High-resolution mapping of a green water resource

opportunity for California irrigated perennial agriculture

**Abstract**

To map the green water resource, the plant available water stored in soil from in situ rainfall, in California irrigated agriculture, the FAO-56 dual crop coefficient modeling approach was used to simulate site-specific irrigation to optimize green water use, considering local climate and soil from 2003-2018 for five major perennial crops, covering 1.46 million irrigated hectares. We also tested different rooting depths and crop water stress irrigation management thresholds to see how the size of the soil water reservoir affects use of the green water resource and, consequently, blue water demand.

Across these soil reservoir scenarios, the 13-year cumulative green water resource ranged from 17-36 million cubic kilometers (km3) out of a 57 km3 rainfall input and 162-263 km3 in cumulative blue water demand. Due to a north-to-south precipitation gradient, 20% of the overall landscape with perennial crops can annually meet, on average, 20% or more of its crop water demand with green water when rooted to 2 m and given 50% allowable depletion. Enlarging the soil reservoir reduced blue water demand more than the increase in green water utilization, due to less frequent but deeper irrigations, which reduced the surface soil evaporative loss.

Managing irrigated perennial agriculture with a conservation-minded approach that makes full use of the soil reservoir can reduce reliance on blue water, not only by decreasing deep percolation of rainfall out of the root zone through crop use of green water, but also by reducing evaporation at the soil surface by irrigating less frequently and more deeply.

**1.1 Introduction**

Irrigated agriculture, climate change, and environmental concerns are forcing Mediterranean 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 2,700 km3 freshwater input (blue water) to irrigation that accounts for 70% of global blue water use 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 storms—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 (NASS, 2015) 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 water use (DWR, 2013). From 2001-2010, California agriculture applied an estimated 43 km3 yr-1 of surface and groundwater for irrigation, 40-50% of all annual streamflow from California’s watersheds (DWR, 2013). With growing concern over the endangerment of native fish species and disappearance of whole freshwater ecosystems in the Sacramento-San Joaquin Delta, water use and non-point source pollution by agriculture is at the heart of long-running, historic conflict over who has a right to clean water in the western US (Hanak *et al.*, 2011).

Moreover, climate change could exacerbate water supply issues due to various changes such as loss of snowpack and increasing precipitation volatility combined with record heat, especially in the western US (Stewart *et al.*, 2005; Seidel *et al.*, 2008; AghaKouchak *et al.*, 2014; Goulden and Bales, 2014; Berg and Hall, 2015; Dettinger *et al.*, 2015; Swain *et al.*, 2018).

To date, water resource policy makers, professionals, and scientists have focused on adapting blue water systems to meeting challenges of increasing competition for supplies and 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 use of green water, the soil stored rainfall potentially available to plants for transpiration (Rockstrom *et al.*, 2010). The green water resource has not been quantified or analyzed in detail in California, despite implicit assumption of its use in California agricultural water demand models that estimate irrigation demand for relatively large hydrologic region units (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 methods. Although there is a wide range of possibilities for irrigation systems and management, California agricultural water demand model studies also have not explored variables such as rooting depth that would affect plant available soil water storage and possible irrigation management strategies, so our study explores this unknown, while maintaining the scale of available soils data in our modeling study.

One technique for utilizing green water in irrigated agriculture in California is to withhold irrigation at the beginning of the growing season until soil-stored water has been depleted to just before the onset of plant water stress. This proportion of plant available water is called the allowable depletion in irrigation management and is commonly found to be approximately 50% of the 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 the 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 the fall when irrigations are withheld.

The objective of this study was twofold. First, we sought to characterize the green water resource at the scale of publicly available data within a water balance framework across five major irrigated perennial crops in California: alfalfa, almonds, grapes, pistachios, and walnuts. Second, as part of the resource analysis, we sought to test how varying the crop rooting depth or level of allowable depletion in irrigation management, both of which change the size of the soil water reservoir available to crops, would affect the available green waterresource but also other aspects of the water balance such as deep percolation, which has implications for salinity management. In quantifying the green waterresource, we considered how over 1.2 million different unique combinations of full root zone soil water storage capacity, surface soil characteristics, irrigation decisions, crop, and climate produce different possibilities of the resource across space and time.

