Climate-smart management of soil water storage: statewide analysis of California perennial crops

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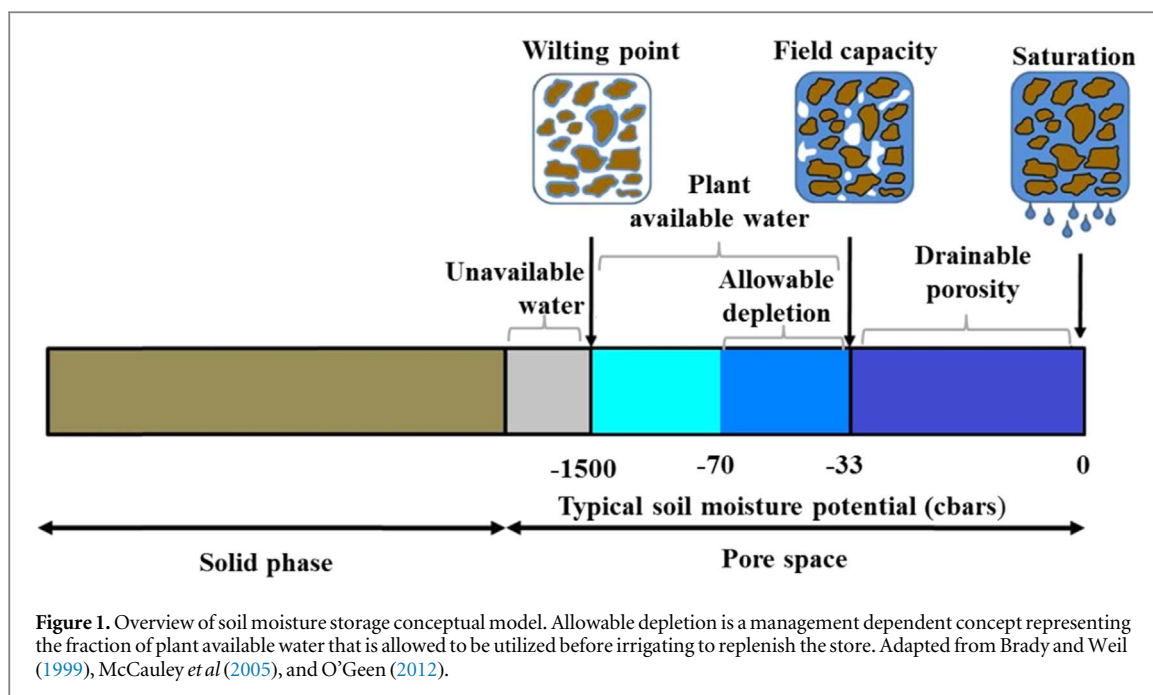
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Abstract

The FAO-56 dual crop coefficient model was used to simulate site-specific irrigation management to quantify the green water resource (rainfall stored in soil) in five California perennial crops (alfalfa, almonds, grapes, pistachios, and walnuts), considering local soil water holding capacity and climate data from 2003 to 2018. We tested different rooting depths and irrigation management thresholds (allowable depletion) across 1.46 million hectares of cropland to determine how the size of the soil water reservoir affects green water utilization and, consequently, blue water demand (irrigation). The 13-year cumulative green water utilization ranged from 17 to 36 million km^3 out of a 57 km^3 rainfall input and 162–263 km^3 cumulative blue water demand. For a deep scenario (2 m rooting; 50% allowable depletion), green water met 12% of cumulative crop water demand. However, green water use was not uniform: 20% of the landscape met over 20% of its annual crop water demand. Deeper rooting or greater allowable depletion reduced blue water demand more than the increase in green water utilization, due to less frequent irrigations, which reduced soil evaporative loss. Compared to a 'business-as-usual' shallow irrigation management scenario (0.5 m rooting; 30% allowable depletion), a moderate scenario (1.0 m rooting; 50% allowable depletion) saved 30 km^3 blue water evaporation and increased green water use by 7 km^3 through 13 years. Such savings would fill California's largest reservoir, Shasta Lake, 6.6 times. This study demonstrates an opportunity for climate-smart management of soil water storage, by delayed spring irrigation, applying deeper irrigations less often, and ending fall irrigation early.

1. Introduction

Irrigated agriculture, climate change, urban growth, and environmental concerns are forcing societies to reconsider how water is managed in order to meet human and ecosystem needs reliably. Globally, irrigated agriculture is responsible for 40% of food production, but relies on a 2700 km^3 freshwater input to irrigation (blue water) that accounts for 70% of global blue water withdrawal by humans (FAO 2015). In Mediterranean climates like in California, reliance on irrigation is necessary to meet crop water demands. This is because growing season potential evapotranspiration typically exceeds combined growing season rainfall and crop root zone soil moisture storage from winter rainfall—in many places by more than 1 m water depth per year. This natural climatic water deficit means that California's globally significant

agricultural industry valued at over \$50B yr^{-1} (CDFA 2018) depends on large inputs of blue water: on average, 80% of California's diverted surface flows and pumped groundwater is for agriculture compared to urban and industrial water use (CDWR 2014). From 2001 to 2010, California agriculture applied an estimated 43 $km^3 yr^{-1}$ of surface and groundwater for irrigation, 40%–50% of all annual stream flow from California's watersheds (CDWR 2014). Water use by agriculture is at the heart of long-running, historic conflict over who has a right to water in the western US, especially California (Hanak *et al* 2011). Climate change is projected to greatly exacerbate western US water supply issues through loss of snowpack and increasing precipitation volatility, combined with record heat (Stewart *et al* 2005, AghaKouchak *et al* 2014, Goulden and Bales 2014, Berg and Hall 2015, Dettinger *et al* 2015, Swain *et al* 2018).

Figure 1. Overview of soil moisture storage conceptual model. Allowable depletion is a management dependent concept representing the fraction of plant available water that is allowed to be utilized before irrigating to replenish the store. Adapted from Brady and Weil (1999), McCauley *et al* (2005), and O'Geen (2012).

To date, water resource policy makers, professionals, and scientists have focused on adapting blue water systems to meet challenges of increasing competition for water supplies and potential scarcity due to climate change. However, as part of an integrated water resource management strategy, there may not only be clever ways to adapt blue water systems, but also opportunities related to more efficient use of green water, soil-stored rainfall potentially available to plants for transpiration (Rockstrom *et al* 2010). The green water resource has not been rigorously quantified or analyzed in California, despite implicit assumption of its use in California agricultural water demand models that estimate irrigation demand for relatively large hydrologic regions (Dogrul *et al* 2011, Orang *et al* 2013, Mancosu *et al* 2016, CDWR 2017b).

Because most precipitation falls during the dormant season of high-value perennial crops in Mediterranean climates, green water is mostly provided through soil storage of winter precipitation. Thus, green water availability is dependent on plant available water storage capacity of soils and amount and timing of precipitation. How the size of the soil reservoir is defined is a central part of this study's approach. Although there is a wide range of possibilities for irrigation systems and management, California agricultural water demand models have not explored variables such as rooting depth that affect accessibility of plant available soil water storage and different irrigation management strategies.

One technique for utilizing green water in irrigated agriculture is to withhold irrigation at the beginning of the growing season until soil-stored water has been depleted just prior to onset of water stress. This proportion of plant available water is called allowable depletion and is commonly found to be ~50% of plant available

water for most crops and a range of soil textures (figure 1) (Hanson *et al* 1999, Hanson *et al* 2000). Delaying irrigation at the beginning of the growing season to use more green water is expected to result in several benefits: (1) reduced water loss to deep percolation and/or surface runoff early in the irrigation season and again in fall; (2) reduced non-point source pollution; (3) reduced energy costs associated with pumping blue water; and (4) fewer stream flow diversions from late winter thru spring and again in fall when irrigations are withheld.

The objectives of this study were twofold. First, we sought to characterize the green water resource within a water balance modeling framework for five major irrigated perennial crops encompassing 1.46 million ha across California: alfalfa, almonds, grapes, pistachios, and walnuts. Second, we sought to test how varying crop rooting depth (assumed to be driven primarily by average depth of irrigations) and level of allowable depletion would affect the green water utilized along with other aspects of the water balance such as deep percolation, which has implications for salinity management. Better understanding spatial and temporal gradients of the green water resource could lead to improved, place-based, and well-timed irrigation strategies that reduce reliance on blue water by strategically using soils as reservoirs.

