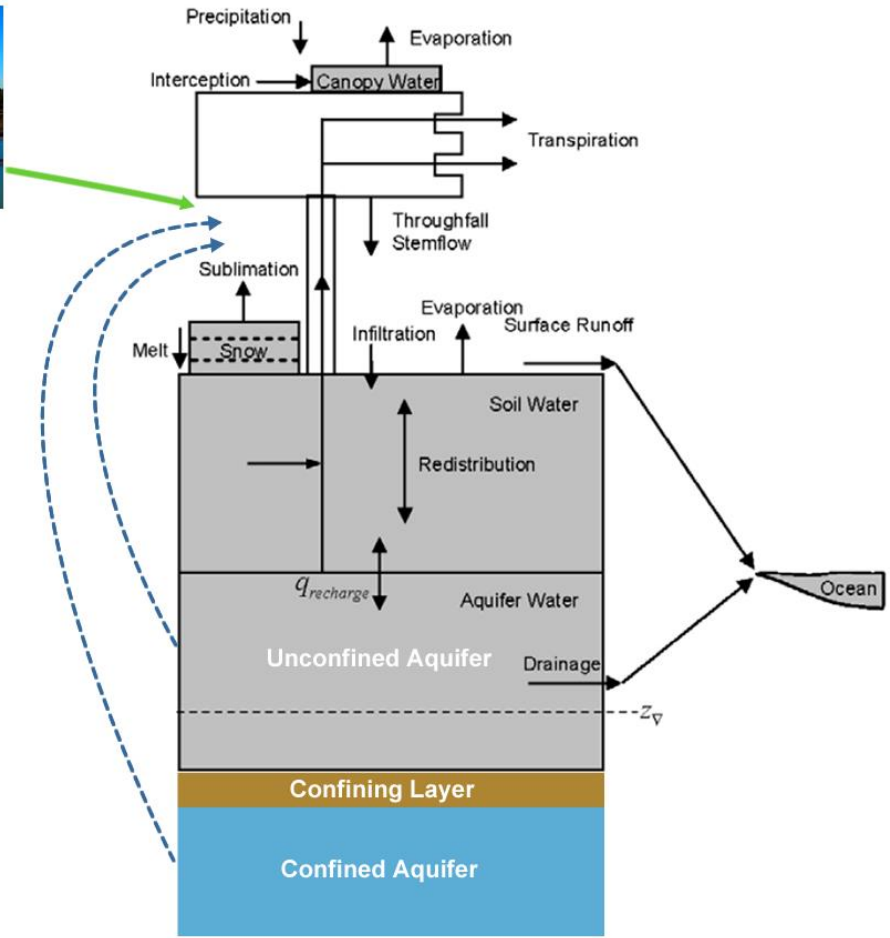
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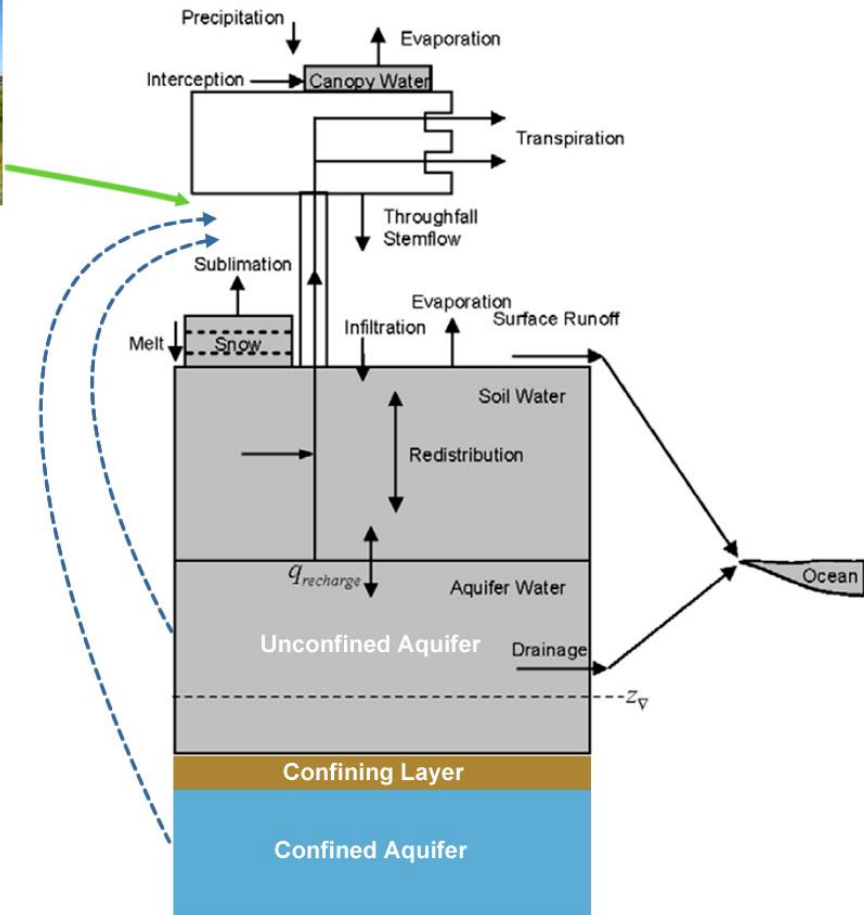


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2 Figure 1: Map of Central Valley, California. a) Underlying Normalized Differential  