In summary, we sought to map the green water resource, improve understanding of overall water balance implications of optimizing for green water in California irrigated agriculture, and study to what extent the green water resource depends on the size of the soil reservoir used to provide crop water. Better understanding the green water resource’s spatial and temporal gradient could lead to improved, place-based, and well-timed irrigation strategies that reduce reliance on blue water by strategically using the farms’ soils as reservoirs.

**1.2 Materials and Methods**

*1.2.1 Overview*

We used a 14+ year, daily simulation to model irrigation of five major perennial crops in California (alfalfa, almonds, grapes, pistachios, and walnuts), using publicly available climate, soils, and crop distribution data. These data sources of varying spatial resolutions were integrated into a common database and processed by an R script that closely follows the FAO-56 reference ET, dual crop coefficient (dual Kc) approach (Allen *et al.*, 1998; Allen *et al.*, 2005a), to simulate crop use of green water and irrigation. Results were tracked within a water balance framework that considers 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, combining different assumed 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 the size of the soil water reservoir affects the green water resource and, consequently, blue water demand (Figure 2). In the results, we choose to highlight 3 of the 12 scenarios as follows: a shallow scenario representing “business-as-usual” in microirrigated orchards and vineyards now dominant in California perennial crops (0.5 m root depth x 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 Kc approach estimates actual crop evapotranspiration (ETc) 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 (ETo). The daily water balance procedure for the root zone and surface soil in this study is detailed in Appendix A. 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 the surface wetted only by precipitation and the surface wetted by both precipitation and irrigation that results from partial surface wetting systems like drip and microspray.

*1.2.2 Estimating green water use*

Green wateruse is quantified as the cumulative difference between growing season ETc and applied irrigation water (Ir) through 13 years (Jan 2005- Dec 2017), excluding the first 15 months of the simulation as a model initialization period (Oct 2003-Dec 2004).

Since crop ETc includes soil surface evaporation, utilization of green water includes soil surface evaporation of precipitation (P) but only during the growing season. This approach also assumes that all irrigation water is meeting crop ETc demand, so that any growing season deep percolation (DP) is assumed to be P derived. As an error check, total model water balance was checked:

Where and all terms above are cumulative from beginning to end of the model, 5273 days.

*1.2.3* *Computational strategy*

The daily simulation was run using the following input datasets: (1) all major soil components for map units of interest from the Soil Survey Geographic Database (SSURGO) 1:24,000 shapefile with 1,143 unique soil component names in the study area comprising 4,345 unique map unit names; (2) daily precipitation at 4 km resolution from the Parameter-elevation Relationships on Independent Slopes Model (PRSIM) (Daly *et al.*, 2008) with 4,262 PRISM raster cells of interest in the study area; (3) daily 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 identified to have alfalfa, almonds, grapes, pistachios, or walnuts (CDWR, 2017a). Dividing these fields by soil map unit, there were 323,422 soil map unit-crop polygons across the study area, recognizing that each map unit typically contains multiple soil components which are not delineated spatially (Figure 3). Of these, there were 107,561 unique major component soil, climate, and crop systems, meaning not all polygons had to be modeled.

For each of these unique soil-climate-crop systems, a 5,273 day (October 1, 2003 – March 8, 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) for a MS Excel spreadsheet and detailed in Appendix A. Nearly 1.3 million simulations were performed for the twelve soil reservoir scenarios of rooting depth and allowable depletion on a desktop computer with a 4-core Intel Xeon 3.80 Ghz CPU and 64 GB of RAM, taking approximately 8 days. 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://www.github.com/smdevine/GreenWater>.