2. Methods

2.1. Overview

A 5273 d simulation was used to model irrigation of the top five California perennial crops by area (alfalfa, almonds, grapes, pistachios, and walnuts), using publicly available weather, soils, and cropping data. These data sources were integrated into a common database and processed by a R script that implements the FAO-56 reference ET, dual crop coefficient (dual K_c)
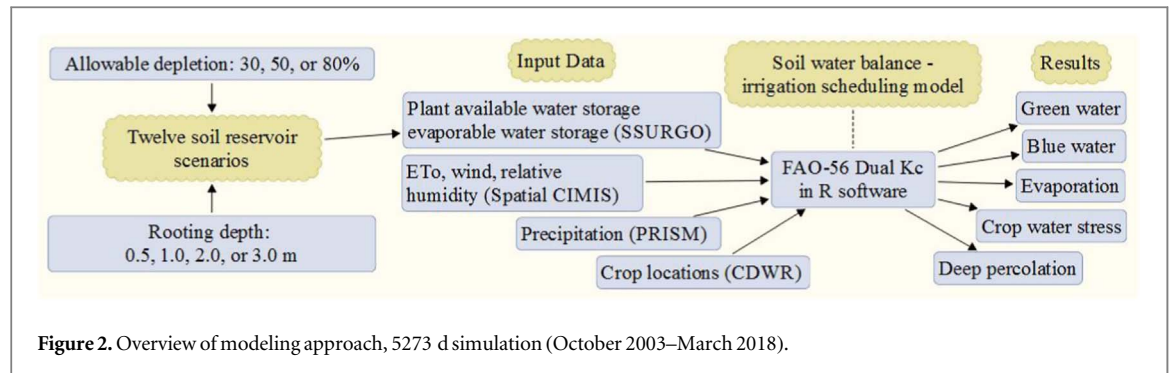
Figure 2. Overview of modeling approach, 5273 d simulation (October 2003–March 2018).

approach (Allen *et al* 1998, 2005a), to simulate crop use of green water and irrigation (i.e. blue water). Results were tracked within a water balance framework that considered green water use, blue water demand, evaporation, transpiration, deep percolation, and crop water stress for all unique combinations of soil, climate, crop, and irrigation management (figure 2).

Twelve different soil reservoir scenarios were tested, including different crop rooting depths (0.5, 1.0, 2.0, and 3.0 m) and crop water stress irrigation management thresholds (30%, 50%, and 80% allowable depletion) to explore how varying size of the soil water reservoir affects the green water resource and, consequently, blue water demand (figure 2). Our scenarios are based on the plant physiology concept of hydropatterning, whereby the availability of soil water shapes the plant root architecture (Bao *et al* 2014) and is of particular interest to crop breeders working to create more drought tolerant varieties that grow roots deeply towards available water as shallower moisture is depleted (Dietrich 2018). Our scenarios assume that the dominant control on rooting depth at maturity will be the average depth of irrigations, so that a 1.0 m rooting depth reflects a scenario where irrigation is regularly applied to refill a soil profile to 1.0 m depth. The range of crop rooting depths tested in our scenarios brackets the expected range in rooting depths for these crops at maturity (Hanson *et al* 1999). In the results, three of the 12 scenarios were highlighted as follows: a shallow scenario representing 'business-as-usual' in perennial crops (0.5 m root depth and 30% allowable depletion); a moderate scenario representing a hybrid approach (1.0 m root depth and 50% allowable depletion); and a deep scenario representing a 'conservation-minded' approach to irrigation (2.0 m root depth and 50% allowable depletion).

The FAO-56 dual K_c model estimates actual crop evapotranspiration (ET_c) by computing two linked daily soil water balances (surface and full root zone) to separately estimate soil evaporation and crop transpiration relative to a Penman–Monteith reference ET (ET_o). The daily water balance procedure for the surface and full root zone is detailed in Devine (2019). The computational approach closely follows Allen *et al* (1998) and includes the extension in Allen *et al* (2005a)

for differentiating the surface water balance between surface wetted only by precipitation and surface wetted by both precipitation and irrigation that results from partial surface wetting systems like drip and microspray.

2.2. Estimating green water use
Green water use was estimated using the cumulative water balance results. Specifically, it was calculated as the cumulative difference between growing season ET_c and applied irrigation water (Ir) through 13 years (January 2005–December 2017), excluding the first 15 months of the simulation as a model initialization period (October 2003–December 2004). Since crop ET_c includes evaporation from surface soil layers, utilization of green water includes soil surface evaporation of precipitation (P) but only during the growing season. This estimation approach also assumes that all applied irrigation water is consumed to meet crop ET_c demand. As an error check, the total model water balance was evaluated:

$$\text{absolute water balance error} = P + Ir - DP - ET_c - \Delta S, \quad (1)$$

where $\Delta S = \text{soil storage}_{31 \text{ December, } 2017} - \text{soil storage}_{31 \text{ December, } 2004}$ and all terms above are cumulative from beginning to end of the modeling period.

2.3. Computational strategy
The daily simulation was run using the following input datasets: (1) plant available water storage of all major soil components for map units of interest from the Soil Survey Geographic Database (SSURGO) 1:24 000 shapefile with 1143 unique soil component names in the study area comprising 4345 unique map unit names; (2) daily precipitation at 4 km resolution from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) (Daly *et al* 2008) with 4262 PRISM raster cells of interest in the study area; (3) daily reference evapotranspiration, wind, and minimum relative humidity from the California Irrigation Management Information System spatial model at 2 km resolution (spatial CIMIS) (Hart *et al* 2009) with 12 524 CIMIS raster cells of interest in the study area; and (4) 2014 land-use data for California irrigated lands with 140 819 different fields and 1.46

million ha identified to have alfalfa, almonds, grapes, pistachios, or walnuts (CDWR 2017a).

Several steps were needed to integrate spatial datasets, because they differed by type (raster versus shapefile), resolution, and projection. First, the crops dataset was intersected with SSURGO map units, which created 313 573 unique polygons of different soil and crop combinations that were successfully modeled. To get the appropriate climate data, centroids were calculated for each polygon feature. Then field centroids were tagged with each of the climate dataset's raster number with the *cellFromXY* function in the *raster* R package (Hijmans 2017), so that the appropriate climate data could be looked up in a pre-processed table created from thousands of rasters. This meant that all crop and soil map unit polygons whose center fell in a particular 4 km raster cell (PRISM) or 2 km raster cell (spatial CIMIS) received the same particular climate data vectors during the model run. For the PRISM data, field polygon centroids were projected to geographic coordinates before identifying the PRISM raster cell number. Centroids for grapes and alfalfa fields were further identified as to their growing region using the EPA level 4 ecoregion shapefile to determine which region specific growing assumptions were used in the simulation for each unique combination of soil, crop, and climate.

For each of these unique soil-climate-crop systems, a 5273 d (1 October, 2003–8 March, 2018) water balance model was implemented in R 3.4.3 software following the dual crop coefficient computational framework detailed in Allen *et al* (1998) and Devine (2019). Nearly 1.3 million simulations were performed for twelve soil reservoir scenarios of rooting depth and allowable depletion. The set of R scripts used to download data, integrate the data into a common database, run the dual crop coefficient model, and aggregate and analyze results are available at https://github.com/smdevine/GreenWater.

2.4. Soils—plant available and evaporable water

Several steps were needed to estimate root zone plant available water from SSURGO for perennial crops where 1–2 m deep tillage is common during establishment. The 2017 updated shapefile for 1:24 000 scale SSURGO soil map units in California was used to estimate plant available water storage for rooting depths of 0.5, 1.0, 1.5, 2.0, and 3.0 m by summing SSURGO available water capacity for each horizon in the rooting zone. Since SSURGO typically reports information to depths of 1.5–2.0 m, we assumed equivalent profile-weighted, plant available water deeper than the available SSURGO data for all soils without lithic or paralithic contacts, with an exception for soils with pedogenic restrictive layers (e.g. claypans or duripans) and cropped to alfalfa. To populate available water capacity for soils with paralithic or lithic contacts (denoted by a Cr or R horizon

nomenclature), we used SSURGO's soil component restrictions table, *crstrcts.txt*, and then assumed that plant available water storage terminates at the depth of these root restrictive contacts for all crops in these locations (table 1). For soils with pedogenic restrictive layers underlying almonds, grapes, pistachios, and walnuts, the standard practice of deep tillage was assumed to have occurred that either removes or thoroughly mixes these horizons into the profile, transforming soil to one without root growth restrictions (table 1). Profile-weighted plant available water was then assumed for these restrictive horizon depths. Effectively, this assumes that any root impenetrable horizon shattered upon tillage (e.g. duripans) would have been pulled to the surface by deep shanks as large clods and then removed from the field. For alfalfa, no deep tillage is assumed, because it is not commonly used for this crop. Thus, plant available water is assumed to terminate at the depth of either R, Cr or restrictive layers (cemented horizons or claypans) under alfalfa.