3 Vegetation Index (NDVI) from the MODerate resolution Imaging Spectroradiometer  
4 (MODIS) 250m, 16 day product (July 2006) illustrating irrigated regions of the Central Valley  
5 (black outline). Darker green indicates higher NDVI and vegetation cover. b) Map of the  
6 United States with the inset area of (a) outlined in red.  
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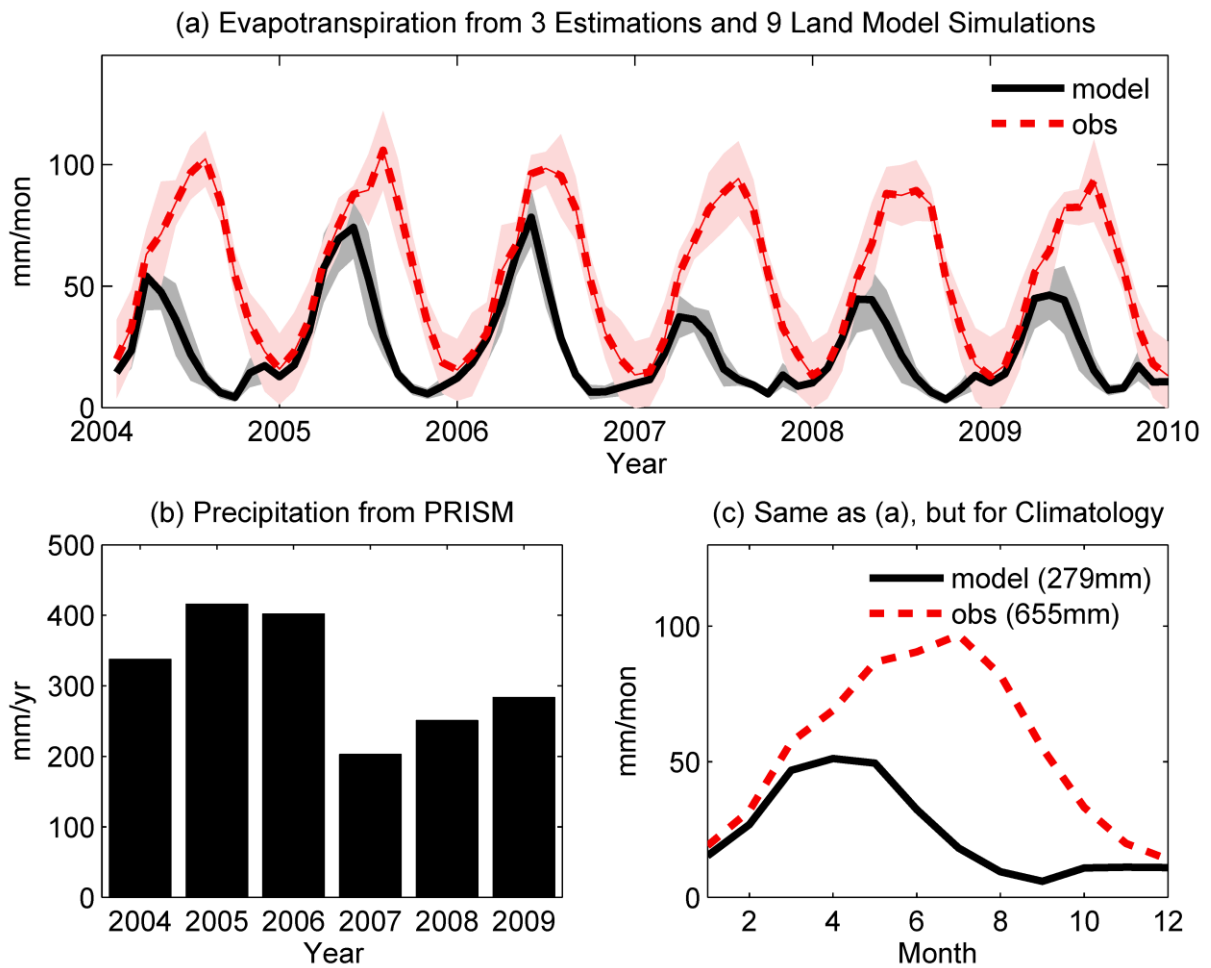


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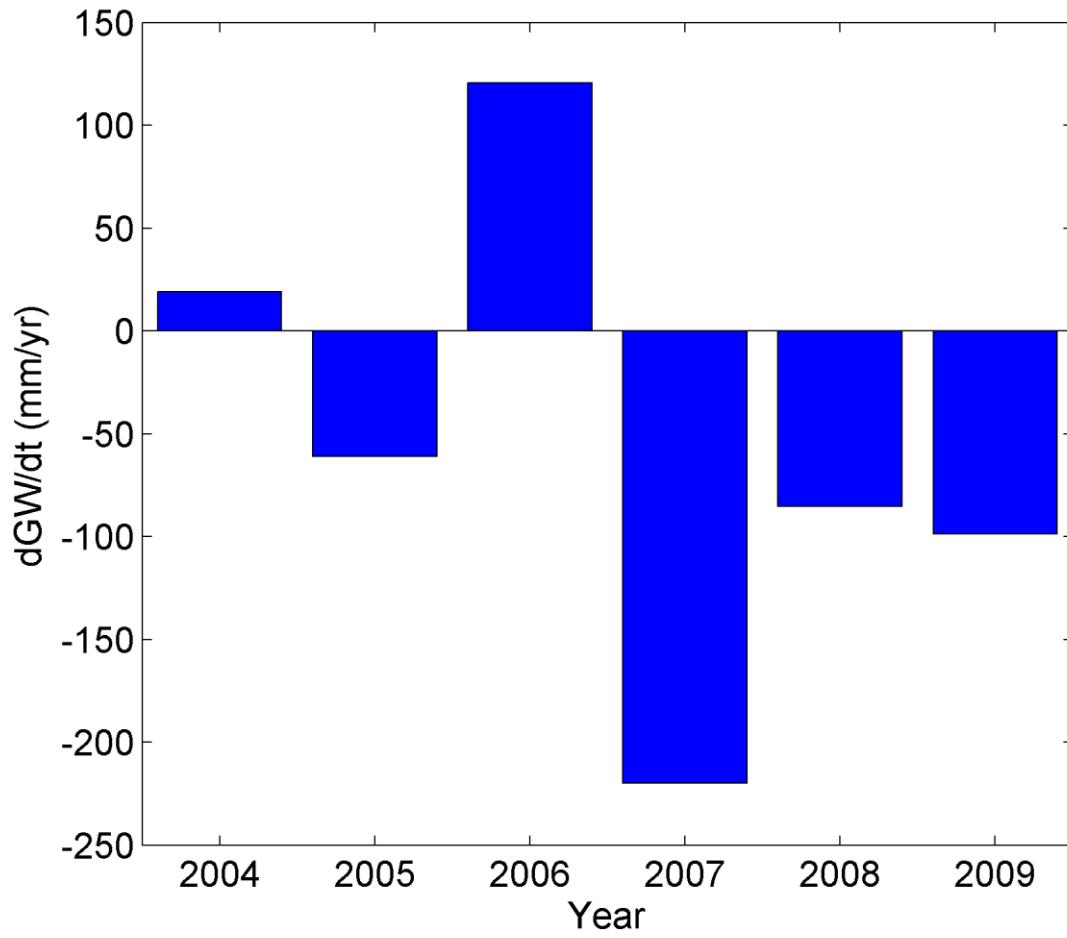


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2 Figure 2: Conceptual schematic of land hydrological processes, modified from Oleson et al.  