*1.2.4 Soils – plant available and evaporable water*

Several steps were needed to estimate root zone plant available water from the Soil Survey Geographic Database’s (SSURGO) tabular data for perennial crops where deep tillage is common during establishment in California. The 2017 updated shapefile for 1:24,000 scale SSURGO soil map units in California was accessed from the California Soil Resource Lab at the University of California, Davis. This shapefile was intersected with the crops shapefile to identify the necessary soil survey area symbols for downloading associated tabular data. Downloading mapunit, component, and horizon level data (Figure 3) was done with the “SDA\_query” function from the SoilDB package in R (Beaudette *et al.*, 2018)[[1]](#footnote-1).

For each soil in California, plant available water storage was estimated for rooting depths of 0.5 m, 1.0 m, 1.5 m, 2.0 m, and 3.0 m by summing SSURGO representative available water capacity for each horizon in the rooting zone. Since SSURGO typically reports information to depths of only 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 and cropped to alfalfa. To populate available water capacity for soils with paralithic or lithic contacts (denoted by a Cr or R horizon in SSURGO 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 horizons (e.g. claypans or duripans) underlying almonds, grapes, pistachios, and walnuts, deep tillage is assumed to have occurred that either removes or thoroughly mixes these horizons into the profile, transforming the 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 chunks and then removed from the field. For alfalfa, no deep tillage is assumed. Thus, plant available water is assumed to terminate at the depth of both geologic and pedogenic restrictive horizons under alfalfa.

Several additional 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 Kc routine, since these variables are not defined in SSURGO. The broad goal here was to avoid implementing stepwise functions based on different textural classes, such as in Table 19 of Allen *et al.* (1998). First, we defined TEW using the widely implemented equation (Allen *et al.*, 1998):

(2) ,

Where is the plant available soil water storage, is the soil water content at wilting point, both available from SSURGO, and is the depth of the surface layer subject to evaporation, estimated in-house using a function that relates to the mean weighted mean particle size diameter derived from SSURGO particle size fraction data for the surficial layer (see Appendix A for details). 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). Our function represented this logic. The readily evaporable water (*REW*) was calculated based on surface horizon texture, following the equations published in Allen *et al.* (2005b) and scaling by the soil’s estimated Ze value.

Finally, when there is more than one major component in a soil map unit, percent weighted averages of major component model results were calculated (Figure 3).

*1.2.5 Climate data*

Daily, 4 km resolution precipitation rasters covering the contiguous United States from October 1, 2003 – March 8, 2018 were downloaded from the PRISM Climate Group (<http://www.prism.oregonstate.edu/>) using the *prism* R library’s “get\_prism\_dailys” function. Precipitation data was extracted to a single table for all cells of interest by day[[2]](#footnote-2).

Daily reference ETo, wind, dewpoint temperature, and maximum temperatures from October 1, 2003 – March 8, 2018 were downloaded from the Spatial CIMIS dataset on a UC Davis server (<http://cimis.casil.ucdavis.edu/cimis/>) and extracted to a single table for each variable[[3]](#footnote-3). Daily minimum relative humidity for input into the FAO-56 algorithm was estimated by modifying the equations from Hart et al. 2009 for actual vapor pressure () and saturated vapor pressure () using the suggestion from Allen et al. 2005 when only mean daily dewpoint temperature is available, as is the case for the Spatial CIMIS dataset:

(3)

(4)

(5)

Where Tdew is the mean daily dewpoint temperature and Tmax is the daily maximum temperature in °C. All climate data was subjected to QC checks for negative, missing, or values above 100% for RHmin. All precipitation data passed these QC checks. Less than 0.02% of the Spatial CIMIS dataset required gap-filling or correction. Corrections were based on multi-year means for that location and date.

*1.2.6 Crops*

Perennial crop distribution was assumed from the 2014 Department of Water Resources land use classification for irrigated lands (Figure 4D) (CDWR, 2017a). Crops were assumed to be unchanged across the simulation years (2003-2018) (Table 1).