Several steps were needed to produce continuous functions of total evaporable water (TEW) and readily evaporable water (REW) in order to implement the FAO-56 dual K_c routine, since these variables are not defined in SSURGO. First, TEW was defined using the widely implemented equation (Allen *et al* 1998):

$$\text{TEW} = 1000 \times (\theta_{\text{AWS}} + 0.5 \times \theta_{\text{WP}}) \times Z_e, \quad (2)$$

where θ_{AWS} is the plant available soil water storage, θ_{WP} is the soil water content at wilting point, both available from SSURGO, and Z_e is depth of the surface layer subject to evaporation, estimated using a function that relates Z_e to the depth-weighted particle size diameter derived from SSURGO particle size data (see Devine 2019 for details).

Z_e is assumed to be 10–15 cm thick (Allen *et al* 1998) with 10 cm recommended for coarse soils and 15 cm recommended for fine textured soils (Allen *et al* 2005a). REW was calculated based on surface horizon texture, following equations published in Allen *et al* (2005b) and scaling by soil's estimated Z_e value. When there was more than one major component in a soil map unit, weighted-average percentages of major component model results were calculated.

2.5. Climate data

Daily, 4 km resolution precipitation rasters from 1 October, 2003–8 March, 2018 were downloaded from the PRISM Climate Group (http://prism.oregonstate.edu/) using the *prism* R library's 'get_prism_dailys' function. Precipitation data were extracted to a single table for all cells of interest by day[1].

Daily reference ET_o, wind, dewpoint temperature, and maximum temperatures from 1 October, 2003–8 March, 2018 were downloaded from the Spatial

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[1] See R script: https://github.com/smdevine/GreenWater/blob/master/GetData/download_PRISM.R.

Table 1. Seasonal crop growth assumptions and soil features by crop. For the basal crop coefficient values (K_{cb}), the subscripts ini, mid, and end refers to beginning of the growing season, mid-season, and end of the growing season, respectively. For alfalfa, these values are for each individual cutting cycle.

Crop	Total area	Pedogenic restrictive horizon[a]	Lithic/Paralithic	End dormancy	Peak growth/cuttings	Senescence	Dormancy	$K_{cb,ini}$	$K_{cb,mid}$	$K_{cb,end}$
		——————ha——————								
Alfalfa, Central Valley[b,c]	206 690	29 804	1896	NA	7	NA	NA	0.3	1.15	1.1
Alfalfa, Imperial Valley[c]	80 214	0	0	NA	10	NA	NA	0.3	1.15	1.1
Alfalfa, Intermountain[c]	64 888	22 580	9269	1 April	3	16 October	23 November	0.3	1.15	1.1
Almonds	455 970	80 470	30 348	15 February	1 June	4 September	11 November	0.2	0.95	0.65
Grapes, Central Valley	248 866	63 138	3133	15 March	15 June	17 August	22 October	0.2	1.05	0.8
Grapes, Coast and Foothills	111 634	3317	32 526	15 March	15 June	17 August	22 October	0.2	0.7	0.55
Pistachios	137 590	21 289	4337	25 April	15 June	4 September	15 November	0.3	0.95	0.65
Walnuts	149 352	27 170	9495	1 April	7 July	4 September	11 November	0.4	1.05	0.6

[a] Pedogenic restrictive horizons constraining to root growth were identified in SSURGO's component restrictions table and were mostly duripans and claypan.

[b] Peak growth assumed to resume 14 February with irrigation first considered on 7 February for alfalfa in the Central Valley. Time to last irrigation depends on average climate, soil water holding capacity, and rooting depth for all crops except alfalfa in the Imperial Valley where year-round irrigation is practiced.

[c] Alfalfa K_{cb} is reduced to 0.3 ($K_{cb,ini}$) after each cutting.

Letters

CIMIS dataset on a UC Davis server (http://cimis.casil.ucdavis.edu/cimis/) and extracted to a single table for each variable[2]. Daily minimum relative humidity for input into the FAO-56 algorithm was estimated by modifying equations from Hart *et al* (2009) for actual vapor pressure (e_a) and saturated vapor pressure (e_s) as suggested by Allen *et al* (2005a) when only mean daily dewpoint temperature was available, as was the case for the Spatial CIMIS dataset:

$$\text{RH}_{\min} \approx 100 \times \frac{e_a}{e^0(T_{\max})} \qquad (3)$$

$$e_a = e^{(17.27 \times T_{\text{dew}})/(T_{\text{dew}}+237.3)} \qquad (4)$$

$$e^0(T_{\max}) = e^{(17.27 \times T_{\max})/(T_{\max}+237.3)}, \qquad (5)$$

where T_{dew} is mean daily dewpoint temperature and $T_{\max}$ is daily maximum temperature in °C. All climate data were subjected to quality control checks for negative, missing, or values above 100% for $\text{RH}_{\min}$. All precipitation data passed these quality control checks. Less than 0.02% of the Spatial CIMIS dataset required gap-filling or corrections, which were based on multi-year means for that location and date.

2.6. Crops

Perennial crop distribution was used from the 2014 Department of Water Resources land-use classification for irrigated lands (figure 3(d)) (CDWR 2017a). The top five California perennial crops by land area were modeled, which cover 84% of California's land cropped to perennials and 47% of all cropland (CDWR 2017a). Crops were assumed to be unchanged across simulation years (table 1). Basal crop coefficients (K_{cb}) were chosen to reflect high-density production of mature trees with the exception of wine grapes managed by regulated deficit irrigation management which were assumed to exist outside the Central Valley in coastal or foothill locations, including Napa and Sonoma Valleys (table 1). K_{cb} for almonds, grapes in the Central Valley, pistachios, and walnuts were taken from high-density orchard and table grape values from table 3 in Allen and Pereira (2009), while grapes outside the Central Valley were assumed to have K_{cb} values similar to grapes grown for high-quality wine. Irrigation management for higher quality wine grapes typically includes intentional crop water stress after veraison to help control canopy growth, meaning lower K_{cb} values compared to table grapes or high yielding wine grapes (Prichard *et al* 2004). K_{cb} values for alfalfa were taken from table 17 in chapter 7 of Allen *et al* (1998) with different cutting cycles depending on region. Seasonal timing to guide basal crop coefficient curves for each crop was based on the California-specific crop coefficient calendars (Goldhamer and Snyder 1989). Corresponding fraction of vegetative cover (f_c) values for almonds, grapes,
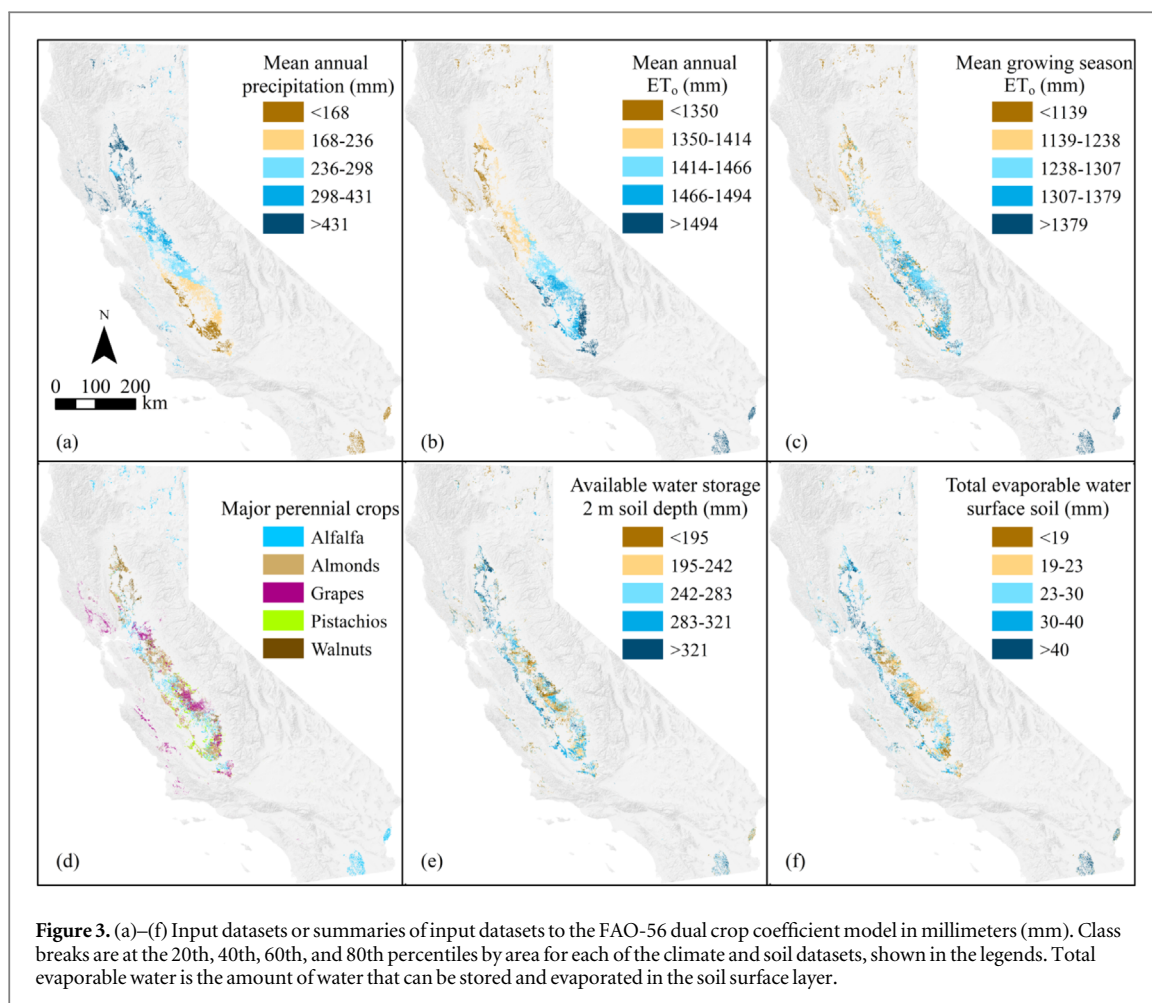
pistachios, and walnuts was taken from tables 2 and 3 in Allen and Pereira (2009) and linearized to run parallel to K_{cb} curves. Assuming bare soil and no cover crops, a dormant season K_{cb} value of 0.15 was chosen for all crops with dormancy. Cover crops are commonly grown in the higher rainfall regions of the study area, but no spatially explicit data is available about their use. While K_{cb} is intended to represent transpiration, the coefficient also includes 'background' diffusive evaporation from deeper soil layers (Allen *et al* 1998, Huntington *et al* 2014). Finally, while mean crop rooting depth would be expected to vary by crop (Hanson *et al* 1999), we assumed that rooting depth in the scenarios is driven primarily by mean depth of applied irrigation via a hydrotropic root growth response (see section 2.1 above).

