Author response to reviewer comments

We thank the two anonymous reviewers for their 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 the reviewers below in this font (Arial, font size 12 point, blue text). Potential, concrete changes to the manuscript in response to reviewer comments are detailed in the same font, but are additionally underlined to distinguish the manuscript changes from our responses.

Anonymous Reviewer 1
The authors use satellite-estimated ET over the California Central Valley to modify the CLM land surface model in order to better represent diversion and extraction for irrigation. This is an interesting analysis. As it stands, the m/s lacks context, explanation and interpretation in some important aspects, but with moderate revision it should be a worthwhile addition to the literature.
We thank the reviewer for recognizing the contribution of this manuscript, and we will make changes to add to the interpretation as detailed below.

General comments:
- More description of the Central Valley water system is needed : hydrogeology, the surface water system (sources, reservoirs, diversion points) where does the surface water come from, what is the spatial and/or temporal pattern of surface vs groundwater use?
We agree that more details would be useful to the reader, but we feel a strong need to balance this against making the manuscript too long. We will add the following text in a revision, "Relevant aspects of the Central Valley's geology (Planert and Williams, 1995; Faunt et al., 2009), climatology (Zhong et al., 2004), hydrology (Scanlon et al., 2012) and anthropogenic inter-basin water transfers (Chung and Helweg, 1985; Fischhendler and Zilberman, 2005) are extensively reviewed elsewhere." We also will add details about the consumption of blue water in the Central Valley. We feel that it is relevant to point out that the pattern of surface vs. groundwater use varies extensively depending how wet or dry the preceding winter is as many farmers can use both surface and groundwater in their irrigation system. Furthermore, until recently, there were minimal reporting requirements for well owners, so per well water extraction is often publicly unknown.

- in several instances you use "observed" when referring to satellite-based ET estimates. In my view that is stretching the term too far; ET is estimated using a model that requires not only satellite data but also other input data, and the uncertainty in the assumptions and input data is considerable. Using "satellite ET" or "remotely sensed ET" would be appropriate.
While we agree that satellite techniques for determining ET may not be precise as good micrometeorological or lysimetric methods, the precision of some satellite algorithms is sufficiently good to permit their use for water management and water rights regulation by governmental agencies (see, for example, http://idwr.idaho.gov/GeographicInfo/mapping_evapotranspiration.htm). Nevertheless in recognition of the reviewer's concerns, we will rename "observed ET" to "satellite

observed ET" throughout the text where there is not already a sufficient modifier present (e.g. remote-sensing). We believe this change should indicate that the data come from satellite algorithms while still conveying our opinion that the satellite data have sufficient quality, precision, and independence to be an "observation" against which modeling results can be tested.

- The relevance of comparing to GLDAS-1 and NLDAS-2 for this study is not clear. Please explain better.

We do not intend to compare GLDAS-1 and NLDAS-2, but we use all of them to increase the number of models and forcings in ensemble average to have more confidence on the model's natural simulations of ET. GLDAS and NLDAS use different forcing and different models (only NOAH is the same), so we just want to increase our confidence in the mean and uncertainty of non-irrigation ET.

Specific comments:

Page 3567, Line 6) "for" rephrase

We agree this could be better phrased. We will change the surrounding text "and conservation of water volume for soil moisture approach" to "and a lack of conservation of water volume for models using a prescribed soil moisture approach"

8) "against" replace with "using"?

We will replace "against" with "compared to" to better indicate that we are using the difference for our irrigation parameterization.

10) Pls better explain what you mean by iterative and partition

We will revise the manuscript to improve clarity here. It will read, "We then incorporate the irrigation flux into the Community Land Model (CLM), and use a systematic trial-and-error procedure to determine the ground- and surface-water withdrawals that are necessary to balance the new irrigation flux. The resulting CLM simulation with irrigation produces ET that matches . . .".

11-12) Is it surprising it matches it well? That is by design, is it not?

It is not surprising that the new ET parameterization matches well, but it is not guaranteed given that a different ensemble of models was used to parameterize non-irrigation ET. The good agreement indicates that irrigation is an essential hydrologic flux in the Central Valley.

P3568, l1) consider including China.

We will add the recent study of Lei et al. (2015) who examine similar issues over the Haihe Basin, China.

4) You can find more analysis on the effect of groundwater extraction on sea water level in this paper: http://www.hydrol-earth-syst-sci.net/18/2955/2014/hess-18-2955-2014.html

We thank the reviewer for bringing this study to our attention. We will cite this study alongside Wada et al., 2010.

10) it may be worth adding that many irrigation areas are in (semi-) arid areas, which increases the contrast.

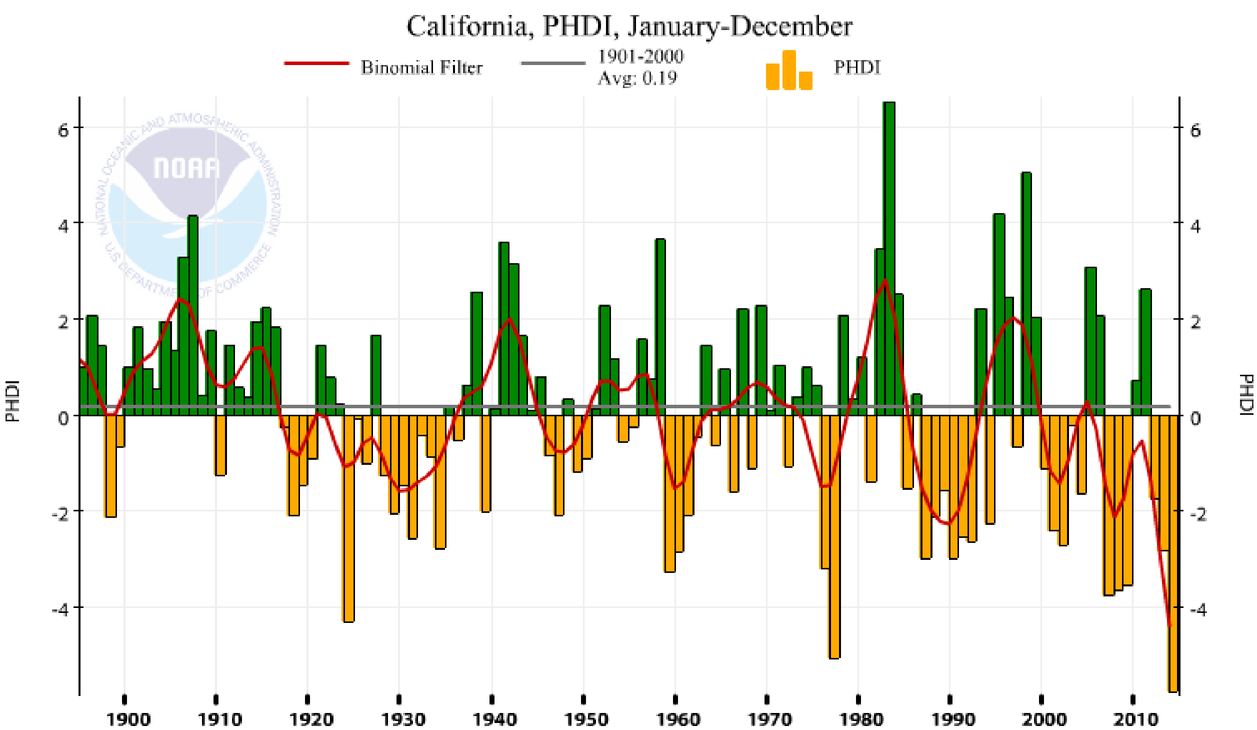
We wholeheartedly agree on this point and further point out the enhanced contrast due to the asynchronous precipitation and growing seasons. We would add the following text to a revised manuscript, "Given that irrigation is predominantly used in semi-arid to arid regions or where precipitation and growing seasons are asynchronous, this lack of parameterization can be highly significant for modeling regional hydrology."

21-25) Pls be explicit which of these limitations apply to which of the numbered items. More in general, please explain in more detail the assumptions and approach in each case, along with the benefits and limitations.

We agree that better connecting the approaches to disadvantages would benefit the reader. We have sought to distill the most essential differences in parameterizations between the four approaches. In our view, adding more details about each study and its assumptions would add greatly to the length of the text without further clarifying our approach in comparison to previous work. In a revised manuscript, we will add text that more explicitly identifies which limitation goes with which approach.

24) "drought and pluvial" change to "dry and wet"; more generally, please do not use the terms dry (below-average rainfall) and drought (extremely low rainfall) indiscriminately.

California tends to have more extreme hydrologic variability. For instance, during the last decade, there have only been three years that have had a Palmer Hydrologic Drought Index within the range of +2 to -2 (see chart from NOAA below). However, we will change "drought" to "dry" and "pluvial" to "wet" in most locations in the manuscript.



29) Why "although" what is the apparent contradiction?
There is no apparent contradiction. We used "although" to draw attention to multiple potential causes of different results in irrigation-climate feedback studies. To enhance clarity on this point, we will change "although" to "while".

3569, 5) change to "more robust"
We will change "robust" to "more robust".

15) Explain what exactly they did that you are building on here.
Lo and Famiglietti used a static surface and ground water irrigation inventory dataset to parameterize their LSM. We will add text in a revised manuscript clarifying this difference.

18) Provide reference for CLM
We will add reference to Lawrence et al. (2011) and Oleson et al. (2008), which covers CLM.

24) suggest "value" instead of "importance"
We will change "importance" to "value" in a revised manuscript.

3570, 22-25) Don't see why this is relevant here?
The potential for restricted groundwater pumping and altered irrigation methods could have a considerable impact on land surface parameterizations due to altered timing and amount of irrigation water. In a revised manuscript, we would add the following text to the end of this paragraph: "and potentially altering the amount and seasonality of irrigation. The potential for rapid hydrologic changes in the Central Valley is one reason why a potentially dynamic, satellite-based irrigation parameterization would be useful for land surface modeling."

3571, 3) Does it have a name?
This implementation of the SEBAL algorithm is unnamed in Anderson et al. (2012) and remains unnamed here.

7) Sounds like the trapezoid method. Is it different?
Tang et al.'s method is effectively the trapezoid method. However, they do not describe it by the theoretical shape (I have also seen it called the triangle method). We would prefer to leave the description as is to keep precision and to avoid adding additional text or potential for confusion.

11-14) How do irrigation areas stand out using this method, not explained. Also, pls explain why the several publicly available ET products (e.g., MODIS, MPI, GLEAM etc) are not used. I imagine it may be because of their coarse resolution, but it is left unexplained.
Although active delineation of irrigation areas is not required for this methodology to work, irrigation areas are quite clear in the Central Valley due to the asynchronicity

between winter precipitation and summer ET. We will modify the manuscript in this section to read, "All three products were clearly able to distinguish peak summertime ET in the Central Valley, which is asynchronous with largely winter precipitation and a characteristic sign of irrigation. Other ET products (Miralles et al., 2011; Mu et al., 2011; Jung et al., 2010) were not used as they were either too coarse in resolution (>0.25° X 0.25° cell size) or were unable to detect irrigation in the Central Valley."

3572, 19) Confused terminology: I assume you mean groundwater discharge into rivers, rather than runoff; furthermore that is not equal to baseflow (baseflow describes a part of the hydrograph, it's not itself an interpretation of hydrological pathway)
To reduce confusion, we changed "groundwater runoff (base flow)" to "groundwater discharge".

3573, eq. 4) Your figure shows an unconfined and a confined aquifer. Please discuss this conceptualisation and explain which of these terms you assume affect which.
Fig. 2 is a very basic conceptualization of how CLM handles confined and unconfined aquifers. We will revise the figure caption as follows "Figure 2: Conceptual schematic of land hydrological processes, modified from Oleson et al. (2008). Blue dash and green lines indicate the irrigation water fluxes applied in the CLM. In the Central Valley, the groundwater is variably confined with some regions having no confinement."

9) that doesnt sound very realistic; presumably farmers would not apply water if it rains. Perhaps summer rain is a rare event? Pls discuss.
Summer rain is very rare in the Central Valley. This fact will be referred to both in the study area section and in the discussion of ET products.

14-15) I am confused about this. Presumably q_recharge is a function of soil water content?
In general, yes q_recharge would be a function of soil moisture content. However, in order to determine GW_WD where pumping data are not available, we force q_recharge in equation 4 to a specified value, which allows us to determine GW_WD as described in this section. We then obtain q_recharge in equation 3. When q_recharge in both equation 3 and 4 match, we then have a GW_WD that we can use to partition the irrigation flux. This process is used only to determine GW_WD.

15) But GRACE total water storage anomalies include contributions from both soil moisture (DELTA SMH) and groundwater (DELTA GW), whereas here you appear to ignore the former. If I interpret this correctly you need to demonstrate that that is a reasonable assumption.
We used GRACE data (Famiglietti et al., 2011) that has already had storage variations from soil moisture, snow, and surface water removed, leaving only delta GW. We recognize that the original phrasing lead to confusion about the level of processing. We will change "GRACE GW observations" to "processed GRACE delta GW".