Basal crop coefficients (Kcb std) were chosen to reflect high density production with the exception of wine grapes managed by regulated deficit irrigation management and assumed to exist outside the Central Valley in coastal or foothill locations, including Napa and Sonoma Valleys (Table 1). Kcb std 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 Kcbvalues similar to grapes grown for high-quality wine. Kcb std values for alfalfa were taken from Table 17 in chapter 7 of Allen *et al.* (1998) with different cutting cycles depending on the region of California. Irrigation management for higher quality wine grapes typically includes intentional crop water stress after veraison to help control canopy growth, meaning lower Kcb values compared to table grapes or high yielding wine grapes (Prichard *et al.*, 2004). Seasonal timing to guide basal crop coefficient curves for each crop was based on the California specific, crop coefficient calendars in Goldhamer and Snyder (1989). Corresponding fraction of vegetative cover (*fc*) values for almonds, grapes, pistachios, and walnuts were taken from Table 2 and 3 in Allen and Pereira (2009) and then linearized to run parallel to Kcb curves. Assuming no cover crops, a dormant season Kcb value of 0.15 was chosen for all crops with dormancy. While intended to represent transpiration, this underlying basal crop coefficient represents “background”, diffusive evaporation from deeper soil layers (Allen *et al.*, 1998) and is similar to the 0.12 value assumed by a BLM study of climate change impacts on irrigation water demand in the western US that also used the FAO-56 dual Kc approach but at regional input data aggregations (Huntington *et al.*, 2014).

*1.2.7 Irrigation decisions*

There are two fundamental irrigation parameters that need to be defined for the dual Kc model: (1) the proportion of the soil surface wetted and (2) the depth and timing of the irrigations. Standard microspray fw values of 0.65 were assumed for almonds, pistachios, and walnuts to represent microsprinkler irrigation. Drip irrigation fw values of 0.35 were assumed for table and wine grapes. Border or sprinkler irrigation fw values of 1.0 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 when a given crop-soil-climate system reached its allowable depletion during the growing season. So, for crops with dormancy, no irrigation was allowed until the crop’s bloom/leaf-out date (Table 1). 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 climatic 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 the soil at allowable depletion at dormancy. In other words, an irrigation-free period during the fall is defined for each system before running the 5000+ day model. This has the effect of creating some crop water stress during dry falls.

We also included 3 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 the northern California intermountain region, where alfalfa is dormant from late November to late March each year with 3 assumed cuttings through September followed by fall regrowth before winter induced dormancy; or (3) alfalfa in the Central Valley with 7 assumed cuttings but no irrigations or cuttings from Nov-Jan 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 California 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 when 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% plant available water when the soil stress coefficient (Ks) reached 0.8 (60% allowable depletion); in the 50% allowable depletion scenario irrigation was applied to restore soil back to 50% plant available water when Ks reached 0.5 (75% allowable depletion); and in the 80% allowable depletion scenario irrigation was applied to restore soil back to 50% plant available water when Ks reached 0.2 (90% allowable depletion). Then, the target end-of-season soil water content was equal to 30, 50, or 80% allowable depletion at leaf-drop, depending on scenario. For Central Valley grapes, irrigation was practiced the same as for tree crops, outlined above.

1.2.8 *Spatial data projections and resolutions*

Several steps were needed to integrate these various spatial datasets, because they were not all available in the same projection and were in a mix of vector and raster spatial formats. First, the crops dataset was intersected with the NRCS soil map units, which created over 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 of these polygon features. Then these field centroids were tagged with each of the climate dataset’s raster number with the *cellFromXY* function in the *raster* R package (Hijmans, 2016). For the PRISM data, the 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.

**1.3 Results**

*1.3.1 Green water availability*

The results section focuses on 3 of the 12 modeled scenarios: a shallow, moderate, and deep scenario. These represent a spectrum of irrigation management possibilities, from the “business-as-usual”, shallow approach commonly practiced in microirrigated orchards and vineyards today to a “conservation minded” approach that utilizes a 2.0 m deep soil reservoir to help meet crop water demand (see Methods).