2.7. Irrigation decisions

Two fundamental irrigation parameters need to be defined for the dual K_c model: (1) proportion of the soil surface wetted and (2) depth and timing of irrigation events. We assumed different irrigation systems for each crop based on the most prevalent system currently in use but represented only one system per crop (Tindula *et al* 2013). While this was a simplifying assumption, there is currently no spatially explicit data on irrigation system type in California. Microsprinkler irrigation was assumed for almonds, pistachios, and walnuts with a 0.65 fraction of surface wetting. Drip irrigation was assumed for table and wine grapes with a 0.35 fraction of surface wetting. Full surface wetting from border or sprinkler irrigation was assumed for alfalfa. Importantly, regardless of irrigation surface coverage, the full volume of soil was assumed to be rooted by perennial crops.

Regarding timing, irrigation was applied the day following a given crop-soil-climate system reached its allowable depletion during the growing season. For crops with dormancy, no irrigation was allowed until the crop's bloom/leaf-out date (table 1). To our knowledge, dormant season irrigation is not common in California's orchards and vineyards, although recent very dry and warm winters have spurred research to understand whether or not crops such as almonds would benefit from winter irrigation before bloom during severe droughts (Milliron *et al* 2018). The irrigation applied was a depth to moisten the root zone to field capacity, except for wine grapes. An exception to this irrigation timing rule was followed at the end of the growing season for all crops to determine time-to-last irrigation, except alfalfa in the Imperial Valley. A 14-year late summer/fall average was calculated for each unique soil, crop, and climate system to determine an optimal time for last irrigation. The objective was to estimate a specific number of days before leaf-drop that, if irrigated back to field capacity, would on average leave soil at allowable depletion at dormancy. In other words, an irrigation-free period

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[2] See R script: https://github.com/smdevine/GreenWater/blob/master/GetData/spatialCIMIS.R.

Figure 3. (a)–(f) Input datasets or summaries of input datasets to the FAO-56 dual crop coefficient model in millimeters (mm). Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area for each of the climate and soil datasets, shown in the legends. Total evaporable water is the amount of water that can be stored and evaporated in the soil surface layer.

during the fall was defined for each system before running the 5273 d model. This had the effect of creating some crop water stress during dry falls.

We also included three different options for the alfalfa irrigation decision algorithm that varied by California region: (1) alfalfa in the Imperial Valley where there is year-round production and irrigation in 10 assumed cutting cycles; (2) alfalfa in northern California intermountain region, where alfalfa is dormant from late November to late March each year with three assumed cuttings through September followed by fall regrowth before winter induced dormancy; or (3) alfalfa in the Central Valley with seven assumed cuttings but no irrigation or cuttings from November–January despite assuming continued winter transpiration.
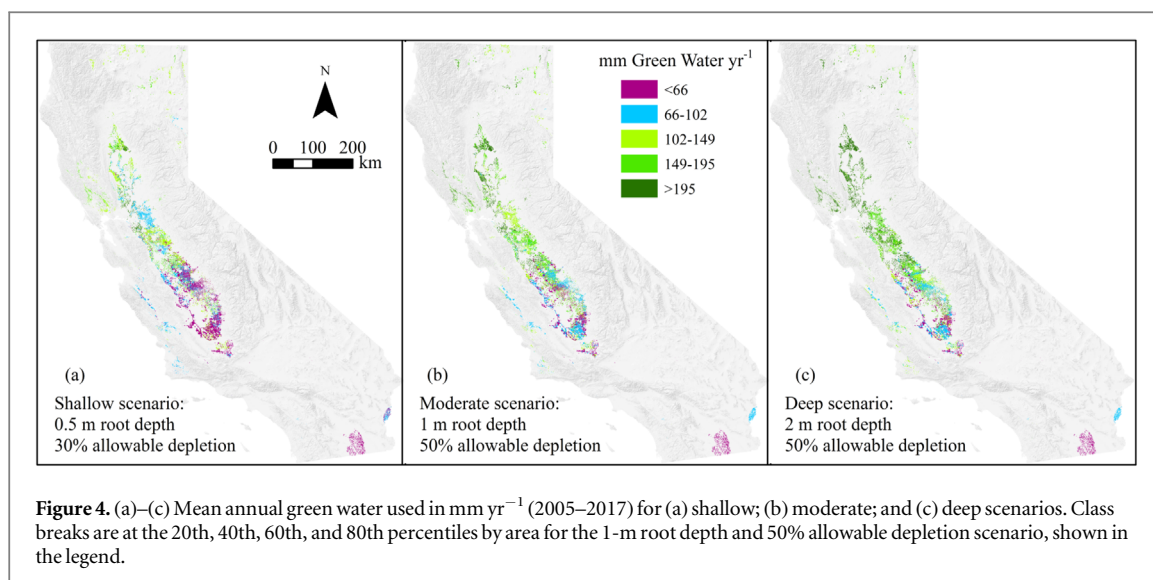
We also included a different irrigation strategy for each of the two broadest grape growing regions. For grapes in the coast or foothills, a version of regulated deficit irrigation was assumed that accompanies high-quality wine production. Soil moisture levels were managed with irrigation at a level to maintain crop water stress from the time green water was depleted until a month before leaf-drop (Prichard *et al* 2004). Specifically, in the 30% allowable depletion scenario, irrigation was applied to restore soil back to 50% of plant available water when the soil stress coefficient

(K_s) reached 0.8 (60% allowable depletion). In the 50% allowable depletion scenario, irrigation was applied to restore soil back to 50% of plant available water when K_s reached 0.5 (75% allowable depletion). In the 80% allowable depletion scenario, irrigation was applied to restore soil back to 50% of plant available water when K_s reached 0.2 (90% allowable depletion). Then, the target end-of-season soil water content was equal to 30, 50, or 80% of allowable depletion at leaf-drop, depending on scenario. For Central Valley grapes, irrigation was practiced the same as for tree crops, outlined above.

3. Results

3.1. Green water utilization
Relative to the 57.1 km³ precipitation input for 1.46 million ha of perennial crops, the 13 year, cumulative green water utilization was 17.4, 24.6, and 29.6 km³ in the shallow (0.5 m and 30% allowable depletion), moderate (1 m and 50% allowable depletion), and deep (2 m and 50% allowable depletion) scenarios (figures 4(a)–(c); table 2). Utilized green water comprised a relatively small part of total crop water demand in aggregate, cumulatively meeting 6%–12% of growing season ET in shallow-to-deep scenarios with low levels of crop water stress (table 2).

Figure 4. (a)–(c) Mean annual green water used in mm yr^{-1} (2005–2017) for (a) shallow; (b) moderate; and (c) deep scenarios. Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area for the 1-m root depth and 50% allowable depletion scenario, shown in the legend.

Table 2. Cumulative water balance component totals from modeling the different soil storage scenarios from 2005 to 2017. Sorted by mean area-weighted allowable depletion (mm) for a given scenario. Last three columns are mean, area-weighted irrigation timing results. Precipitation input was 57.1 km^3 over 13 years. Dormant season surface soil evaporation was 14.3–14.4 km^3 over 13 years across all scenarios.