21) "locate"do you mean "spatially distribute"?
No, we meant "find". We will change "locate" to "find".

3573, 3) What basis do you have for that assumption? Needs discussion and potentially uncertainty analysis.
The US Geologic Survey atlas (Planert and Williams, 1995 - citation in manuscript) reports well depths in the Central Valley from near surface to as deep as >1000 m in the southern part of the San Joaquin Valley. We acknowledge that precise determination of this ratio of confined to unconfined pumping is difficult as well operators are not yet required to publicly post their well depths and as the aquifer is partially confined. We can reasonably presume that a farmer would not pump from a deeper confined layer when water in the shallower unconfined layer is available in order to conserve on expensive well drilling and electrical costs. Confined pumping would be expected to occur in the Southern and Western parts of the Central Valley where surface water is scarcer and the unconfined aquifer is already depleted. In the Northern and Eastern parts, we would expect to find more pumping in the unconfined aquifer as it is shallower there. We would not expect to find confined pumping leading to increased discharge due to a shallow aquifer table rising.

3574, 7) "occurring" rather than "coming"
We have changed "coming" to "occurring".

12) Are there no reservoir dams? Or are they too small to mitigate against year-to-year variations? Pls explain.
There are significant reservoirs in the Central Valley, but they are of insufficient size and operational flexibility to mitigate against multi-year drought (as compared to the Colorado River Basin). Many reservoirs (particularly in the Southern Central Valley) mainly serve to protect against major floods and to hold surface water for release later in the summer.

17-19) That suggests to me that additional constraints are needed. Are there no data on dam releases or the surface water budget that you could use?
We do not believe this section requires additional constraints. Dam releases, outflow through the California delta, and a surface water budget was calculated in Anderson et al. (2012 – cited in manuscript). The purpose of our manuscript is to introduce constraints on the irrigation flux using only remotely-sensed data so that the method can be applied to other, data-poor, regions of the world.

3575, 1) Presumably you mean fig. 5? I don't understand how to interpret fig. 5, pls explain.
We do mean Fig. 5, and we will correct this in a revised manuscript. We will also add additional text to the caption of Fig. 5: "The x-axis represents the trial recharge used in equation 4 to obtain GWWD and the y-axis represents the output recharge from equation 3."

9) why call it an inventory approach? What you describe sounds like a water budget approach.
We called it an inventory approach because that was the description that was used in Anderson et al. (2012). It refers to using the data from dam releases and outflow to

construct an inventory. We prefer this over "water budget" as we believe water budget is a more generic term.

11) "Agreement" not "comparison". Also, how did Anderson et al estimate GW_wd?
Anderson et al. (2012) did not estimate GW_wd. They focused on estimating surface water consumption using remote-sensing and intercomparison to the inventory approach. Using the iterative approach in Fig. 5 is one significant advance on Anderson et al. (2012) and is necessary to obtain direction hydrologic fluxes (as opposed to net flux) to better use satellite data in land surface modeling. We will change "comparison" to "agreement".

25-26) This needs an interpretation. I assume this may be a consequence of wetter soil conditions causing greater rainfall-runoff response, but given it is modelled you can (and should) trace why this is predicted.
We agree that more interpretation is needed. We will add the following to the end of the sentence, "which is an expected consequence due to the wet soil from irrigation leading to higher surface runoff".

29) losing streams – this term is missing in Eq. 4. Pls discuss.
Losing streams would be represented by a negative Q_discharge (representing river recharging aquifers), and would not require an additional term. The discussion of this stream property is meant to refer to that groundwater tables no longer intersect stream beds in many parts of the Central Valley (unlike historical conditions). Therefore, changes in irrigation are unlikely to increase Q_discharge.

3577, 2) once again, no need for "may" – you should be able to deduct this from your modelling.
We feel this hedge with "may" is warranted given the heterogeneous cropping patterns that exist at sub-CLM (0.125°X0.125° grid cell) resolution. All of the CLM grid cells in the Central Valley have both annual and perennial crops, with flood and drain crops (rice) present primarily in the Northern Central Valley.

28) "global inventory" - pls explain.
We refer to the irrigation data set of Siebert et al. (2010) here. We will revise this sentence to read, "than a global inventory (Siebert et al., 2010), based approach".

3578, 14-17) sounds like a fairly speculative thought bubble. Argue better or delete.
Right now, observations of soil moisture are either non-existent or too coarse or inaccurate (SMOS, AMSR-E) to enable regional soil moisture mapping. SMAP was specifically designed to produce soil moisture observations at a sufficiently high spatiotemporal resolution for weather and land surface models. We will rephrase this section to ". . . with precise and accurate regional and global soil moisture observations from upcoming missions such as the Soil Moisture Active Passive, whose outputs are specifically designed to improve inputs to numerical weather prediction and land surface models (Entekhabi et al., 2010)."

18) "sufficiently coarse"?? Rephrase.
We will change "coarse" to "low".

26) "dry" not "drought". "missions" - what missions?
We will replace "drought" with "dry" and specify the four missions discussed by the citations at the end of this sentence.

28) "higher spatial scales" – do you mean higher spatial resolution?
Yes, and we will change "scales" to "resolution".

Anonymous reviewer 2:
General comments This paper introduces a new method to account for irrigation water management in land surface models using optical and gravimetry satellite data.
This is an important topic because it will help analyzing the impacts of irrigation water abstraction on the hydrological and the climate system.
We appreciate the reviewer's recognition of these aspects of our manuscript.

The method is developed for the Central Valley in California that is probably a very unique irrigated region with a lot of available data and large irrigated fields that are easily 'seen' by the remote sensing ET products. In many other regions in the world where plot sizes are and perhaps irrigation intensity is much smaller the signal might not be as strong, and the approach might not work at all. Some methods use absolute values as thresholds and it is not clear how they will be determined elsewhere. To be more relevant for the problem, it would be interesting to see at least some discussion on how the approach can be applied in other regions with different irrigation practices and hydro-geolocial conditions. Ideally, the approach should be tested in another region. Some of the methods are not sufficiently well justified and should be clarified for somebody who is not familiar with the CLM modeling system (see detailed comments below).
We note that satellite ET products come in many spatial resolutions. Landsat based products (e.g. METRIC) can come in resolutions as high as 30m, so we do not think that the spatial resolution will be a hindrance in applying this approach elsewhere. We note that the satellite ET algorithms used here do not rely on absolute thresholds, determination of irrigation practices, or knowledge of underlying hydrogeological conditions. Our method and approach was to use as little *in-situ* observations or data to develop the method (hence the use of satellite-based ET and running the land surface model with reanalysis products), but to assess the results using our knowledge of the Central Valley and the *in-situ* observations. We also note that the Central Valley is still an important study region given the conflicting previous studies on the implications of Central Valley irrigation for precipitation elsewhere in the Western United States (Lo and Famiglietti, 2013; Sorooshian et al., 2011), which is especially relevant given current and potential future drying in the Western US. We agree that testing this type of parameterization in other, data-poor, irrigated regions would be a good future research direction.

Specific questions and technical corrections

Section 2.1. A bit more information on the irrigation practices would be useful :Fraction of total area irrigated, main crops, number of crops per year, irrigation infrastructure (canals, sw reservoirs, etc) , water use as fraction of total available water resources? Parts of section 3.2 could be moved here.

Unlike many irrigated regions around the world, the Central Valley is notable for its incredible diversity of crops and lack of a few predominant crops. For example, in one Central Valley county (Fresno) where the one of the authors (Anderson) has previously worked, there are more than 300 varieties of different crops/cultivars (the more than 200 crops number was a conservative number to distinguish between different crops). <u>Some additional information requested by reviewer 2 will already be provided in response to reviewer 1. Additional details, including total blue water consumption and a reference to the Census of Agriculture details on cropping and irrigation area, will be included in a revision.</u>

Section 2.2. Somehow it is unclear why the ensemble ET is superior to any of the individual products. What is the spatial resolution of the ET, Precip, and the CLM grid cell resolution? There are significant uncertainties in the remote sensing estimates that should at least be discussed and perhaps the ET ensemble should not be called 'observed' values (later in the manuscript). What is meant by uncertainty of ET (line 1).

Using an ensemble of satellite hydrology products developed using different methodologies is a well-recognized approach to constraining the value of the parameter one wants to observe. By avoiding a single approach (and its assorted biases) we obtain a range where there is greater confidence in the actual ET value. <u>Following the suggestion of both reviewers, we will revise the "observed" language as detailed in response to reviewer 1. Spatial resolutions are now reported for all products. To reduce confusion, "uncertainty" has been replaced by "standard deviation"</u>

Section 2.3. Some more details for the CLM (spatial and temporal resolution) and a justification for the use of the 9 member ensemble would be interesting.

The reason to use the 9 member ensemble is to include as many as possible of the current the state-of-the-art models' simulations. The 9 member ensembles are based on different models and different atmospheric forcings. Therefore, we have more confidence on their ET simulations in a pre-irrigation, pre-development environment.

Eq. 5 assumes that all water abstracted from ground and surface water becomes ET. In reality, a considerable amount is returned to the soil and gw storage, as loss. It is probably not relevant on monthly time steps if you consider the net abstraction only but at least it should be mentioned. Line 24 on 3572 and Fig.2 seem to suggest that the abstraction (delta ET) will be added to precipitation in the model, in which case it will be redistributed. Will this violate the grid cell water balance? Why is deltaET in Eq. 5 taken as the 6 year mean? There should be considerable differences between wet and dry years that are worth exploring. This can be seen in figure 3a and 3b.

The irrigation water is taken from both surface water and groundwater. The Central Valley aquifer system is a combination of unconfined and confined aquifers; we assume that groundwater withdrawals are equally distributed between both types of aquifers. Because the CLM lacks a confined aquifer component, confined withdrawal is from a hypothetical water store. Unconfined withdrawals were taken from the saturated zone of the soil. The reviewer is correct that Eq. 5 assumes all abstracted water becomes ET. But Eq. 5 is used only to obtain an estimate for SW_WD, which then determines (in part) the P to be input in a simulation. So the CLM cell water balance in a given simulation is not affected. We will mention the limitation with equation 5 in our revision. We will also revise the last part of section 2.4 to read "Since the Central Valley aquifer system is a combination of unconfined and confined aquifers; we assume that groundwater withdrawals are equally distributed between both types of aquifers (Fig 2). Because the CLM lacks a confined aquifer component, confined withdrawal is taken from a hypothetical water store which is constrained together with the unconfined aquifer using equation 4 and GRACE estimated groundwater. Unconfined withdrawals were taken from the saturated zone of the soil."

With respect to the deltaET, we agree that there are some differences between wet and dry years, and that the use of such additional information could use the annual data to make the simulations better. However, high resolution estimates of ET may not be available for other regions or times, so in this study we would rather use the climatological irrigation water demand as determined from the multi-annual mean of the satellite observed ET.

The 'grid search' is unclear. Is there is search distance or is water only taken from the same grid cell? If so, the amount of water available from surface water will highly depend on the resolution of the model. The 'trial and error' approach in figure 5 is not clear and needs a better explanation. What is the justification for using values between 5 and 20 mm? Are these values related to the total Central valley area or only the irrigated areas? Here and elsewhere in the manuscript it would be worthwhile to report number (irrigation depth etc.) related to the irrigated area, and not averaged over the entire area.
Our inclusion of "grid search" as a parenthetical comment was not necessary and needlessly created confusion; the "grid" we were referring to was not the CLM grid, but rather the gridded values of groundwater recharge shown in Fig. 5. We trust that our removal of that comment will help clarify things. As noted on pg. 3573, ln 23, we started the search for a satisfactory value of GW_{WD} at 20 mm because that was the value necessary to match the no-irrigation, baseline simulation. The choice to increase GW_{WD} in increments of 5 mm was arbitrary, but was made because it seemed to provide reasonably fine resolution without requiring an excessive number of model simulations. We will remove "grid search".

Section 3.2. The mean deltaET (376mm) needs to be put into perspective with total water use and available water. Can you add a figure showing the monthly time series of reported (inventory) and simulated abstraction from gw and sw ? What would be interesting is the different partitioning of the two in response to drought conditions.
The inventory of water use for the Central Valley and partitioning of surface and groundwater consumption (not abstraction) is already reported in Anderson et al. (2012) and a figure of inventory water use would duplicate that report (see Table 1 and Fig 2.

from Anderson et al. (2012) below). The simulated abstraction of gw and sw is constant during the summer months (May-October) as we discuss in section 3.2. Following the suggestion of both reviewers, we now report the total blue water consumption to better conceptualize the size of the Central Valley hydrologic system. However, we want to keep the emphasis of the study on the model development aspect instead of focusing on the nuances of the Central Valley.