The 13-year, cumulative green water resource was 17.4, 24.6, and 29.6 km3 in the shallow, moderate, and deep scenarios, out of a 57.1 km3 precipitation input for 1.46 million hectares of California perennial crops (Figure 5A-C; Table 2). Utilized green water comprised a relatively small part of the total crop water demand in aggregate, cumulatively meeting 6-12% of growing season ET in these shallow-to-deep scenarios with low levels of crop water stress (Table 2).

Although a relatively small portion of statewide growing season crop ET can be supplied by green water, there were substantial portions of the landscape where green water availability was much greater (Figure 5A-C; Table 3). On average, assuming the moderate to deep scenarios, 20% of the perennial landscape can meet 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 availability met only 11% of its annual crop water needs on average with green water. The highest green water availability 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 greater variability across the landscape in a deep compared to a shallow scenario (Figure 5A-C; Table 3).

This north-to south trend (Figure 5A-C) was due to a precipitation gradient (Figure 4A). However, the general green water resource trend was regionally complicated by topographic effects on precipitation, soil property effects on plant available water and evaporable water storage, and differences in crop growing seasons and canopy coverage (Figure 4A-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 resource, all years with 2.1-2.9 km3yr-1 green water used and a maximum annual availability close to the volume of Trinity Lake (3.0 km3), California’s third largest reservoir. In the deep scenario, the annual availability increased to 2.6-3.6 km3 yr-1 for the same 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 an order of magnitude larger than the increase in green water utilization 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 (see Methods; Table 2).

In all of these scenarios, we assumed bare soil conditions during dormancy, so wintertime surface evaporation of precipitation was substantial. In the deep scenario, the annual green water use was only 52% of precipitation, even though deep percolation had been reduced to just 19% of precipitation. This was because of dormant season soil evaporation, which was constant at 1.1-1.65 km3 yr-1 (30-33% of cumulative precipitation) across all scenarios (Table 2). In the shallow and moderate scenarios, green water use was 30% and 43% of total precipitation, respectively.

*1.3.2 Blue water (irrigation) demand*

Cumulatively, irrigation (blue water) demand was 263, 225, and 210 km3 in the shallow, intermediate, and deep scenarios, respectively. Greater green water availability in the intermediate 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, 15.0-19.1 km3 yr-1 in the moderate scenario, and 18.0-21.8 km3 yr-1 in the shallow scenario. Larger soil reservoirs enhanced inter-annual variability in blue water demand, while reducing the annual average demand. Wet years tended to have lower potential evapotranspiration conditions, such that annual blue waterdemand was reduced even more. The north-to-south potential evapotranspiration gradient (Figure 4B-C) resulted in larger blue waterdemand in more southern locations for all crops (Figure 6A-C). The blue water demand gradient is steepened when soil reservoirs are enlarged across the entire study area.

*1.3.3 Soil water storage capacity effects*

Enlarging the soil water storage reservoir enhanced green water resource availability. Increasing the soil water storage capacity had the most benefits for green water availability when going from the shallowest soil storage scenario to a moderate soil storage scenario (Table 3). Using this comparison, the landscape showed a mean increase in green water availability of 0.66 mm green water per mm increase in allowable depletion (Figure 7A). When going from a moderate to deep scenario, the landscape saw a lower mean increase of 0.57 mm green water per mm increase in allowable depletion, since a sizable proportion of the study area experienced little-to-no additional benefits from green water when the rooting depth is increased beyond 1 m (Figure 7D). This precipitation limited area is in the southern DWR regions (Table 3; Figure 4D). Increasing the rooting depth further from 2.0 to 3.0 m shows that most of the study area would see no additional benefits from green water by rooting deeper than 2 m, though there are certainly some locations that would benefit.

The basic strategy by which green water is utilized is by delaying irrigation at the beginning of the season, tracking early growing season precipitation to spread out early season irrigations, and ending irrigation at a specified date in the fall before dormancy to make room in the soil reservoir for capture of winter precipitation. As the allowable depletion was increased, the effect was a progressively shorter irrigation season length and lower irrigation frequency (Figures 7C and E). Utilizing additional green waterin 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 8A-C; Table 2).