 3 (2008). Blue dash and green lines indicate the irrigation water fluxes applied in the CLM. In  
 4 the Central Valley, the aquifer is variably confined with some regions having no confinement.

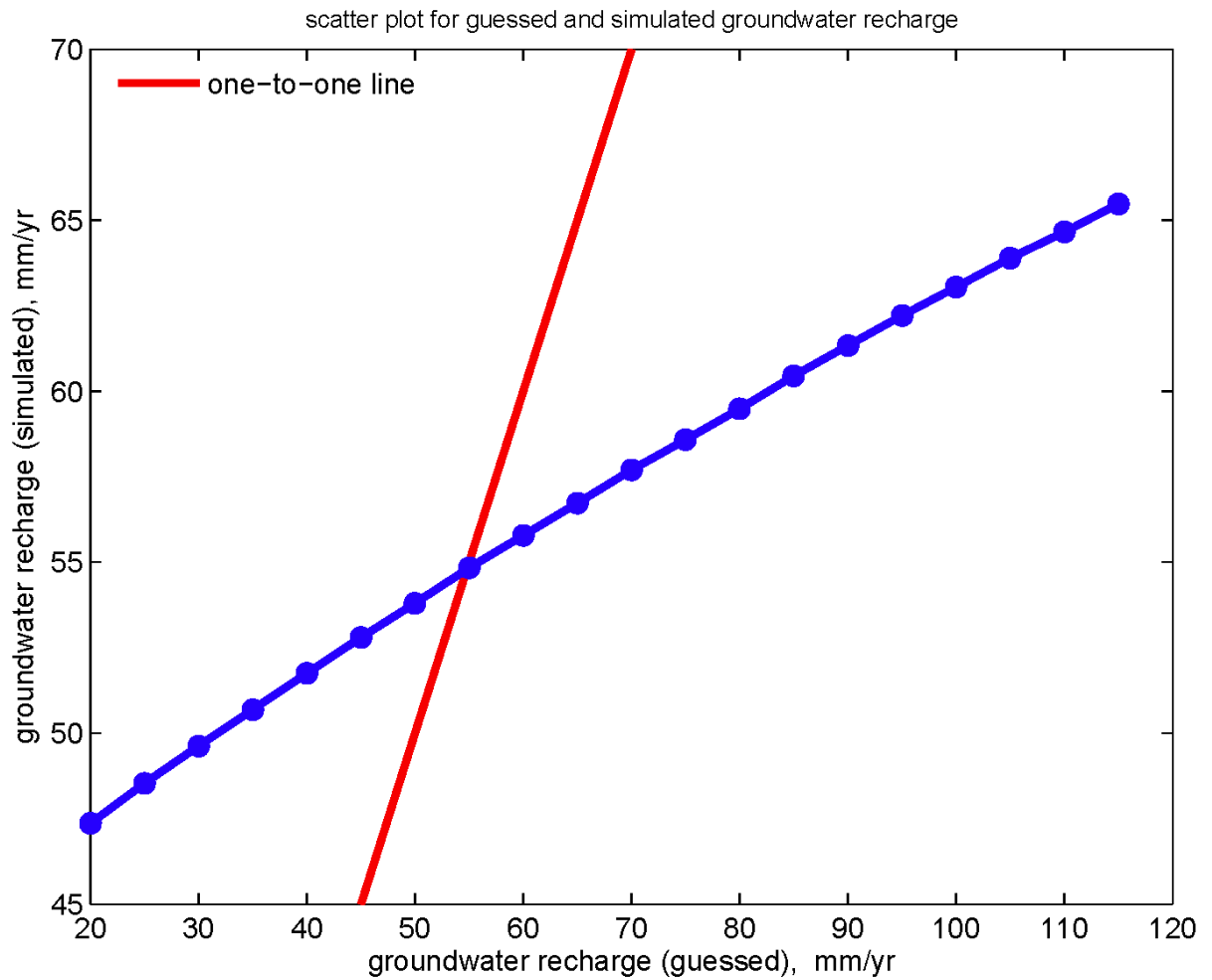


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 2 Figure 3: (a) the comparison between the remote sensing estimated ET, and 9 GLDAS,  
 3 NLDAS, and CLM models. The lines indicate the ensemble mean while the shading indicates  
 4 uncertainty around the ensemble mean, (b) annual precipitation for the Central Valley, and (c)  
 5 monthly climatology for satellite observed and modeled ET