Table 1. Water Year Statistics[a]

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

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

[a]All fluxes are in mm/year. Mean fluxes are averaged over the study period. SJ and Sac refer to San Joaquin/Tulare Lake and Sacramento basins, respectively. All values rounded to nearest mm. dGW/dt and dSM/dt are not shown for SJ and Sac due to spatial resolution limitations.

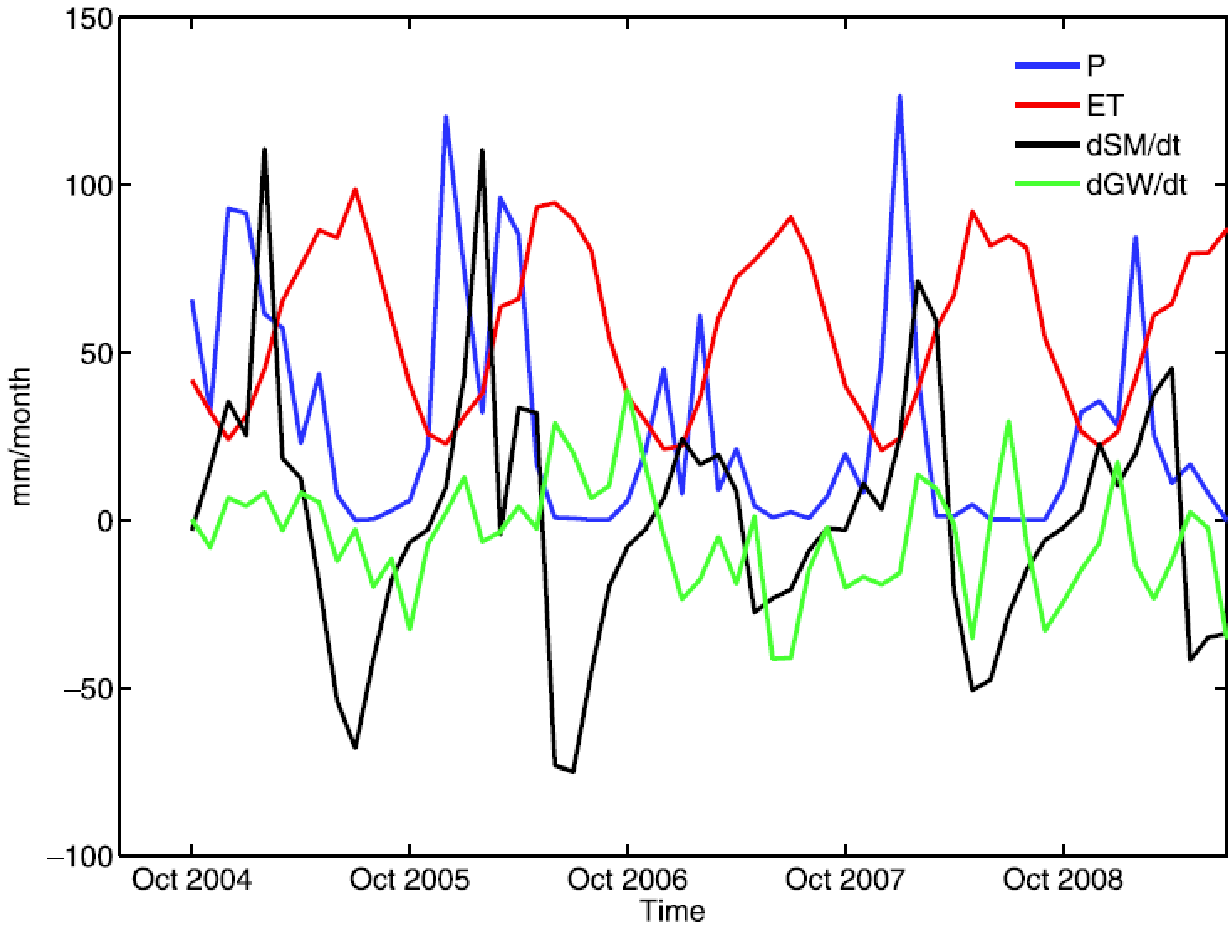


Figure 2. Monthly precipitation (P), evapotranspiration (ET), groundwater change $\left({}^{dGW}\!/_{dt}\right)$, and soil moisture $\left({}^{dSM}\!/_{dt}\right)$ from July 2004–June 2009 (mm/month).

Figure 3.a Explain the range of the shaded regions. The thick lines are mean values ? Figure 3.c. Should "time" be replaced by "month"? Figure 6 needs a better legend. Align the color schemes in figures 6 and 7.

We will add text explaining the range of the shaded region and will alter the figures as the reviewer suggests.

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

R.G. Anderson[1,*], M.-H. Lo[2,*], S. Swenson[3], J.S. Famiglietti[4], Q. Tang[5], T. H. Skaggs[1], Y.-H. Lin[2], and R.-J. Wu[2]

[1]{USDA, Agricultural Research Service, US Salinity Laboratory, Contaminant Fate and Transport Unit, Riverside, California, USA}[1]

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

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

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

---

[1] Note: The U.S. Department of Agriculture (USDA) prohibits discrimination in all its programs and activities on the basis of race, color, national origin, age, disability, and where applicable, sex, marital status, familial status, parental status, religion, sexual orientation, genetic information, political beliefs, reprisal, or because all or part of an individual's income is derived from any public assistance program. (Not all prohibited bases apply to all programs.) Persons with disabilities who require alternative means for communication of program information (Braille, large print, audiotape, etc.) should contact USDA's TARGET Center at (202) 720-2600 (voice and TDD). To file a complaint of discrimination, write to USDA, Director, Office of Civil Rights, 1400 Independence Avenue, S.W., Washington, D.C. 20250-9410, or call (800) 795-3272 (voice) or (202) 720-6382 (TDD). USDA is an equal opportunity provider and employer.

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

[*] These authors contributed equally to this manuscript.

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

Abstract

Irrigation is a widely used water management practice that is often poorly parameterized in land surface and climate models. Previous studies have addressed this issue via use of irrigation area, applied water inventory data, or soil moisture content. These approaches have a variety of drawbacks including data latency, accurately prescribing irrigation intensity, and a lack of conservation of water volume for models using a prescribed soil moisture approach. In this study, we parameterize irrigation fluxes using satellite observations of evapotranspiration (ET) ~~against~~compared to ET from a suite of land surface models without irrigation~~.~~ We then ~~apply this water~~ incorporate the irrigation flux into the Community Land Model (CLM~~)~~), and use ~~an iterative approach to estimate groundwater recharge~~ a systematic trial-and~~ partition the water flux between groundwater~~-error procedure to determine the ground- and surface~~ water.~~ -water withdrawals that are necessary to balance the new irrigation flux. The ~~ET simulated by~~resulting CLM simulation with irrigation produces ET that matches the magnitude and seasonality of observed satellite ET well, with a mean difference of 6.3 mm/month and a correlation of 0.95. Differences between the new CLM ET values and

satellite observed ET values are always less than 30 mm/month and the differences show no pattern with respect to seasonality. The results reinforce the importance of accurately parameterizing anthropogenic hydrologic fluxes into land surface and climate models to assess environmental change under current and future climates and land management regimes.

1 Introduction

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

Current land surface models (LSMs), such as the Community Land Model (CLM – Oleson et al., 2008), that are run without an irrigation parameterization usually have unrealistically low evapotranspiration in agricultural regions (Lei et al., 2015; Lo et al., 2013;

Lobell et al., 2009; Sorooshian et al., 2011; Ozdogan, 2010). Given that irrigation is predominantly used in semi-arid to arid regions and/or regions where precipitation and growing seasons are asynchronous, this lack of parameterization can be highly significant for modeling regional hydrology. Some LSMs and their associated regional climate models (RCMs) or global climate models (GCMs) prescribe enhanced water availability in agricultural regions due to irrigation. Representations vary considerably depending on the simulation; they include (1) prescribing a static soil moisture at field capacity for all irrigated crops (Kueppers et al., 2007), (2) prescribing a total flux based on a prescribed estimate across the entire agricultural domain (Lo and Famiglietti, 2013), (3) assigning a fraction of land surface to be irrigated (Leng et al., 2013 and 2014; Lobell et al., 2009; Tang et al. 2007), and (4) assigning a seasonally-based soil moisture curve to represent irrigation only during the active irrigation season (Sooroshian et al., 2011). Each of these approaches has significant disadvantages. The approaches that assign irrigation based on soil moisture (approaches 1 and 4 above) do not consider basin scale limitations on available irrigation water (particularly during ~~drought~~dry years) and may overestimate the total amount of irrigation water as well as the differential impacts between ~~drought~~dry and ~~pluvial~~wet years. The prescribed/inventory based flux (approach 2) has the advantage of a mostly conserved water budget, but there are latency issues for much of the data which are based on potentially outdated or incomplete national and regional statistics. Assigning a fraction of land area to be irrigated (approach 3) has the disadvantage of assuming a particular irrigation intensity, and this approach cannot easily distinguish between full and deficit irrigation. Finally some prescribed flux approaches work primarily where groundwater is the sole source for applied irrigation and others based on irrigated area may not account for irrigation intensity. ~~Although~~While process differences in RCMs/GCMs and LSMs can account for variations in the sensitivity of irrigation-climate feedbacks and teleconnections, it should be noted that studies with different irrigation parameterizations over the same region have had significantly different climatic feedbacks and downwind impacts (Kueppers et al., 2007; Lo and Famiglietti, 2013; Sooroshian et al., 2011).

Satellite remote sensing can be used to provide more robust, regional observations of irrigation water consumption. Evapotranspiration (ET) is routinely monitored over irrigated agriculture using observations of surface temperature and vegetation greenness (Allen et al., 2007; Anderson et al., 2007; Tang et al., 2009). When combined with satellite gravimetry (Swenson and Wahr, 2003) and large scale meteorological products (Hart et al., 2009) the amount of irrigation water coming from surface water supplies (Anderson et al., 2012) and net groundwater depletion (Famiglietti et al., 2011) can be assessed. Together, these satellite algorithms can provide a much more detailed and current input dataset for LSMs and RCMs/GCMs to assess irrigation-climate feedbacks.

In this study, we follow on the work of Lo and Famiglietti (2013) by using remote sensing observations of ET, surface water consumption, and total water storage anomalies to infer surface and ground water fluxes~~.~~, instead of using a static surface and ground water irrigation inventory dataset for parameterization. We use these fluxes to improve and test an irrigation parameterization in the Community Land Model (Lawrence et al., 2011; Oleson et al., 2008) in a well instrumented basin with a large amount of irrigated agriculture, the Central Valley of California. We use ET from an ensemble of three satellite products, combined with gridded precipitation, to determine the seasonality and interannual variability of additional ET from irrigation. We then use an iterative recharge parameterization, combined with satellite gravimetry, to determine relative amounts of irrigation applied from groundwater and surface water. The results show the ability and ~~importance~~value of using diagnostic remote sensing observations and models for improving prognostic algorithms necessary to increase LSM skill in predicting hydrologic, biogeochemical, and climatic impacts and feedbacks under future greenhouse gas emission and land used change scenarios.

2 Methods

2.1 Study region

We evaluate our approach in the Central Valley of California~~. The Central Valley~~, which is a large (~54,000 km^2), low elevation (<200 m a.s.l) ~~valley~~region (Fig. 1). The Central Valley is a highly-productive agricultural region, with over 200 cultivated crops and an annual crop value of more than $35 billion US Dollars in 2012 (California Department of Food and Agriculture, 2014~~).~~, USDA National Agricultural Statistics Service, 2014). Relevant aspects of the Central Valley's geology (Planert and Williams, 1995; Faunt et al., 2009), climatology (Zhong et al., 2004), hydrology (Scanlon et al., 2012), and anthropogenic inter-basin water transfers (Chung and Helweg, 1985; Fischhendler and Zilberman, 2005) are extensively reviewed elsewhere. Average (2004-2009 water years) blue water (surface water plus ground water) consumption was 2.03±0.02 X10^{10} m^3 as determined using an inventory method (Anderson et al., 2012). Agriculture in the Central Valley is heavily dependent upon irrigation from both surface and ground waters, with a large variation in the relative consumption of surface and ground water due to high inter-annual variation in precipitation and an almost complete lack of precipitation during the peak summer growing season (Anderson et al., 2012; Scanlon et al. 2012). In addition to its agricultural importance, the Central Valley has multiple attributes that are useful for developing and validating new model processes to better represent anthropogenic impacts on regional hydrology and climatology. These include (a) well understood hydrogeology, surface water use, and extensive *in-situ* meteorological observations (Hart et al., 2009; Faunt et al., 2009; Planert and Williams, 1995); (b) well constrained groundwater systems with little to no subsurface outflow to the ocean (Faunt et al., 2009~~), (b~~); (c) well gauged and modeled surface water flows into and out of the Valley (Anderson et al., 2012~~),~~); and (~~c~~d) anthropogenic hydrologic processes (irrigation, crop evapotranspiration, and drainage) that have a very distinct seasonality from the winter precipitation and spring runoff dominated natural processes that occurred prior to irrigation and agricultural development (Lo and Famiglietti, 2013).