RD	AD		GW	Ir	E	DP*	CS	ET	DP$_a$	ΔS	Ir freq	First ir	Last ir
-m-	-%-	-mm-	13 year total, growing season cubic kilometers (km^3)							Model run	times yr^{-1}	Mean DOY	
0.5	30	21	17.4	263	63.1	4.3	3.1	280	22.3	−0.6	59	68	293
0.5	50	34	20.1	245	51.8	2.4	6.6	265	20.1	−0.7	37	76	288
1	30	40	21.2	244	46.1	2.0	1.2	265	18.4	−1.0	32	79	286
0.5	80	55	22.3	199	37.1	0.8	35.9	221	18.3	−0.7	22	91	281
1	50	67	24.6	225	33.4	0.9	4.2	249	15.6	−1.1	19	89	278
2	30	76	25.4	224	30.3	0.9	0.6	250	14.4	−1.4	17	90	275
1	80	107	27.5	179	23.5	0.3	37.2	206	13.4	−1.2	11	106	268
3	30	113	28.3	215	24.1	0.8	0.4	244	11.7	−1.7	12	97	267
2	50	127	29.6	210	22.3	0.6	3.0	239	10.7	−1.6	10	99	264
3	50	188	32.5	204	18.6	0.5	2.6	236	7.9	−1.7	8	106	254
2	80	203	33.1	167	16.7	0.2	36.9	200	8.0	−1.5	6	123	251
3	80	300	35.9	162	14.7	0.1	36.4	198	5.4	−1.6	4	134	236

RD = root depth; AD = allowable depletion; GW = green water utilized; Ir = irrigation (blue water); E = surface evaporation; DP* = deep percolation from first to last irrigation during the growing seasons; CS = crop stress; ET = evapotranspiration; DP$_a$ = annual deep percolation; ΔS = change in soil storage; Ir freq = irrigation frequency, average number of irrigations applied per year; First ir = average first day of irrigation; Last ir = average last day of irrigation; DOY = day of year.

Although a relatively small portion of statewide growing season crop ET can be supplied by green water, there were regions where green water utilization was much greater (figures 4(a)–(c); table 3). On average, assuming moderate and deep scenarios, 20% of the study area met 16%–20% or more of its crop water needs with green water. In contrast, in the shallowest soil storage scenario, the 80th percentile in green water utilization met only 11% of its annual crop water needs on average with green water. Highest green water utilization was north of the Sacramento-San Joaquin Delta, where 24% of annual crop water demand was met in a deep scenario, compared to 12% south of the Delta (table 3). There was also greater variability across the study area in deep compared to shallow scenarios (figures 4(a)–(c); table 3). This north-to south trend (figures 4(a)–(c)) was due to a precipitation gradient (figure 3(a)).

However, the general green water resource trend was regionally complicated by topographic effects on precipitation (rain shadow), soil property effects on plant available water and evaporable water storage, and differences in crop characteristics (figures 3(a)–(f); table 1).

In addition to spatial concentration of the green water resource, there was also temporal concentration. A handful of wet years supplied much of the green water resource. In the moderate scenario, the wettest 6 of 13 years provided 62% of the cumulative green water resource. These wetter years used 2.1–2.9 km^3 yr^{-1} green water, a volume similar to Trinity Lake (3.0 km^3), California's third largest reservoir.

Table 3. Summary of green water (GW) utilized by California Department of Water Resources' hydrologic region and soil reservoir scenario (shallow, moderate, and deep). The top half of the table summarizes perennial crops north of the Sacramento-San Joaquin Delta. The bottom half summarizes perennial crops south of the Delta. The South Coast and South Lahontan regions are not included, where only 1500 hectares of perennials were modeled.

Region North of Delta	Perennials –ha–	Shallow[a]	Mod[b]. Cumulative GW	Deep[c]	Shallow	Mod. Crop water use met by GW	Deep	Shallow	Mod. Mean annual GW availability	Deep
		——km³——						——mm yr⁻¹——		
North Coast	51 001	0.92	1.19	1.45	15%	22%	27%	139	180	218
North Lahontan	15 174	0.22	0.29	0.33	11%	15%	17%	113	149	170
Sacramento R.	238 514	4.70	6.68	8.42	11%	17%	23%	152	215	272
San Fran. Bay	24 563	0.45	0.58	0.73	16%	27%	36%	140	181	229
Northern Total	329 252	6.3	8.7	10.9	12%	18%	24%	147	204	255
South of Delta										
Central Coast	52 606	0.53	0.66	0.79	9%	14%	18%	78	96	115
Colorado R.	80 224	0.56	0.61	0.66	3%	3%	3%	53	58	64
San Joaquin	438 960	6.00	8.63	10.43	7%	11%	14%	105	151	183
Tulare Lake	552 648	4.01	5.93	6.79	4%	6%	7%	56	83	95
Southern Total	1124 438	11.1	15.8	18.7	5%	8%	10%	76	108	128
Total	1453 690	17.4	24.6	29.6	6%	10%	12%	92	130	157

[a] The shallow scenario is 0.5 m rooting depth and 30% allowable depletion.

[b] The moderate scenario is 1 m rooting depth and 50% allowable depletion.

[c] The deep scenario is 2 m rooting depth and 50% allowable depletion.

In the deep scenario, annual green water availability increased to 2.6–3.6 km³ yr⁻¹ in wet years.

Allowing for substantial crop water stress (80% allowable depletion level) increased the amount of green water utilized for a given rooting depth, but the effect on cumulative crop water stress was nearly an order of magnitude larger for each rooting depth (table 2). Increasing the allowable depletion as an irrigation management strategy from 30% to 50% for a given root depth had the side effect of slightly more fall crop water stress due to our fall irrigation decision algorithm (table 2).