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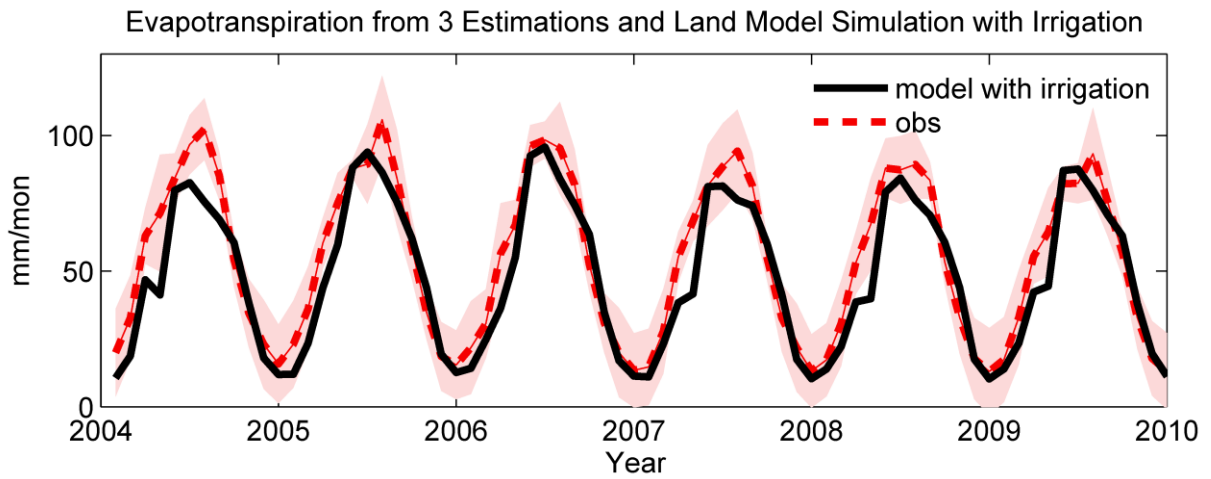
Figure 4: Annual groundwater change for the Central Valley derived from GRACE.



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Figure 5: Parameterized (guessed) groundwater recharge versus recharge simulated in CLM 4 (see section 2.3). The x-axis represents the trial recharge used in equation 4 to obtain  $GW_{WD}$  and the y-axis represents the output recharge from equation 3. The intersection of the parameterized values with simulated values (55 mm/year) represents where recharge comes to convergence, and is the value of recharge used to separate total water use into ground and surface water pumping components.