Previous remote-sensing based and mechanistic modeling studies have shown sustained and substantial depletion of groundwater in the Central Valley (Famiglietti et al., 2011; Faunt et al., 2009), which has accelerated in the most recent drought from 2012 to present (Borsa et al., 2014; Famiglietti, 2014). Recent groundwater regulation legislation will likely restrict future groundwater pumping differentially across groundwater basins (Harter and Dahlke, 2014), making alternative irrigation methods and strategies, such as drip and deficit irrigation, more common~~.~~ and potentially altering the amount and seasonality of irrigation. The potential for rapid hydrologic changes in the Central Valley is one reason why a potentially dynamic, satellite-based irrigation parameterization would be useful for land surface modeling.

2.2 Evapotranspiration, precipitation and total water observations

We calculated the monthly mean and ~~uncertainty~~standard deviation of evapotranspiration (ET) using an ensemble of three products. One is a surface energy balance product (Anderson et al., 2012) based on the SEBAL algorithm (Bastiaanssen et al., 1998) that is applied to the Central Valley at 250 m resolution using a 250 m vegetation index and 1 km thermal data from the MODerate resolution Imaging Spectroradiometer (MODIS) in conjunction with gridded meteorology. The second product (Tang et al., 2009) uses the scatter plot relationship between the vegetation index and surface temperature (VI-Ts) to estimate the Evaporative Fraction (EF) and ET at 0.05° resolution using MODIS vegetation and thermal data in conjunction with Geostationary Operational Environmental Satellite (GOES) surface radiation products. The third product (Jin et al., 2011), uses the Priestley-Taylor equation (Priestley and Taylor, 1972) with the coefficient term (α) optimized using Ameriflux data and net radiation and ground heat flux parameterized from the MODIS and Clouds and the Earth's Radiant Energy System (CERES) instruments to estimate ET at 1 km resolution. All three products were clearly able to distinguish peak summertime ET in the Central Valley, which is asynchronous with largely winter precipitation and which is a characteristic sign of irrigation. Other ET products (e.g. Miralles et al., 2011; Mu et al., 2011; Jung et al., 2010) were not used as they were either too coarse in resolution (>0.25° X 0.25° cell size) or were unable to detect irrigation in the Central Valley.

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

2.3 Land surface models

For intercomparison with satellite observed fluxes and determination of additional water application in CLM, we use an ensemble (9 members) of three North American Land Data Assimilation System (NLDAS-2 - Mitchell et al., 2004; Xia et al., 2012b), four Global Land Data Assimilation System (GLDAS-1 - Rodell et al., 2004) outputs, and two CLM simulations. For NLDAS-2 and GLDAS-1, we used the Noah, Mosaic, VIC, or CLM models from each system with the primary NLDAS-2 and GLDAS-1 forcings. Along with the NLDAS/GLDAS outputs, we also include outputs from different versions of the CLM (including CLM3.5 and CLM4) with the GLDAS-1 atmospheric forcings. In addition, we evaluated the CMIP5 control outputs (Taylor et al., 2012) to assess the larger performance of climate models in assessing latent heat fluxes across agricultural regions. Details about the CMIP5 models and simulations are provided in supplemental section S1. For our study, CLM is run at 0.125° by 0.125° grid cells with 30 minute temporal resolution.

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

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

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

where ΔSM is soil moisture change, P is precipitation, ET is evapotranspiration, Q_S is surface runoff, $q_{recharge}$ is groundwater recharge, ΔGW is groundwater storage changes, and Q_d is groundwater ~~runoff (base flow).~~discharge. However, equations 1 and 2 only reflect the natural hydrology and neglect the substantial contribution of irrigation in major agricultural regions as previously discussed. A more reasonable equation should include the aforementioned irrigation water from surface (river) water (SW_{WD}) and from groundwater withdrawal (GW_{WD}) as shown in Figure 2 and equations 3 and 4. We will incorporate the estimated irrigation water use into the CLM version 4 and the withdrawn water in the irrigation process will be treated as an extra water input (effective precipitation).

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

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

2.4 CLM groundwater and surface water application parameterization

We use the difference (ΔET) between remote sensing observed ET (ET_{obs}) and the original model parameterized ET (ET_{om}) to constrain total applied surface and groundwater as shown in equation 5.

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

ΔET in equation 5 is determined as an inter-annual (2004-09) mean difference between satellite observed and modeled ET. Water is applied evenly in CLM4 throughout the primary growing and irrigation season (May-October). We can constrain the partitioning of the total withdrawn irrigation water into SW_{WD} and GW_{WD} by requiring that equations 3 and 4 are both satisfied by the CLM4 simulation. A systematic, trial-and-error procedure ~~(grid search)~~ is used to determine the necessary partitioning using groundwater recharge since it is a common variable to both equations. For each trial, a value of $q_{recharge}$ is guessed. GW_{WD} is then determined from re-arranging equation 4, with ΔGW and Q_d being set to average values derived from processed GRACE ~~observations~~ΔGW and the baseline simulations for the study period (2004-2009), respectively. SW_{WD} is then found as a residual from equation 5, and CLM4 is run. The model run generates a simulated recharge (equation 3). If the trial (or "parameterized") recharge value and the simulated recharge value agree, then equations 3 and 4 are satisfied and the partitioning is accepted. Equation 5 notes that all abstracted water eventually contributes to ET. While this assumption may be violated at a field scale, it likely holds at a regional scale in the Central Valley where extensive conjunctive use and reuse of water occurs (Canessa et al., 2011).

To ~~locate~~find the correct recharge and withdrawal partitioning, we ran a series of trials in which the parameterized recharge was increased in 5 mm/year increments, from 20 mm/year (the first point in the left in Figure 5 and the minimum value of recharge necessary to generate the baseline Q_d of 20 mm/year) to 115 mm/year. With the average ΔGW and Q_d (section 3.1), this corresponds to a GW_{WD} range of 60 to 155 mm/year. The procedure assumes only minimal differences exist in Q_d computed for the baseline and trial simulations, an assumption that we verified by inspecting irrigation simulation outputs. ~~For all simulations, we assumed that pumping removed groundwater equally from the confined and unconfined aquifer layers (Fig. 2).~~Since the Central Valley aquifer system is a combination of unconfined and confined aquifers, we assume that groundwater withdrawals are equally distributed between both types of aquifers (Fig 2). Because the CLM lacks a confined aquifer component, confined withdrawal is assumed to come from a hypothetical water store. Unconfined withdrawals were taken from the saturated zone of the soil.

3 Results and Discussion

3.1 Existing model parameterizations and satellite observed hydrologic fluxes

Monthly satellite observed and simulated evapotranspiration (ET) for the Central Valley showed strong and differing seasonality (Fig. 3a). ~~Observed~~Satellite observed monthly ET ranged from 13 mm (December 2009) to 106 mm (July 2005). Seasonal maxima and minima of ~~observed~~ ET coincided with seasonal maxima and minima of regional solar radiation and temperatures that control potential ET (solar radiation and temperature data not shown). Over the entire 2004-2009 study period, mean (± one standard deviation) satellite observed ET was

54.6±12.8 mm/month (655 mm/year). GLDAS-1, NLDAS-2, and CLM simulated ET was substantially lower than satellite observed ET (Fig. 3a), with mean simulated ET of 23.3±5.0 mm/month (280 mm/year). Simulated ET ranged from 19 mm/month (September 2008) to 69 mm/month (April 2006). GLDAS-1/NLDAS-2/CLM simulated seasonal maxima and minima of ET coincided with maximal and minimal natural soil moisture availability following the end of the winter rainy season and at the end of the dry summer season (Fig. 3c). On an average seasonal basis, satellite observed ET showed the greatest difference from simulated ET in July, when ~~observed~~satellite ET was 79 mm/month larger. In winter (November-February), observed ET exceeded simulated ET by less than 10 mm/month (Fig. 3c).

While the seasonality of satellite observed and simulated ET was different, the annual patterns of ~~observed and simulated~~ ET matched annual precipitation well, although satellite observed ET had considerably lower interannual variation than simulated ET (Fig. 3). Annual precipitation ranged from 202 mm/year (2007 calendar year) to 416 mm/year (2005 calendar year). Mean (± one standard deviation) calendar year precipitation for 2004-2009 was 315.8±84.8 mm/year. Annual changes in groundwater vary considerably from year to year, with a maximum increase of 120 mm/year in 2006 and a maximum decrease of 220 mm/year in 2007 (Fig. 4). Mean groundwater decrease across the entire study period is approximately 60 mm/year. Annual precipitation and groundwater change are well correlated (r=0.78), with the largest groundwater decrease ~~coming~~occurring in one of the driest years in California history (2007) and the largest increase in 2006 following a succession of wet years. Mean annual satellite observed ET showed less variation than precipitation, ranging from 624 mm/year in 2009 to 690 mm/year in 2005. Since precipitation in the surface water source regions for the Central Valley (Sierra Nevada Mountains) is very well correlated with precipitation in the Valley (Daly, 1994; Daly et al., 2008), variations in precipitation are also assumed to be variations in surface water availability. Together, this lower variation in ET in spite of higher variation in precipitation and surface water availability and the inverse relationship between groundwater level change and precipitation is consistent with the relatively steady water demand from Californian agricultural crops, many of which are perennial crops with large, multi-year investments (Ayars, 2013; Blank, 2000), and the long-standing practice of increasing groundwater use to compensate for deficits in surface supplies and precipitation (Howitt, 1991).

3.2. Application of Groundwater and Surface Water in CLM and impact on CLM-simulated ET

The mean amount of additional water that is consumed or transpired under irrigation in the Central Valley is 376 mm/year (satellite observed ET minus mean GLDAS-1/NLDAS-2/CLM ensemble simulated ET). The parameterized recharge estimates plotted against CLM simulated recharge are shown in Figure 5. Simulated recharge ($q_{recharge}$) showed a more dampened response to a wide range of parameterized recharges, with simulated recharge ranging from 47 to 66 mm/year across the parameterized recharge space (20-115 mm/year). The parameterized and simulated recharge comes to convergence at approximately 55 mm/year (Fig. 45), which is the value we used to partition applied surface water and groundwater. Using equation 4, we calculated mean applied groundwater (GW_{WD}) as 95 mm/year over the 2004-2009 study period. Mean applied surface water (SW_{WD}) was 281 mm/year.

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

Figure 6 shows the impact of the irrigation water parameterization on CLM simulated ET compared to observational data. With the new parameterization, monthly CLM simulated ET ranged from a minimum of 10 mm (December 2008) to a maximum of 96 mm (June 2006), with a mean of 48.3 mm. The differences between CLM simulated ET and satellite observed ET (CLM minus ~~observed~~satellite) ranged from -30 mm/month to 11 mm/month with a mean difference of -6.3 mm/month. There was low correlation between seasonality (month) and the discrepancy between satellite observed and non-irrigated simulated ET (r<0.5) as assessed with a geometric mean regression. Conversely, the relationship between satellite observed monthly ET and CLM simulated ET was excellent (r=0.95, slope=0.94, intercept=-3.1 mm/month).

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

3.3 Impact of parameterizations of irrigated agriculture in land surface modeling

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

Compared with previous parameterizations of irrigation water in the Central Valley our remote-sensing based approach resulted in a lower consumed amount of water than the soil moisture-based parameterizations (Kueppers et al., 2007; Sorooshian et al., 2011) and a slightly higher amount of consumed water than a global inventory- (Siebert et al., 2010), based approach (Lo and Famiglietti, 2013). For the summer months of May-August, a high soil moisture parameterization at field capacity (Kueppers et al., 2007) resulted in an annual summer irrigation water consumption of 612 mm/summer whereas a variable soil moisture parameterization (Sorooshian et al., 2011) resulted in a summer irrigation water consumption of 430 mm/summer. These values do not include potential water consumption from the shoulder irrigation months of April, September, and October. The inventory data of Siebert et al. (2010) used in the Lo and Famiglietti (2013) parameterization was only about 25 mm lower (350 mm/year versus 376 mm/year) than our remote sensing parameterization, but the amount of consumed water from groundwater (140 mm/year) was substantially higher than our applied groundwater (95 mm/year). Furthermore, our satellite-ET derived estimate is also likely to be a lower envelope estimate of applied water due to the slight increase in surface runoff observed in CLM. The overestimation of

ET and latent heat fluxes with the soil moisture parameterization suggests challenges in using this type of parameterization; however, soil moisture parameterization may become significantly more feasible ~~and~~with precise ~~with~~and accurate regional and global soil moisture observations from upcoming missions such as the Soil Moisture Active Passive, whose outputs are specifically designed to improve inputs to numerical weather prediction and land surface models (Entekhabi et al., 2010).