Wintertime surface evaporation of rainfall was substantial in all scenarios, limiting the supply of green water. In the deep scenario, annual green water use was 52% of precipitation, even though deep percolation had been reduced to just 19% of precipitation. This is because dormant season surface soil evaporation averaged 1.1 km³ yr⁻¹ (25% of cumulative precipitation across all scenarios), and thus, was unavailable to meet growing season demand. In moderate and shallow scenarios, green water use was 43% and 30% of total precipitation, respectively. While substantial wintertime evaporation is surprising given the low reference ET during the winter (average annual dormant season ET_o is the difference between figures 2(b) and (c)), the assumed bare soil during crop dormancy and frequent wetting by winter rainfall drives the steady but low evaporation rates of rainfall. Nonetheless, the much higher reference ET during the growing season made wintertime surface evaporation just 5.1%–6.6% of cumulative annual ET across all scenarios. Growing season transpiration is the dominant component of the water balance in these crops when grown in high-density plantings, which is what we assumed (tables 1 and 2; see Methods section 2.6).
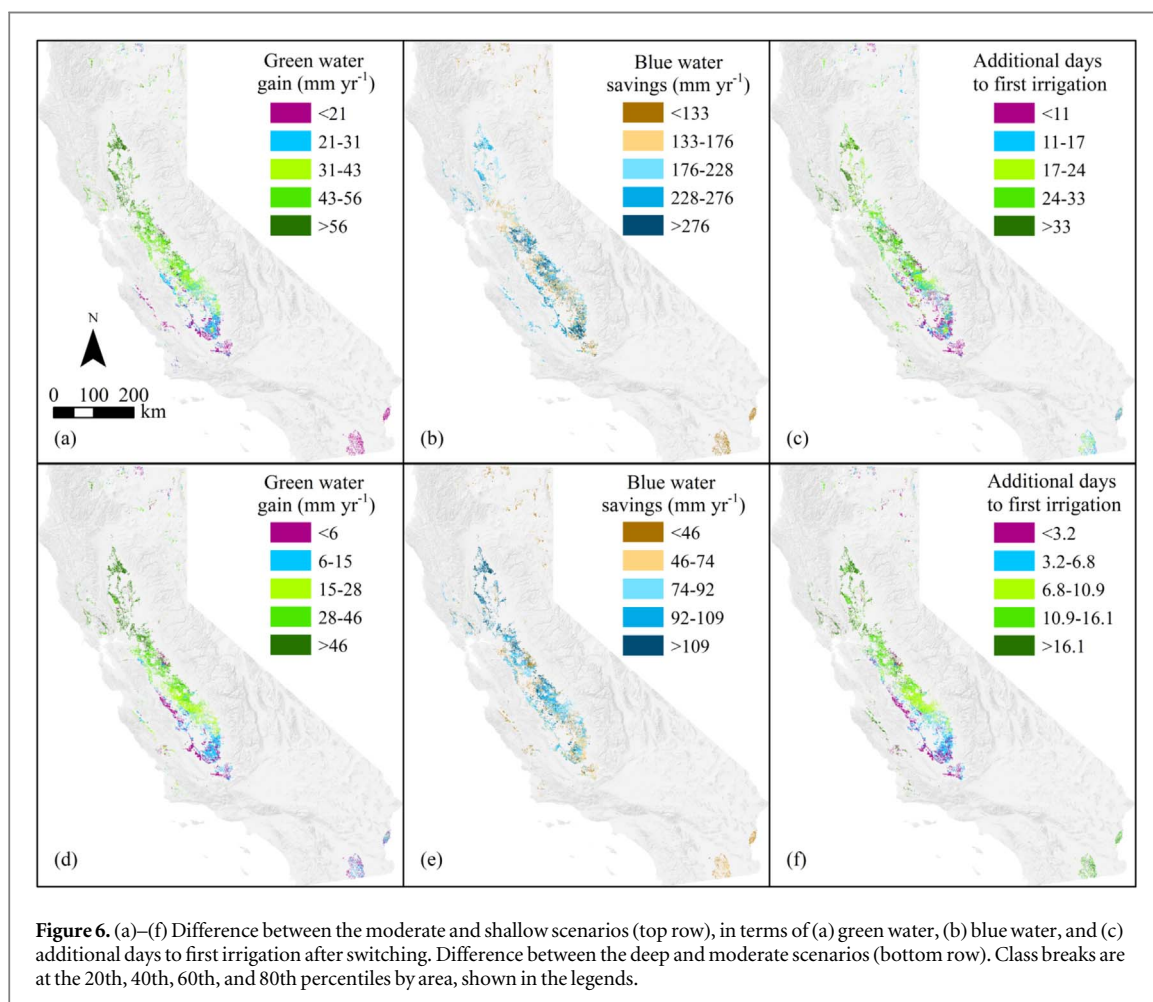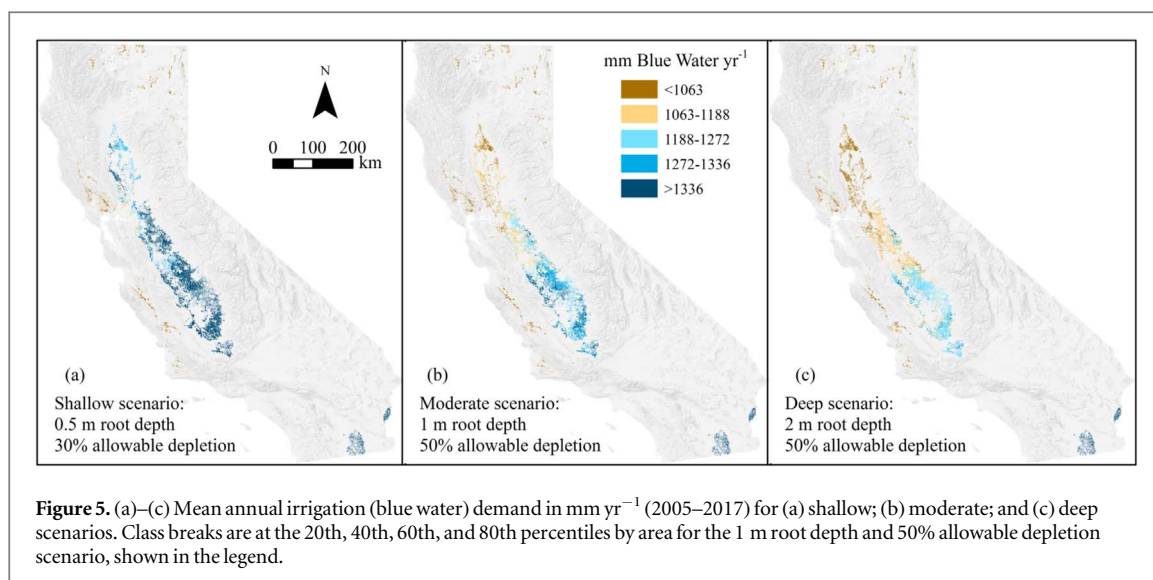
3.2. Blue water (irrigation) demand

Cumulatively, irrigation (blue water) demand was 263, 225, and 210 km³ in shallow, moderate, and deep scenarios, respectively. Greater green water utilization in moderate and deep scenarios explained part of the reduced blue water demand, but, surprisingly, decreased soil surface evaporation explained about 75% of this cumulative, reduced-irrigation demand (table 2).

Annual variability in the green water resource was driven by a 4-fold range in annual precipitation (1.5–7.0 km³ yr⁻¹), and this affected annual variability in blue water demand, which ranged from 13.7–18.2 km³ yr⁻¹ in the deep scenario, 15.1–19.0 km³ yr⁻¹ in the moderate scenario, and 18.0–21.8 km³ yr⁻¹ in the shallow scenario. Deep scenarios (larger soil reservoirs) enhanced inter-annual variability in blue water demand, while reducing annual average demand. Wet years tended to have lower potential evapotranspiration conditions, such that annual blue water demand was reduced even more. The north-to-south potential evapotranspiration gradient (figures 3(b)–(c)) resulted in larger blue water demand in more southern locations for all crops (figures 5(a)–(c)). The blue water demand gradient was steepened when rooting was deeper (soil reservoirs are enlarged) across the entire study area.
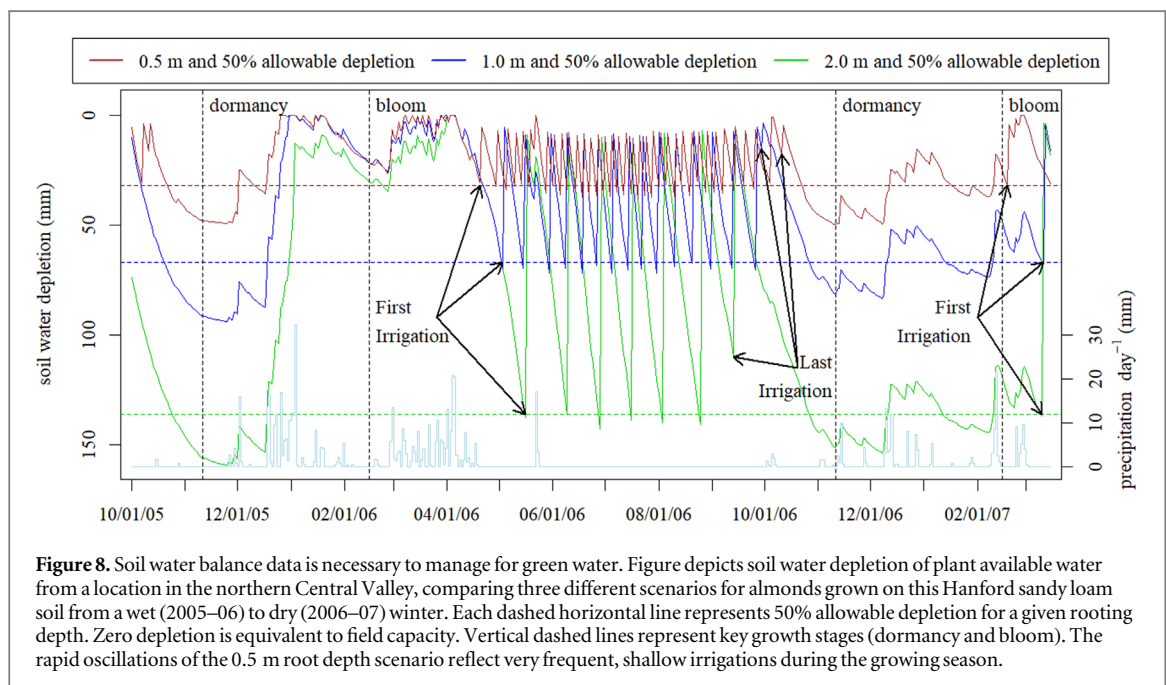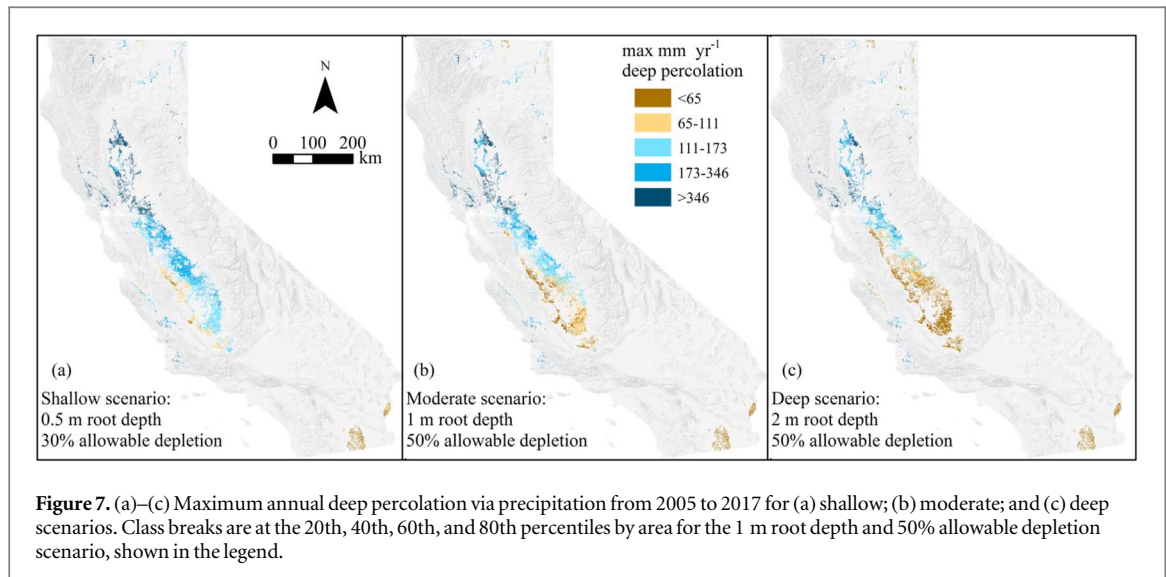
3.3. Soil water storage capacity effects