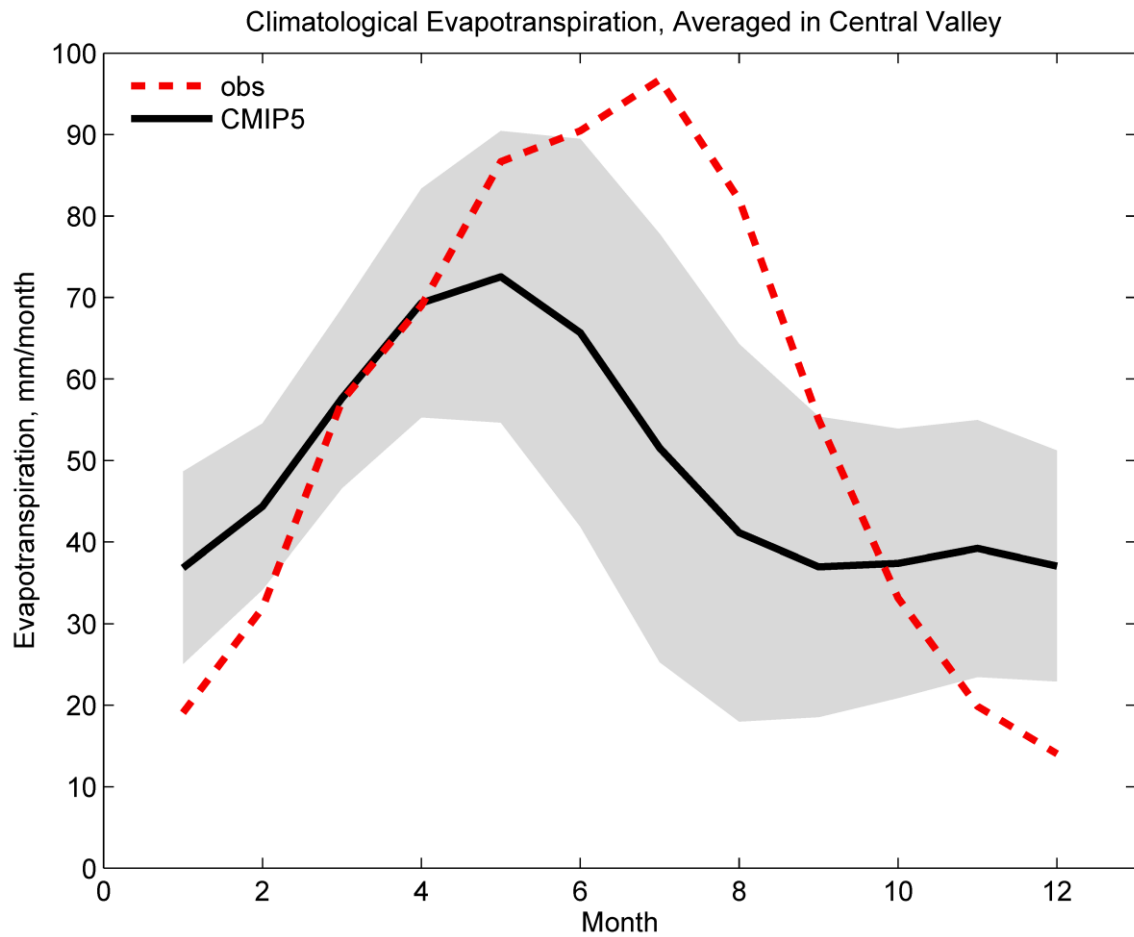
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3 Figure 6: Monthly ET from CLM 4 with the improved irrigation parameterization when  
4 compared to observations. Lines indicate model or ensemble mean while shading  
5 indicates uncertainty of the satellite observed ET.

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Figure 7: Mean seasonal cycle from the CMIP5 suite of models compared against satellite observed ET. Solid line shows mean value of CMIP5 model members and shaded region shows uncertainty (two standard deviations around mean).