Currently, both inventory and remote sensing based approaches have sufficiently ~~coarse~~low spatial and temporal resolution so that irrigation water parameterization is typically done on inter-annual time scales for large basins. This temporal resolution for water parameterization works well for accurately modeling the hydrology of the Central Valley, likely due to the lower amount of inter-annual variation in ET and the use of groundwater to compensate for surface water deficits. However, it is unclear how well this approach will work in irrigated regions where ET may be more variable due to a lack of supplemental reservoirs and thus a necessary fallowing of land during ~~drought~~dry periods. Current and future missions (GPM, SMAP, SWOT, GRACE-Follow On/GRACE II) have the potential to sufficiently improve the resolution of satellite hydrologic products to enable annual quantification of surface and ground water application at higher spatial ~~scales~~resolution (Biancamaria et al., 2010; Entekhabi et al., 2010, Smith et al., 2007; Zheng et al., 2015). These higher resolution parameterizations may enable better quantification of hydrologic impacts of changing management and cropping patterns, including shifts in irrigation regimes and changes between annual and perennial crops. Parameterizations from inventory methods may improve if public monitoring and reports requirements become more widespread (similar to those for Arizona's Active Management Areas – see Jacobs and Holway, 2004).

4 Summary and Conclusion

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

The results emphasize the need for irrigation parameterization in land and climate models to accurately assess land-atmosphere energy and mass fluxes in regions with major anthropogenic modifications. Given the potential for intense irrigation to modify regional climate (Kueppers et al., 2007) and to enhance convection precipitation in downwind regions (Lo and Famiglietti, 2013), it is important that the additional water consumption from irrigation is properly represented to better model the local and more distant impacts of anthropogenic land surface modification. An improved parameterization will also be useful for assessing regional climatic impacts of possible future changes in irrigated agricultural regions due to increased logistical, political, and/or economic restrictions on groundwater pumping or changes in surface water use.

Acknowledgements

The GLDAS and NLDAS data used in this study were acquired as part of the mission of NASA's Earth Science Division and archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Center (DISC). This study was supported by the Ministry of Science and Technology, Taiwan, (grants MOST 103-2111-M-002-006 and MOST 100-2119-M- 001-029-MY5), by the United States Department of Agriculture-Agricultural Research Service, National Program 211: Water Availability and Watershed Management (project number 2036-61000-015-00), and by the University of California Multicampus Research Programs and Initiatives (MRPI).

References

Allen, R. G., Tasumi, M. and Trezza, R.: Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC)—Model, J. Irrig. Drain. Eng., 133(4), 380–394, doi:10.1061/(ASCE)0733-9437(2007)133:4(380), 2007.

Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A. and Kustas, W. P.: A climatological study of evapotranspiration and moisture stress across the continental United States based on thermal remote sensing: 1. Model formulation, J. Geophys. Res., 112(D10), D10117, doi:10.1029/2006JD007506, 2007.

Anderson, R. G., Lo, M.-H. and Famiglietti, J. S.: Assessing surface water consumption using remotely-sensed groundwater, evapotranspiration, and precipitation, Geophys. Res. Lett., 39(16), L16401, doi:10.1029/2012GL052400, 2012.

Ayars, J. E.: Adapting Irrigated Agriculture to Drought in the San Joaquin Valley of California, in Drought in Arid and Semi-Arid Regions, edited by K. Schwabe, J. Albiac, J. D. Connor, R. M. Hassan, and L. Meza González, pp. 25–39, Springer Netherlands, Dordrecht., 2013.

Biancamaria, S., Andreadis, K. M., Durand, M., Clark, E. A., Rodriguez, E., Mognard, N. M., Alsdorf, D. E., Lettenmaier, D. P. and Oudin, Y.: Preliminary Characterization of SWOT Hydrology Error Budget and Global Capabilities, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 3(1), 6–19, doi:10.1109/JSTARS.2009.2034614, 2010.

Blank, S. C.: Perspective: Is this California agriculture's last century?, California Agric., 54(4), 23–25, doi:10.3733/ca.v054n04p23, 2000.

Borsa, A. A., Agnew, D. C. and Cayan, D. R.: Ongoing drought-induced uplift in the western United States, Science, 345(6204), 1587–1590, doi:10.1126/science.1260279, 2014.

California Department of Food and Agriculture: California Agricultural Statistics Review 2013-2014, [online] Available from: ~~http://www.cdfa.ca.gov/statistics/pdfs/2013/AgStatsOverview.pdf~~http://www.cdfa.ca.gov/statistics/pdfs/2013/AgStatsOverview.pdf (Accessed 12 December 2014), 2014.

Canessa, P., Green, S. and Zoldoske, D: Agricultural Water Use in California: A 2011 Update, Center for Irrigation Technology, California State University, Fresno, [online] Available from: http://www.californiawater.org/cwi/docs/CIT_AWU_REPORT_v2.pdf (Accessed 17 July 2015), 2011.

Chung, I. and Helweg, O.: Modeling the California State Water Project, J. Water Resources Planning Manage., 111(1), 82–97, doi:10.1061/(ASCE)0733-9496(1985)111:1(82), 1985.

Famiglietti, J. S.: The global groundwater crisis, Nature Clim. Change, 4(11), 945–948, doi:10.1038/nclimate2425, 2014.

Famiglietti, J. S., Lo, M., Ho, S. L., Bethune, J., Anderson, K. J., Syed, T. H., Swenson, S. C., de Linage, C. R. and Rodell, M.: Satellites measure recent rates of groundwater depletion in California's Central Valley, Geophys. Res. Lett., 38(3), L03403, doi:10.1029/2010GL046442, 2011.

Ferguson, I. M. and Maxwell, R. M.: Human impacts on terrestrial hydrology: climate change versus pumping and irrigation, Environ. Res. Lett., 7(4), 044022, doi:10.1088/1748-9326/7/4/044022, 2012.

Fischhendler, I. and Zilberman, D.: Packaging policies to reform the water sector: The case of the Central Valley Project Improvement Act, Water Resources Res., 41(7), n/a–n/a, doi:10.1029/2004WR003786, 2005.

Haddeland, I., Lettenmaier, D. P. and Skaugen, T.: Effects of irrigation on the water and energy balances of the Colorado and Mekong river basins, J. Hydrol., 324(1-4), 210–223, doi:10.1016/j.jhydrol.2005.09.028, 2006.

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

Harter, T. and Dahlke, H. E.: Out of sight but not out of mind: California refocuses on groundwater, California Agric., 68(3), 54–55, doi:10.3733/ca.v068n03p54, 2014.

Hill, J. E., Williams, J. F., Mutters, R. G. and Greer, C. A.: The California rice cropping system: agronomic and natural resource issues for long-term sustainability, Paddy and Water Environ., 4(1), 13–19, doi:10.1007/s10333-005-0026-2, 2006.

Howitt, R.: When water is scarce: Ground water is key to easing impact of drought, California Agric., 45(3), 4–9, doi: 10.3733/ca.v045n03p4, 1991.

Jacobs, K. L. and Holway, J. M.: Managing for sustainability in an arid climate: lessons learned from 20 years of groundwater management in Arizona, USA, Hydrogeol. J., 12(1), 52–65, doi:10.1007/s10040-003-0308-y, 2004.

Jin, Y., Randerson, J. T. and Goulden, M. L.: Continental-scale net radiation and evapotranspiration estimated using MODIS satellite observations, Remote Sens. Environ., 115(9), 2302–2319, doi:10.1016/j.rse.2011.04.031, 2011.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S. I., Sheffield, J., Goulden, M. L., Bonan, G., Cescatti, A., Chen, J., de Jeu, R., Dolman, A. J., Eugster, W., Gerten, D., Gianelle, D., Gobron, N., Heinke, J., Kimball, J., Law, B. E., Montagnani, L., Mu, Q., Mueller, B., Oleson, K., Papale, D., Richardson, A. D., Roupsard, O., Running, S., Tomelleri, E., Viovy, N., Weber, U., Williams, C., Wood, E., Zaehle, S. and Zhang, K.: Recent decline in the global land evapotranspiration trend due to limited moisture supply, Nature, 467(7318), 951–954, doi:10.1038/nature09396, 2010.

Kueppers, L. M., Snyder, M. A. and Sloan, L. C.: Irrigation cooling effect: Regional climate forcing by land-use change, Geophys. Res. Lett., 34(3), L03703, doi:10.1029/2006GL028679, 2007.

Lawrence, D. M., Oleson, K. W., Flanner, M. G., Thornton, P. E., Swenson, S. C., Lawrence, P. J., Zeng, X., Yang, Z.-L., Levis, S., Sakaguchi, K., Bonan, G. B. and Slater, A. G.: Parameterization improvements and functional and structural advances in Version 4 of the Community Land Model, Journal of Advances in Modeling Earth Systems, 3(3), doi:10.1029/2011MS000045, 2011.

Lei, H., Yang, D., Yang, H., Yuan, Z. and Lv, H.: Simulated impacts of irrigation on evapotranspiration in a strongly exploited region: a case study of the Haihe River basin, China, Hydrological Processes, 29(12), 2704–2719, doi:10.1002/hyp.10402, 2015.

Leng, G., Huang, M., Tang, Q., Sacks, W. J., Lei, H. and Leung, L. R.: Modeling the effects of irrigation on land surface fluxes and states over the conterminous United States: Sensitivity to input data and model parameters, J. Geophys. Res. Atmos., 118(17), 9789–9803, doi:10.1002/jgrd.50792, 2013.

Leng, G., Huang, M., Tang, Q., Gao, H. and Leung, L. R.: Modeling the Effects of Groundwater-Fed Irrigation on Terrestrial Hydrology over the Conterminous United States, J. Hydrometeorol., 15(3), 957–972, doi:10.1175/JHM-D-13-049.1, 2014.

Lo, M.-H. and Famiglietti, J. S.: Irrigation in California's Central Valley strengthens the southwestern U.S. water cycle, Geophys. Res. Lett., 40(2), 301–306, doi:10.1002/grl.50108, 2013.

Lobell, D., Bala, G., Mirin, A., Phillips, T., Maxwell, R. and Rotman, D.: Regional Differences in the Influence of Irrigation on Climate, J. Clim., 22(8), 2248–2255, doi:10.1175/2008JCLI2703.1, 2009.

Miralles, D. G., Holmes, T. R. H., De Jeu, R. A. M., Gash, J. H., Meesters, A. G. C. A. and Dolman, A. J.: Global land-surface evaporation estimated from satellite-based observations, Hydrol. Earth Sys. Sci., 15(2), 453–469, doi:10.5194/hess-15-453-2011, 2011.

Mitchell, K. E.: The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, J. Geophys. Res., 109(D7), G01021, doi:10.1029/2003JD003823, 2004.

Mu, Q., Zhao, M. and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorithm, Remote Sens. Environ., 115(8), 1781–1800, doi:10.1016/j.rse.2011.02.019, 2011.

Oleson, K. W., Niu, G.-Y., Yang, Z.-L., Lawrence, D. M., Thornton, P. E., Lawrence, P. J., Stöckli, R., Dickinson, R. E., Bonan, G. B., Levis, S., Dai, A. and Qian, T.: Improvements to the Community Land Model and their impact on the hydrological cycle, J. Geophys. Res., 113(G1), doi:10.1029/2007JG000563, 2008.

Ozdogan, M., Rodell, M., Beaudoing, H. K. and Toll, D. L.: Simulating the Effects of Irrigation over the United States in a Land Surface Model Based on Satellite-Derived Agricultural Data, J. Hydrometeorol., 11(1), 171–184, doi:10.1175/2009JHM1116.1, 2010.

Planert, M. and Williams, J. S.: Ground water atlas of the United States: Segment 1, California, Nevada, 1995.

Postel, S. L., Daily, G. C. and Ehrlich, P. R.: Human Appropriation of Renewable Fresh Water, Science, 271(5250), 785–788, doi:10.1126/science.271.5250.785, 1996.

Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin*, J. K., Walker, J. P., Lohmann, D. and Toll, D.: The Global Land Data Assimilation System, Bul. Am. Meteorol. Soc., 85(3), 381–394, doi:10.1175/BAMS-85-3-381, 2004.

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

Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L. and McMahon, P. B.: Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley, Proc. Nat. Acad. Sci., 109(24), 9320–9325, doi:10.1073/pnas.1200311109, 2012.

Schwankl, L. J., Prichard, T. L. and Hanson, B. R.: Tailwater Return Systems, University of California. [online] Available from: http://anrcatalog.ucdavis.edu/pdf/8225.pdf (Accessed 6 December 2014), 2007.