Increasing soil water storage capacity by deeper rooting and increasing levels of allowable depletion had the most benefits for green water utilization when going from the shallow soil storage scenario to a moderate soil storage scenario (tables 2 and 3). Using this comparison, the model showed a mean increase in green water utilization of 0.66 mm per mm increase in

Figure 5. (a)–(c) Mean annual irrigation (blue water) demand in mm yr^{-1} (2005–2017) for (a) shallow; (b) moderate; and (c) deep scenarios. Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area for the 1 m root depth and 50% allowable depletion scenario, shown in the legend.

Figure 6. (a)–(f) Difference between the moderate and shallow scenarios (top row), in terms of (a) green water, (b) blue water, and (c) additional days to first irrigation after switching. Difference between the deep and moderate scenarios (bottom row). Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area, shown in the legends.

allowable depletion (figure 6(a)). Comparing a moderate to deep scenario, the model showed lower mean increase of 0.57 mm green water utilization per mm increase in allowable depletion, because in much of the study area precipitation was too low to recharge soil beyond 1 m (figure 6(d)). This green-water-limited area is in the southern DWR regions (table 3; figure 3(a)).

As the allowable depletion was increased, irrigation season length became shorter and irrigation frequency was lower (figures 6(c) and (f); table 2). Utilizing additional green water in deeper rooting or higher allowable depletion threshold scenarios decreased cumulative annual deep percolation, a benefit for non-point source pollution reduction, but this could be a concern for locations with soil salinity issues (figures 7(a)–(c)).

Figure 7. (a)–(c) Maximum annual deep percolation via precipitation from 2005 to 2017 for (a) shallow; (b) moderate; and (c) deep scenarios. Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area for the 1 m root depth and 50% allowable depletion scenario, shown in the legend.

Figure 8. Soil water balance data is necessary to manage for green water. Figure depicts soil water depletion of plant available water from a location in the northern Central Valley, comparing three different scenarios for almonds grown on this Hanford sandy loam soil from a wet (2005–06) to dry (2006–07) winter. Each dashed horizontal line represents 50% allowable depletion for a given rooting depth. Zero depletion is equivalent to field capacity. Vertical dashed lines represent key growth stages (dormancy and bloom). The rapid oscillations of the 0.5 m root depth scenario reflect very frequent, shallow irrigations during the growing season.

When allowable depletion was increased, blue water demand was reduced more than the increase in green water utilized (figures 6(b) and (e)). The results show that more soil water storage in the irrigation management scheme allowed for less frequent, deeper irrigations (table 2; figure 8). This reduced the cumulative surface soil evaporative loss from 63.1 to 33.4 km^3 comparing the shallow to moderate scenario (from 23% to 13% of growing season ET as evaporation) and down further to a cumulative loss of 22.3 km^3 in the deep scenario through 13 years (table 2).

3.4. Green water use accounting accuracy
Episodic dry and wet years created fluctuations in soil moisture recharge and storage during fall and winter with some annual carryover of irrigation water that obscured annual accuracy of green water use estimates.

For instance, in the moderate scenario, inter-annual ΔS ranged from 0.3 to −0.6 km^3 at the end of the growing season (e.g. change in soil water storage from end of growing season 2004 to end of growing season 2005), from 0.4 to −0.6 km^3 at the beginning of the growing season, and from 0.9 to −1.0 km^3 at the beginning of the year across the entire study area. Given the annual green water results ranged from 1.1–2.9 km^3 yr^{-1} in the moderate depth scenario, annual results were susceptible to this error in soil moisture change. Since the change in soil water storage from one year to the next could have been either precipitation or irrigation sourced, precise, annual green water accounting was not possible without a different model. However, results focused on 13 year cumulative amounts or annual averages to avoid this error. A quantification of the 13 year, cumulative potential error from beginning-

to-end of the model run showed ΔS varied from 3.2% to 5.9% of the cumulative green water utilized across soil reservoir scenarios (table 2). This means that the overall model simulation change in soil water storage, assuming it was actually irrigation derived, provided at most 3%–6% of the reported statewide green water use.

4. Discussion

4.1. Green water resource

Results show a relatively modest green water opportunity for California water resource management where soil water storage and *in situ* rainfall can help meet 6%–18% of crop water demand, depending on rooting depth and allowable depletion (table 2). The green water resource was spatially concentrated, so in some areas the proportion of crop water demand met by green water was much larger (figures 4(a)–(c); table 3). For instance, in the deep scenario, the 80th percentile on the landscape provided 20% of crop water needs with green water, while the 20th percentile provided only 6%. During the wettest years, the land at the 80th percentile in the green water resource supplied 29% of crop water demand with green water, assuming the deep scenario (23% in the moderate scenario). In regional terms, while only 23% of perennial crops are north of the Sacramento-San Joaquin Delta, 36% of the annual green water use was in this region for the moderate scenario (table 3). But given the sheer acreage of perennial crops in the drier climates of the San Joaquin and Tulare regions, nearly 60% of the green water use was located here in the moderate scenario (table 3). While modest in total, the green water resource shows both spatial and temporal concentration, demonstrating the need for adaptive management. Each crop-climate-soil system across the state can be envisioned as having its own unique soil water reservoir that has the capacity to supply a depth of green water unique to that location and year (Figures 3; 4(a)–(c)).

Given the scale of irrigated land in California, the small relative contribution of green water to crop ET is a 13 year cumulative total that could fill California's largest manmade reservoir, Shasta Lake with a capacity of 5.6 km³, 3–5+ times over. This highlights the magnitude of hardened irrigation water demand for perennial crops in California, which have expanded across the landscape in recent decades. From 1977 to 2010, orchards grew from 15% to 30% and vineyards from 6% to 15% of California's irrigated land; field crops declined from 67% to 41% (Tindula *et al* 2013). Because orchards and vineyards cannot be fallowed during drought, this hardened irrigation demand is of concern for groundwater resources, which make up the difference in demand during drought years. Our study's results show the potential of green water to meet perennial crop water demand varies regionally and are relevant to the development of sustainable, regional water plans required by the Sustainable Groundwater Management Act in California.

Optimal use of soil-stored precipitation by crops was recently suggested as a strategy to be incorporated into integrated water resource management strategies for adapting to climate change (Rockstrom *et al* 2009, Rockstrom *et al* 2010). This green water use strategy could complement current, multi-billion dollar efforts to adapt blue water systems in California to reduced snowpack water storage and more severe, warmer droughts expected with climate change (Stewart *et al* 2005, AghaKouchak *et al* 2014, Diffenbaugh *et al* 2015, Jezdimirovic and Hanak 2016, Kocis and Dahlke 2017, CDWR 2018, Swain *et al* 2018).

If green water is utilized, less deep percolation and reductions in non-point source pollution would also follow, especially early in the growing season when irrigation can be delayed to allow for crop use of green water. For instance, deep percolation was reduced from 1.7 to 1.2 to 0.8 km³ yr⁻¹ on average, comparing the shallow to moderate to deep soil reservoir scenarios. However, in the drier regions of California, managing for green water using a deep soil reservoir could enhance soil salinity issues in the root zone by eliminating periodic, precipitation driven leaching during wet years and may not be advisable there (figures 7(a)–(c)). Allowing for crop water stress is another way to increase the size of the utilizable soil moisture reservoir, enhance green water utilization, and decrease blue water demand. When the allowable depletion was increased from 50% to 80% for each rooting depth, the growing season ET was reduced by 16%–17% and the amount of green water utilized increased (table 2). While crop water stress can be detrimental, if practiced when the crop is tolerant to some water stress and, if soil water derived from irrigation can be drawn down to this same allowable depletion threshold before winter recharging storms arrive, then the practice could be a viable way to increase green water use in Mediterranean climates. For orchards and vineyards, yields and water use do not always follow a 1:1 relationship as is common in annual crops. For instance, deficit irrigation studies showed that almond growers could apply 10%–15% less water than full ET with only minor reductions in yield (Steduto *et al* 2012).