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

Smith, E. A., Asrar, G., Furuhama, Y., Ginati, A., Mugnai, A., Nakamura, K., Adler, R. F., Chou, M.-D., Desbois, M., Durning, J. F., Entin, J. K., Einaudi, F., Ferraro, R. R., Guzzi, R., Houser, P. R., Hwang, P. H., Iguchi, T., Joe, P., Kakar, R., Kaye, J. A., Kojima, M., Kummerow, C., Kuo, K.-S., Lettenmaier, D. P., Levizzani, V., Lu, N., Mehta, A. V., Morales, C., Morel, P., Nakazawa, T., Neeck, S. P., Okamoto, K., Oki, R., Raju, G., Shepherd, J. M., Simpson, J., Sohn, B.-J., Stocker, E. F., Tao, W.-K., Testud, J., Tripoli, G. J., Wood, E. F., Yang, S. and Zhang, W.: International Global Precipitation Measurement (GPM) Program and Mission: An Overview, in Measuring Precipitation From Space, edited by V. Levizzani, P. Bauer, and F. J. Turk, pp. 611–653, Springer Netherlands, Dordrecht., 2007.

Sorooshian, S., Li, J., Hsu, K. and Gao, X.: How significant is the impact of irrigation on the local hydroclimate in California's Central Valley? Comparison of model results with ground and remote-sensing data, J. Geophys. Res., 116(D6), D06102, doi:10.1029/2010JD014775, 2011.

Swenson, S. and Wahr, J.: Monitoring Changes in Continental Water Storage with GRACE, Space Sci. Rev., 108(1/2), 345–354, doi:10.1023/A:1026135627671, 2003.

Tang, Q., Oki, T., Kanae, S. and Hu, H.: The Influence of Precipitation Variability and Partial Irrigation within Grid Cells on a Hydrological Simulation, J. Hydrometeorol., 8(3), 499–512, doi:10.1175/JHM589.1, 2007.

Tang, Q., Oki, T., Kanae, S. and Hu, H.: Hydrological Cycles Change in the Yellow River Basin during the Last Half of the Twentieth Century, J. Clim., 21(8), 1790–1806, doi:10.1175/2007JCLI1854.1, 2008.

Tang, Q., Peterson, S., Cuenca, R. H., Hagimoto, Y. and Lettenmaier, D. P.: Satellite-based near-real-time estimation of irrigated crop water consumption, J. Geophys. Res., 114(D5), D05114 doi:10.1029/2008JD010854, 2009.

Tapley, B. D., Bettadpur, S., Watkins, M. and Reigber, C.: The gravity recovery and climate experiment: Mission overview and early results, Geophys. Res. Lett., 31(9), L09607, doi:10.1029/2004GL019920, 2004.

Taylor, K. E., Stouffer, R. J. and Meehl, G. A.: An Overview of CMIP5 and the Experiment Design, Bul. Am. Meteorol. Soc., 93(4), 485–498, doi:10.1175/BAMS-D-11-00094.1, 2012.

USDA National Agricultural Statistics Service: 2012 Census of Agriculture, California State and County Data, [online] Available from: http://www.agcensus.usda.gov/Publications/2012/Full_Report/Volume_1,_Chapter_2_County_Level/California/cav1.pdf (Accessed 17 July 2015), 2014.

Van Dijk, A. I. J. M., Renzullo, L. J., Wada, Y. and Tregoning, P.: A global water cycle reanalysis (2003-2012) merging satellite gravimetry and altimetry observations with a hydrological multi-model ensemble, Hydrol. Earth Sys. Sci.,, 18(8), 2955–2973, doi:10.5194/hess-18-2955-2014, 2014.

Voss, K. A., Famiglietti, J. S., Lo, M., de Linage, C., Rodell, M. and Swenson, S. C.: Groundwater depletion in the Middle East from GRACE with implications for transboundary water management in the Tigris-Euphrates-Western Iran region, Water Resources Res., 49(2), 904–914, doi:10.1002/wrcr.20078, 2013.

Wisser, D., Frolking, S., Douglas, E. M., Fekete, B. M., Vörösmarty, C. J. and Schumann, A. H.: Global irrigation water demand: Variability and uncertainties arising from agricultural and climate data sets, Geophys. Res. Lett., 35(24), L24408, doi:10.1029/2008GL035296, 2008.

Xia, Y., Mitchell, K., Ek, M., Cosgrove, B., Sheffield, J., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Duan, Q. and Lohmann, D.: Continental-scale water and energy flux analysis and validation for North American Land Data Assimilation System project phase 2 (NLDAS-2): 2. Validation of model-simulated streamflow, J. Geophys. Res., 117(D3), D03110, doi:10.1029/2011JD016051, 2012a.

Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Lettenmaier, D., Koren, V., Duan, Q., Mo, K., Fan, Y. and Mocko, D.: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products, J. Geophys. Res., 117(D3), D03109, doi:10.1029/2011JD016048, 2012b.

Zheng, W., Hsu, H., Zhong, M. and Yun, M.: Requirements Analysis for Future Satellite Gravity Mission Improved-GRACE, Surveys Geophys., 36(1), 87–109, doi:10.1007/s10712-014-9306-y, 2015.

Zhong, S., Whiteman, C. D. and Bian, X.: Diurnal Evolution of Three-Dimensional Wind and Temperature Structure in California's Central Valley, J. Appl. Meteorol., 43(11), 1679–1699, doi:10.1175/JAM2154.1, 2004.

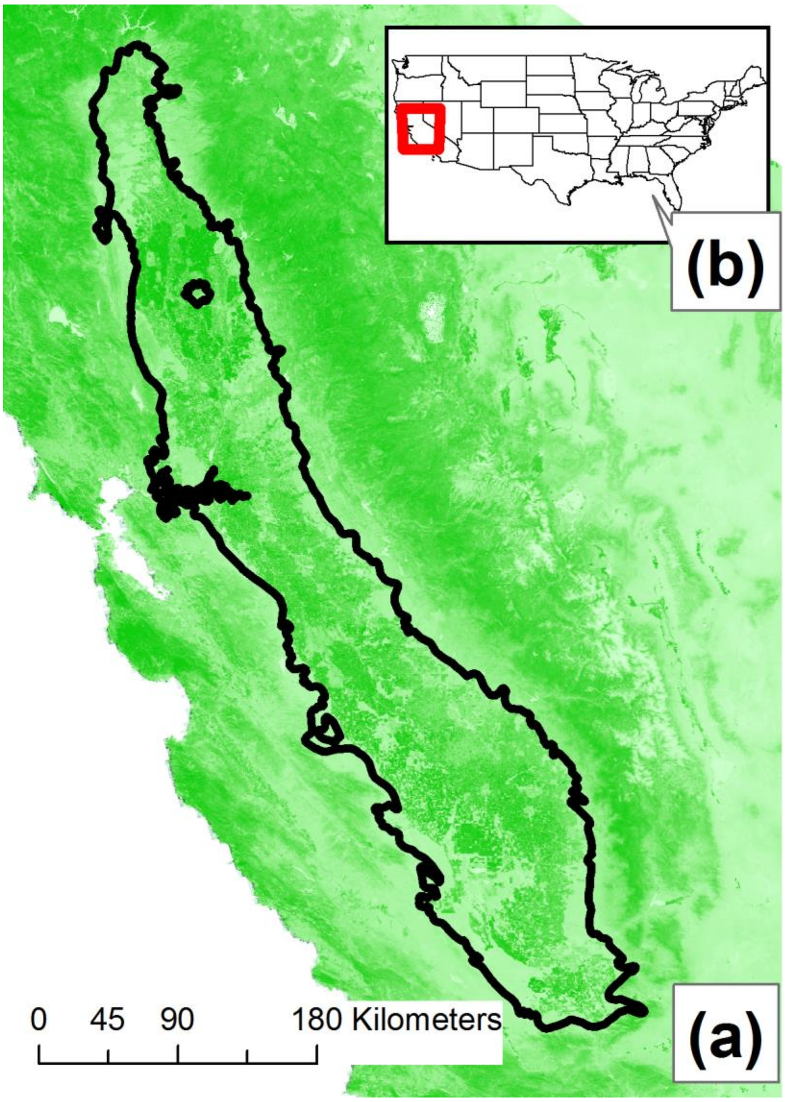


Figure 1: Map of Central Valley, California. a) Underlying Normalized Differential Vegetation Index (NDVI) from the MODerate resolution Imaging Spectroradiometer (MODIS) 250m, 16 day product (July 2006) illustrating irrigated regions of the Central Valley (black outline). Darker green indicates higher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

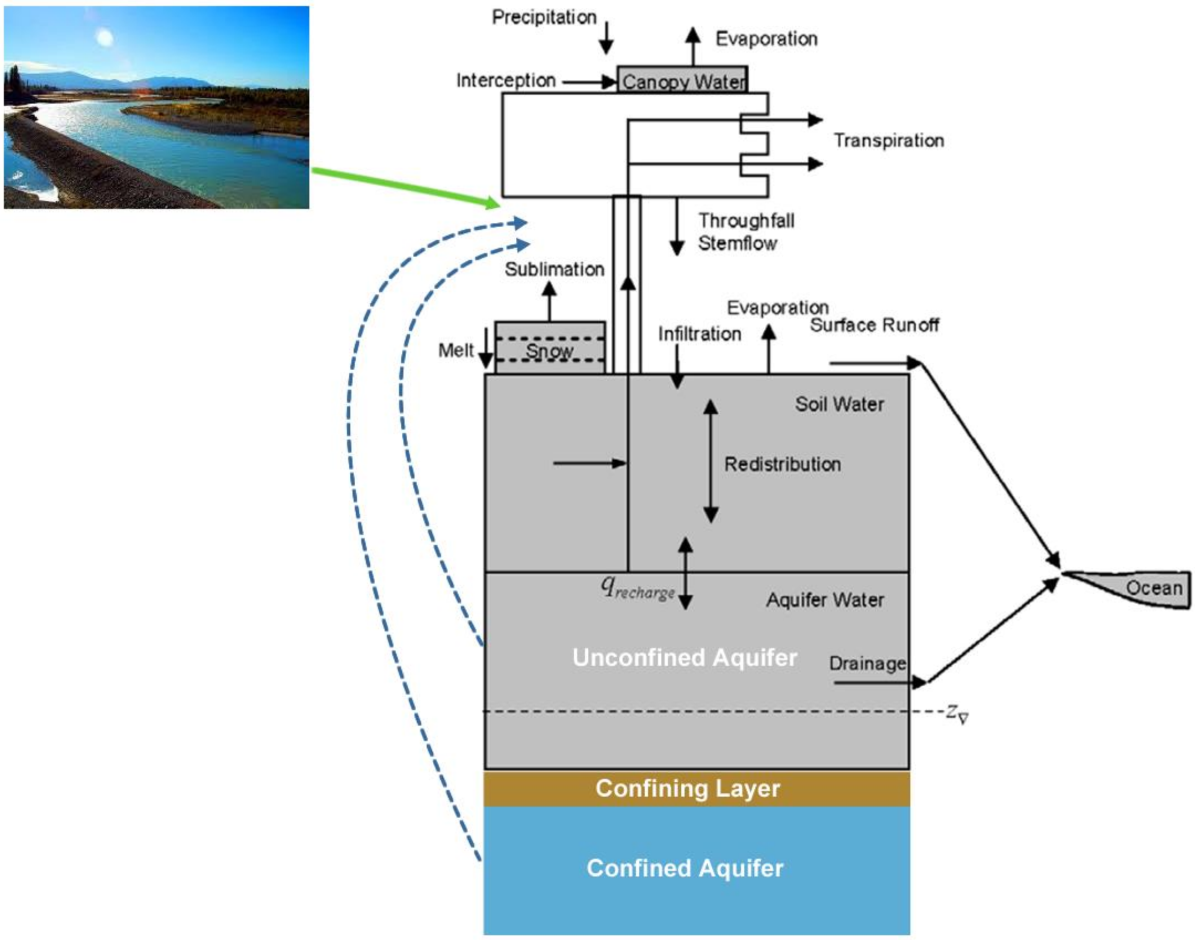
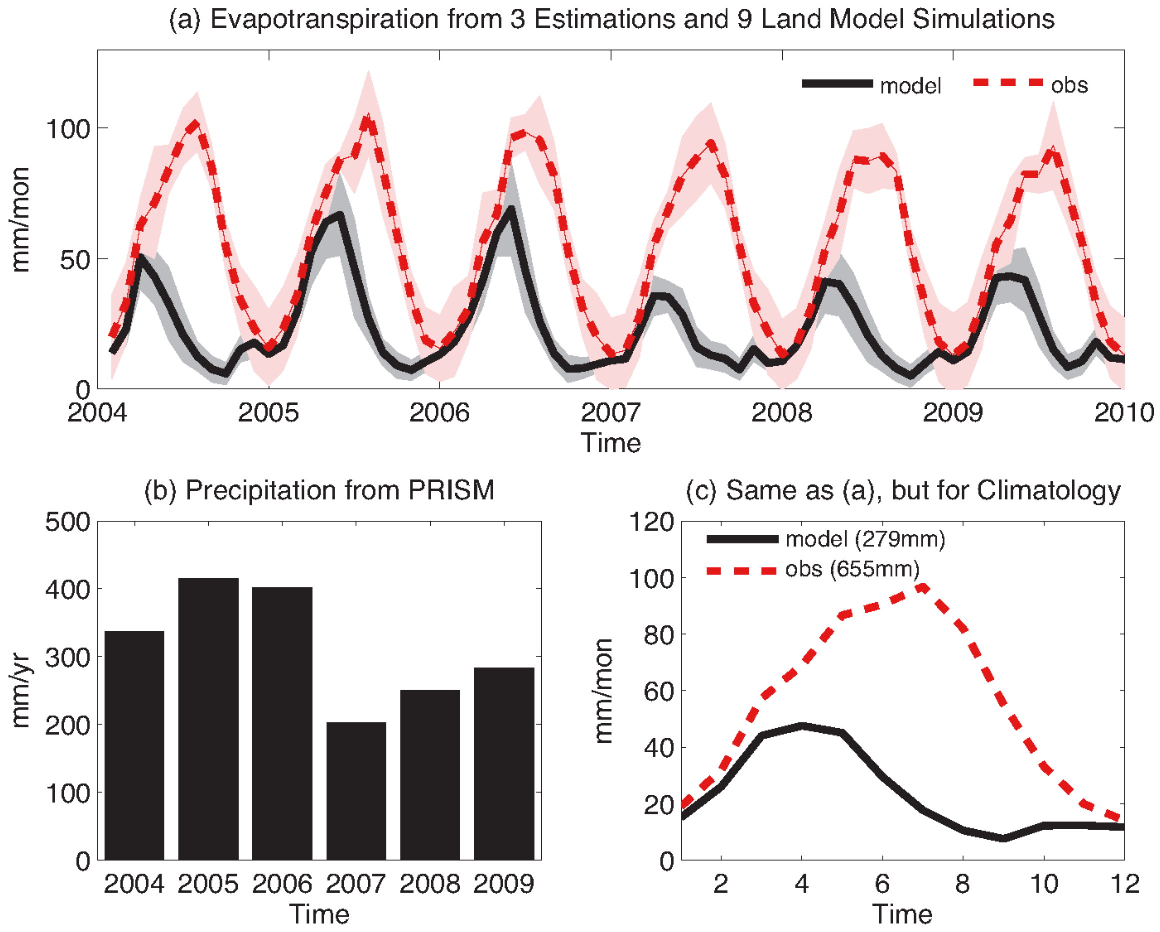


Figure 2: ~~Schematic~~Conceptual schematic of land hydrological processes, modified from Oleson et al. (2008). Blue dash and green lines indicate the irrigation water fluxes applied in the CLM. In the Central Valley, the aquifer is variably confined with some regions having no confinement.

1



(a) Evapotranspiration from 3 Estimations and 9 Land Model Simulations
model
obs
mm/mon
100
50
0
2004
2005
2006
2007
2008
2009
2010
Time
(b) Precipitation from PRISM
mm/yr
500
400
300
200
100
0
2004 2005 2006 2007 2008 2009
Time
(c) Same as (a), but for Climatology
model (279mm)
obs (655mm)
mm/mon
120
100
80
60
40
20
0
2
4
6
8
10
12
Time

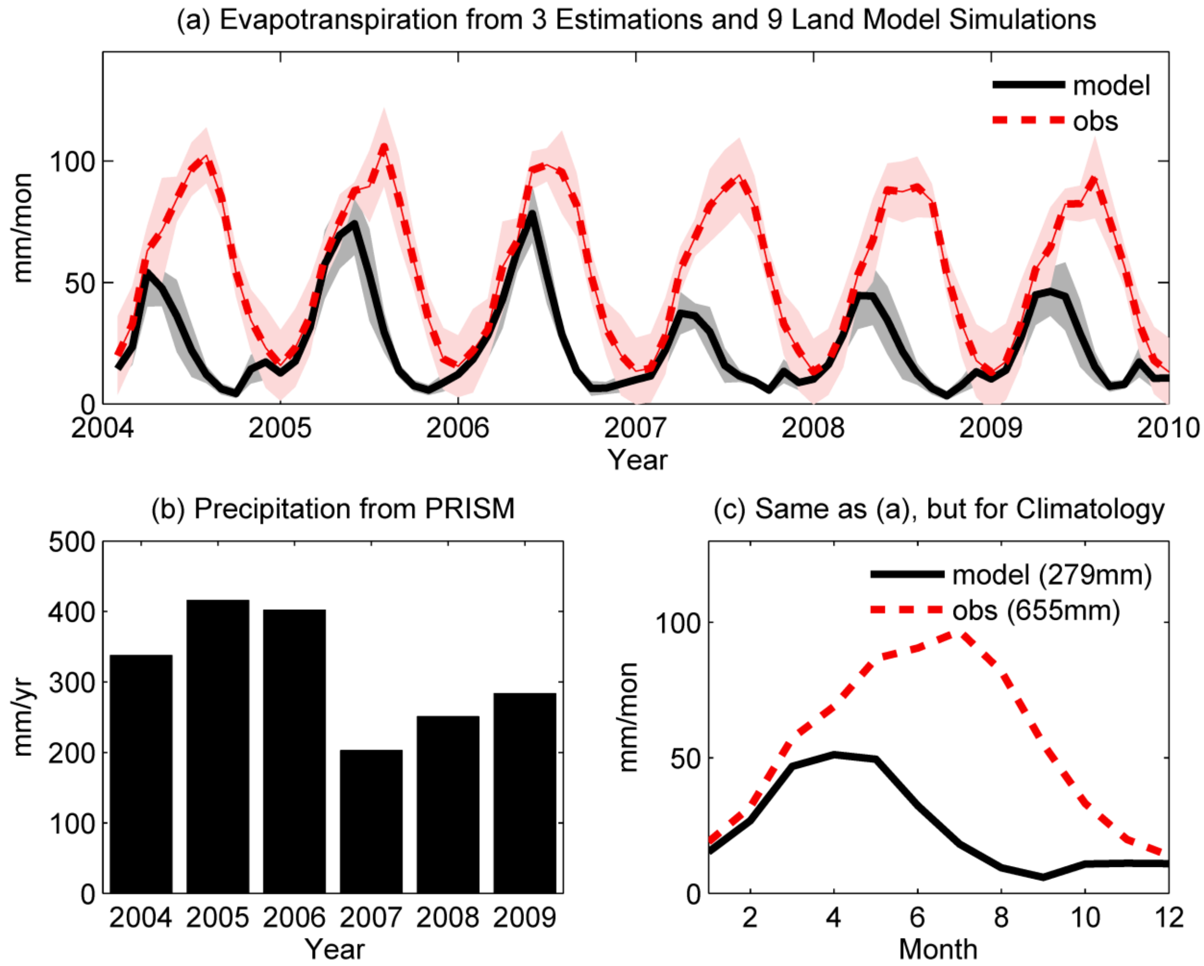


Figure 3: (a) the comparison between the remote sensing estimated ET, and 9 GLDAS, NLDAS, and CLM models. The lines indicate the ensemble mean while the shading indicates uncertainty around the ensemble mean, (b) annual precipitation for the Central Valley, and (c) monthly climatology for satellite observed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

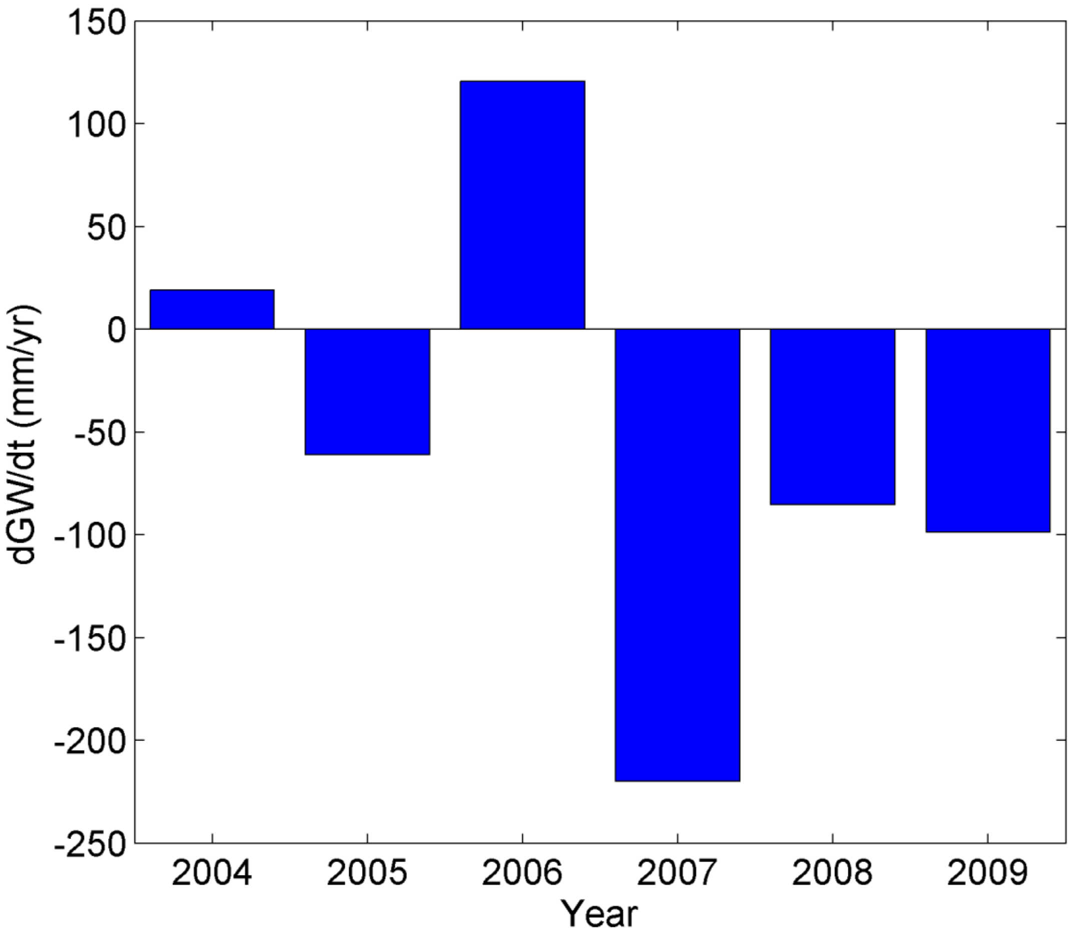


Figure 4: Annual groundwater change for the Central Valley derived from GRACE.

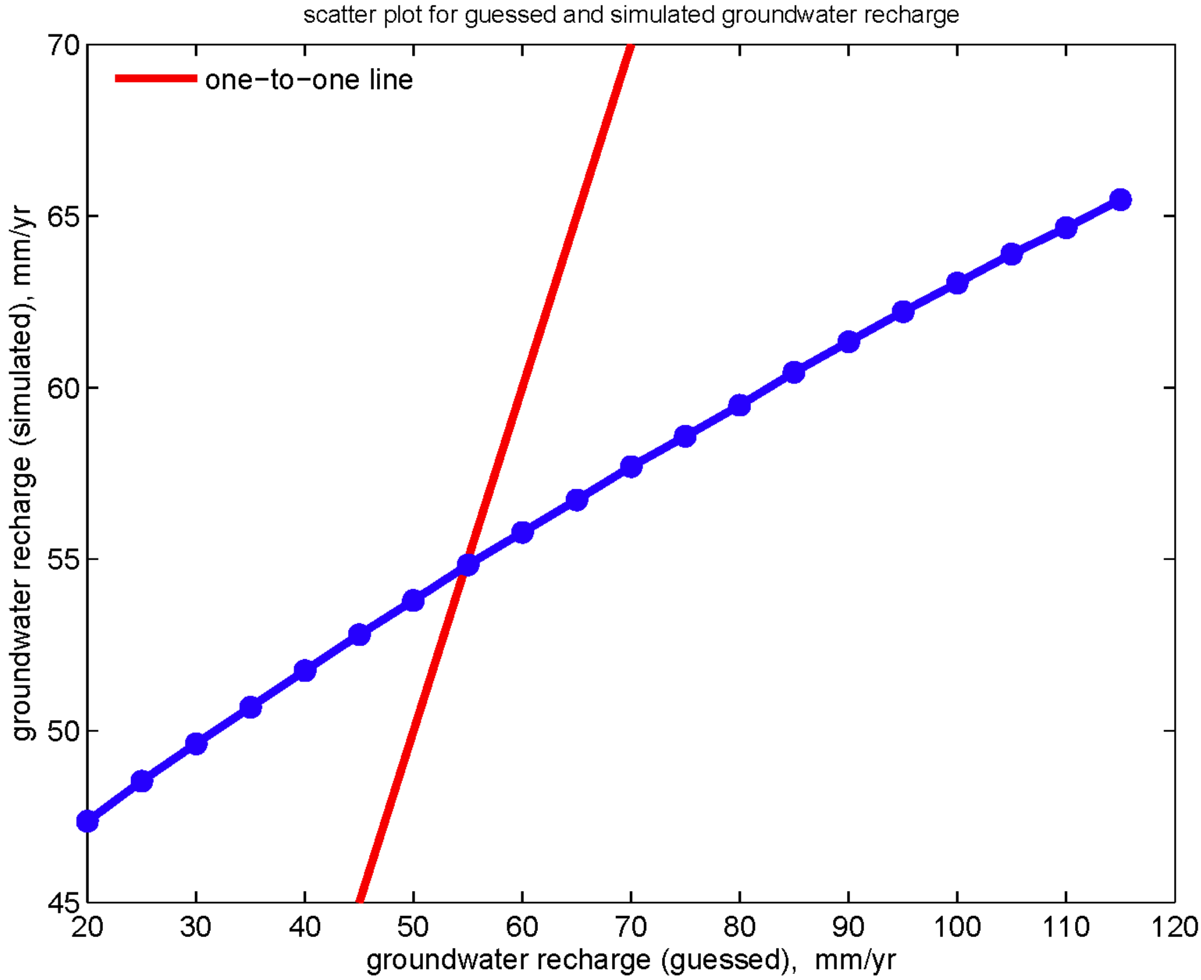


Figure 5: Parameterized (guessed) groundwater recharge versus recharge simulated in CLM 4 (see section 2.3). The x-axis represents the trial recharge used in equation 4 to obtain GW_{WD} and the y-axis represents the output recharge from equation 3. The intersection of the parameterized values with simulated 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.