4.2. Evaporative blue water savings

One of the more surprising findings of this study was that full use of soil water storage can substantially reduce reliance on blue water, not only by substituting green water for blue water, but through evaporative savings at the soil surface. This challenges the conventional view that growing season evapotranspiration in irrigated agriculture is only a function of crop and climate by showing that irrigation management is also a driver of evapotranspiration. When irrigations were less frequent and more deeply applied, the model

showed evaporative savings of 2.3 km^3 yr^{-1}, when comparing shallow and moderate depth scenarios, and a gain in green water use of 0.6 km^3 yr^{-1}. In this comparison, the irrigation frequency was reduced from 59 to 19 irrigations yr^{-1} on average (table 2). In the southern California Central Valley, microsprinkler systems in orchards are commonly managed to apply 25–40 mm in 24 h sets, similar to the depths applied in our study's shallow scenario (mean application of 21 mm, table 2). Some drip systems are run more frequently. Recent advances in high-frequency irrigation control have resulted in situations where 2 mm sets are pulsed 2–4 times a day in some perennial crops (B Sanden, personal communication, 1 June, 2018). When average irrigation frequency was reduced further in the deep scenario to just 10 irrigations yr^{-1} from the moderate scenario, additional savings in soil surface evaporation was 0.9 km^3 yr^{-1}, compared to an additional 0.4 km^3 yr^{-1} gain in use of green water (table 2). The irrigation frequency and depth of our deep scenario would be more typical of a surface irrigation system such as border flood. In the shallowest scenario, 23% of growing season ET was surface soil evaporation, compared to 13% and 9% in moderate and deep scenarios, respectively.

While evaporative losses may seem high, our simulated estimate of evaporation in California's perennial crops may be an underestimate. In their review of evapotranspiration partitioning studies, Kool *et al* (2014a) found that 30 of 52 studies estimated evaporation losses in excess of 30% of total ET with studies generally in the range of 20%–40%. Nevertheless, high evaporative losses from vineyards and orchards are not unequivocal and may be controlled by wetting only a fraction of the surface under vegetative cover with micro-irrigation systems. Bonachela *et al* (2001) used drip irrigation experimental data in olive orchards to model evaporation and estimated losses of 4%–12% of ET as evaporation from a mature olive orchard compared to losses of 14%–42% of ET for a young orchard, but details on irrigation frequency were not provided. Evaporation losses of 7%–17% were estimated from a drip-irrigated desert vineyard (Kool *et al* 2014b). A study of microsprinkler irrigation in California almond orchard found evaporative losses of 21%–27% when irrigating in 25 mm sets every 2–3 d (Koumanov *et al* 1997), very similar to our shallow scenario results. Montoro *et al* (2016) concluded that evaporation losses are tightly linked to irrigation frequency and questioned a strategy of high-frequency irrigation in semi-arid or arid climates. Burt *et al* (2005) discussed how 15 years of data from Westlands Water District suggested ET in high-frequency, drip-irrigated almonds is 10%–15% higher than almonds irrigated by other methods, and hypothesized this was at least partly due to higher evaporative losses in drip irrigation.

Since our study assumed bare soils during winter except for alfalfa in the Central and Imperial Valleys, a needed follow-up question is how winter annual cover crops would affect the water balance and green water availability for crops. Average dormant season evaporative loss of 1.1 km^3 yr^{-1} from bare surface soil under perennials shows that green water is also available for growing cover crops during the winter. While there was only an estimated 6.4 cm yr^{-1} in dormant evaporation for early blooming almonds, there was 10.6–13.0 cm yr^{-1} dormant evaporation for bare soil in the later blooming grapes, pistachios, and walnuts. Cover crops in these perennial tree and vine systems would reduce the soil surface evaporative loss through soil surface shading, but increase winter transpiration. However, cover crops may provide other hydrologic and environmental benefits by improving soil physical properties and soil health (Brennan and Acosta-Martinez 2017, Mitchell *et al* 2017), providing a possible positive feedback to the green water resource.

4.3. Practical limitations of managing for green water

Utilizing green water through a program of well-timed irrigations based on water balance tracking or soil moisture or canopy sensors is not trivial. While a number of water balance based, irrigation management software tools have been developed in recent years across different irrigated regions (Bartlett *et al* 2015, Johnson *et al* 2016, Migliaccio *et al* 2016), none of these applications are tailored to optimize use of green water. Uncertainty in all of the climate, soil, and crop factors affecting the water balance make optimal management decisions for green water a challenge.

Optimizing the use of green water will require water balance monitoring, which is a complicated and expensive endeavor for an individual grower, but provides critical missing information for irrigation managers (figure 8). Given the green water resource potential in California, private or public investment at the scale needed to operate a major California reservoir is justified. Such investment is needed to improve data resolution and quality for water balance modeling and to create software tools that will allow irrigation managers to effectively make optimal decisions for green water use without compromising crop health. Research trials are needed to elucidate these best management practices (e.g. delayed spring irrigation and decreased irrigation frequency) for different crops, varieties, and environmental conditions. Field research investigating hydropatterning (Bao *et al* 2014) in perennial crops would be useful to document relationships between irrigation management and crop root architecture with special attention given to effects of irrigation to encourage deep rooting during orchard and vineyard establishment. Additional crop breeding may also be necessary to select rootstocks that perform well under green water management programs.

Practical considerations of irrigating also complicate management for green water in several ways. First, lack of water supply control at the farm-level has shown to be a significant constraint to improving irrigation management to reduce nitrate loading to groundwater (Dzurella *et al* 2012), and this would also apply to managing for green water. Second, because farms are typically divided into irrigation blocks to match water supply, it can take days to weeks to irrigate a whole farm. For example, if the irrigation system has an 8 d return interval, then the system may need to be started 8 d before the onset of stress in 1/8 of the area covered by the irrigation system and so on, to avoid crop water stress. Finally, an open question is whether or not perennial crops can deplete moderate (1 m) to deep (2 m) soil water to 50% of plant available water storage alongside more shallow soil water reserves without experiencing detrimental crop water stress, as this study assumed for moderate to deep soil reservoir scenarios.

4.4. Model limitations

Our study assumed no limitation to infiltration or percolation when the soil is below field capacity during rainfall. Ignoring the possibility of overland flow loss before saturation of soils may be an erroneous assumption for finely textured or sloping soils managed with no vegetative cover during the winter. However, we assume that daily estimates of plant available water generated by the model are mostly resilient to this simplified approach to modeling soil hydrology, since all water storage between field capacity and saturation is conservatively ignored as deep percolation. So, the reported green water resource may also be underestimated by neglecting water periodically available to crops between saturation and field capacity from more slowly draining soils.

Our study assumed different surface wetting fractions for different crops based on common irrigation systems for these crops, but also assumed that the entire soil volume was still utilized for green water and irrigation applications. As a result, we may have underestimated irrigation frequency for grapes, because a drip irrigation system with only 35% surface wetting likely does not wet the entire soil volume. So, a 2 m rooting depth scenario may actually be wetting to 3 m under the drip emitters but not at all some distance away. This also begs the question as to whether or not high-frequency, low surface coverage irrigation is resulting in shallow, laterally limited crop root architecture, which in turn may limit accessibility of green water to crop roots and increases reliance on blue water.

5. Conclusion

The cumulative green water resource in California perennial crops was enough to fill the state's largest reservoir, Shasta Lake, 3–5+ times through a 13-year simulation. However, given the magnitude of California's crop water demand, green water contributed only 6%–18% of growing season crop water use in total, depending on rooting depth and level of allowable depletion. Green water was concentrated in both space and time, highlighting the need for timely, place-based irrigation and crop management strategies to use green water effectively. Shifts from high- to low-frequency irrigation management schemes with more reliance on the soil water reservoir resulted in evaporative savings larger than the gain in green water use. Moving from a 'business-as-usual' shallow irrigation management scheme to a moderate strategy saved 30 km^3 blue water evaporation and increased green water use by 7 km^3 through 13 years.

Our results set the stage for a regional approach to green water use and highlights current practical and research opportunities to achieve better use of the resource. There is a clear need for tools to enhance green water utilization by advising time-to-first and time-to-last irrigation events in California. Results of this study increase the need for and relevance of practices that enhance infiltration in irrigated agriculture. Related to this, there are research questions as to whether or not cover crops grown by rainfall alone might improve hydrologic functioning of soils and the green water balance, given that 25% of precipitation evaporated under dormant perennials with bare soils in the model scenarios. Finally, breeding of rootstocks capable of growth and water uptake from deep soil, combined with breeding of crops more resilient to water stress, may be necessary to make a deep soil reservoir management approach a viable option in California perennial crops.

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