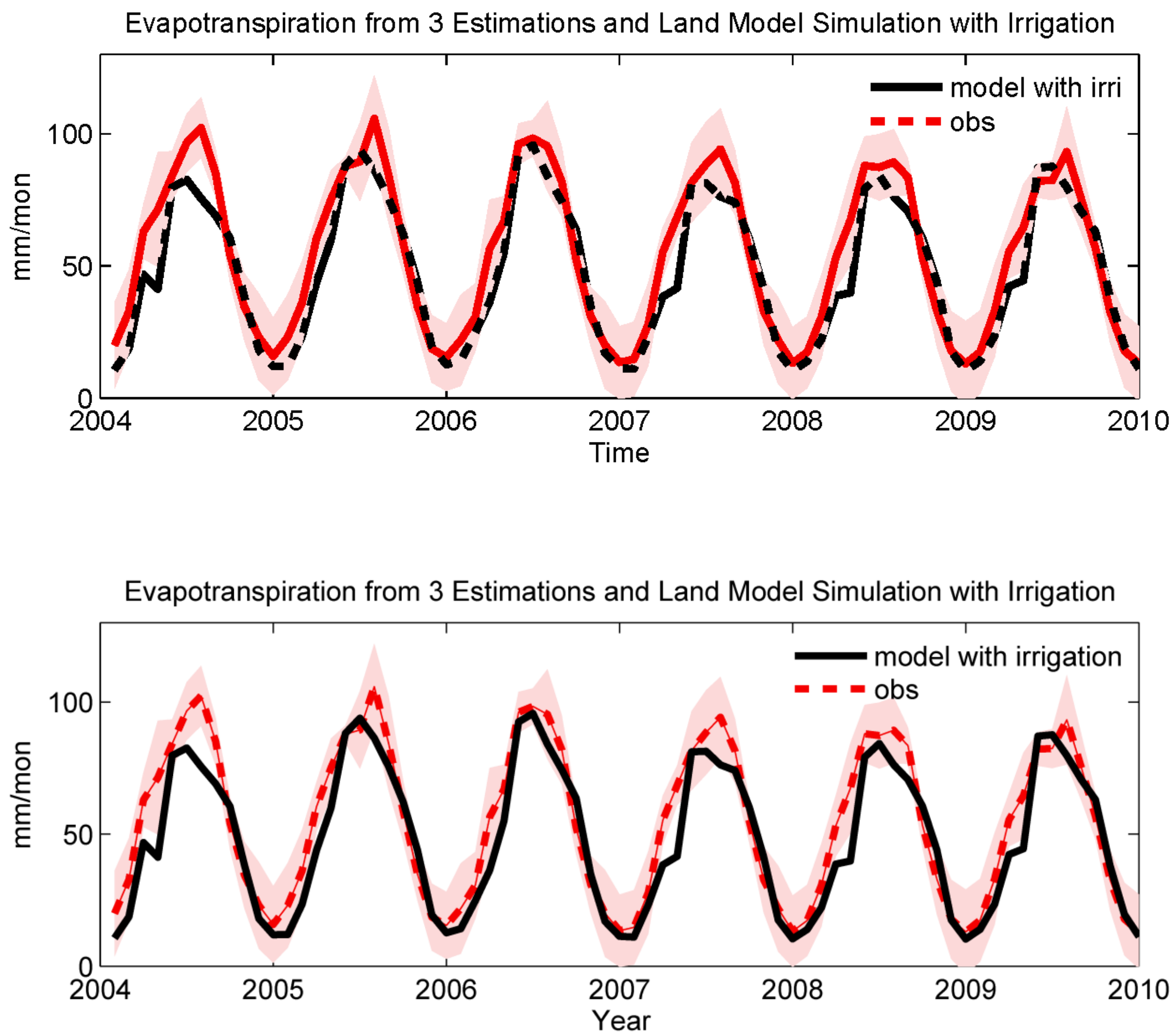
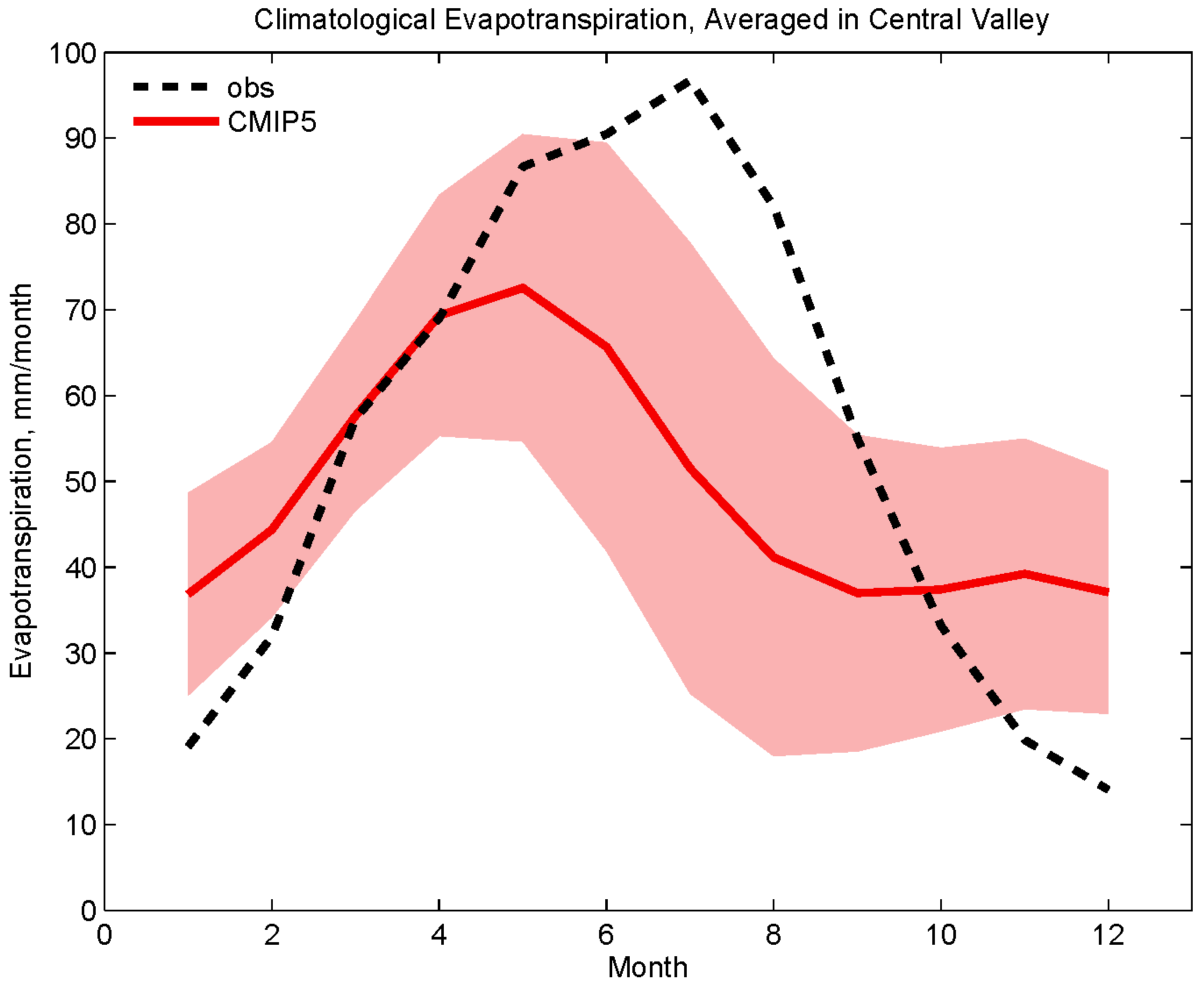


Figure 6: Monthly ET from CLM 4 with the improved irrigation parameterization when compared to observations. Lines indicate model or ensemble mean while shading indicates uncertainty of the satellite observed ET.


Climatological Evapotranspiration, Averaged in Central Valley
obs
CMIP5
Evapotranspiration, mm/month
0
10
20
30
40
50
60
70
80
90
100
0
2
4
6
8
10
12
Month

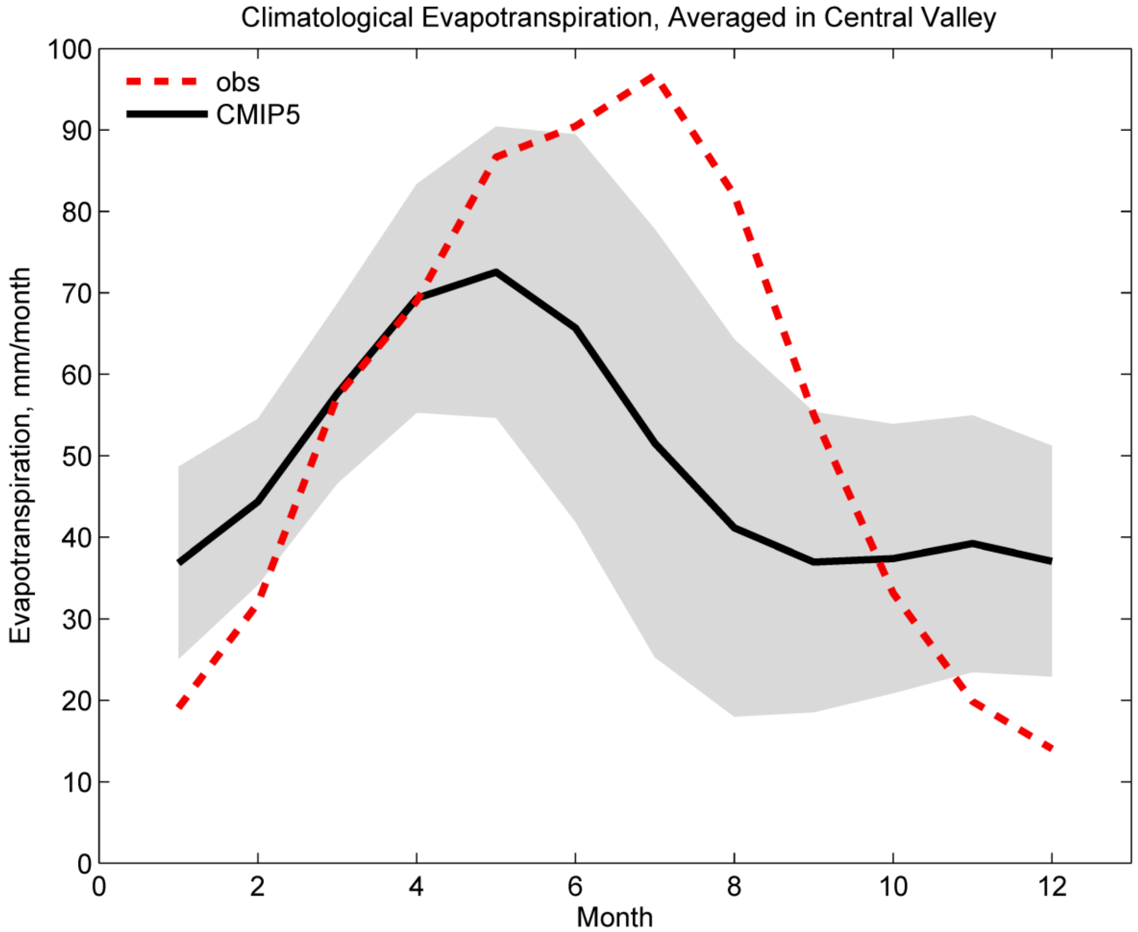


Figure 7: Mean seasonal cycle from the CMIP5 suite of models compared against satellite observed ET. Solid line shows mean value of CMIP5 model members and shaded region shows uncertainty (two standard deviations around mean).