When the soil water storage capacity is increased, blue water demand was reduced more than the increase in green water availability (Figure 7B and E). The results show that more soil water storage in the irrigation management scheme allowed for less frequent, deeper irrigations (Table 2). This reduced the cumulative surface soil evaporative loss from 63.1 to 33.4 km3 going from 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 km3 in the deep scenario through 13 years.

*1.3.4 Green water accounting accuracy*

We used an operational definition to estimate cumulative green water use in the simulation, for the sake of practicality and simplicity, but at the expense of accurately resolving annual fluctuations (Methods, equation 1). Episodic dry and wet years created fluctuations in soil moisture recharge and storage during the 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, interannual ΔS ranged from 0.3 to -0.6 km3 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 km3 at the beginning of the growing season, and from 0.9 to -1.0 km3 on the beginning of the year across the entire study area. Given the annual green water results ranged from 1.1-2.9 km3 yr-1 in the moderate scenario, annual results were susceptible to this soil moisture change error. 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, our results have focused on 13-year cumulative amounts or annual averages to avoid this error. We quantified the 13-year, cumulative potential error and found that beginning-to-end of the model run ΔS varied from 1.1-3.0% of the cumulative green water resource across the 12 different soil reservoir scenarios. This means that the overall model simulation change in soil water storage, assuming it was actually irrigation derived, provided at most 1-3% of the green water.

**1.4 Discussion**

The FAO-56 dual crop coefficient water balance methodology was used to quantify and map the soil stored rainfall (green water) available to five of California’s major perennial crops (alfalfa, almonds, grapes, pistachios, and walnuts), along with other water balance components from a 13-year simulation. The results show a relatively modest green water opportunity for California water resource management to use soil water storage and in situ rainfall to help meet 6-18% of crop water demand, depending on rooting depth and allowable depletion (Table 2).

The resource was spatially concentrated, so in some areas the proportion of crop water demand met by green water was much larger (Figure 5A-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%. In regional terms, while only 23% of perennial crops are north of the Sacramento-San Joaquin Delta, 36% of the annual green water resource was in this region across scenarios (Table 3). If the San Joaquin region is included with those regions north of the delta, then this half of the irrigated perennial acreage accounted for 70% of the green water resource.

As a whole, given the reality of California’s dry, warm climate with its large atmospheric demand for water, green water can at best fill a glass 10-20% full for perennial crops rooted to 1-2 m. Nevertheless, given the scale of irrigated land in California, this small relative annual contribution of green water to crop ET is a 13-year total that could fill California’s largest manmade reservoir, Shasta Lake with a capacity of 5.6 km3, 3-5+ times over. This also shows 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. Thus, our study’s results show the potential of green water to meet perennial crop water demand and are relevant to the development of sustainable, regional water plans required by the Sustainable Groundwater Management Act in California.

Availability of green water can be substantial even in a shallow soil reservoir scenario that is optimized for green water use but is enhanced by deeper rooting or higher allowable depletions (Table 2). Though the San Joaquin and Tulare regions are relatively dry climates, nearly 60% of the green water resource is in this region that has 68% of the perennial crop area (Table 3). This shows the relevance of timely soil reservoir management and precipitation tracking, both of which were assumed in this simulation. 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 climate change and increasing urban and environmental uses of water (Jezdimirovic and Hanak, 2016; Kocis and Dahlke, 2017; CDWR, 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 irrigations can be delayed to allow for crop use of green water. For instance, deep percolation was reduced from 1.7 to 1.2 to 0.9 km3 yr-1 on average, comparing the shallowest 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 (Figure 8A-C).

Utilizing green waterthrough 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. To practice effective water balance tracking, multiple data streams are needed with especially high-quality precipitation and on-farm data required. These data streams have to be integrated to produce metrics for adaptive decisions throughout the growing season: to delay irrigation at the beginning of the season, delay irrigation when growing season precipitation occurs, and intelligently end irrigation before the beginning of crop dormancy to make room in the soil reservoir for capture of winter rainfall but also account for fall crop water stress risk. In addition to these complexities, the practical considerations of irrigating complicate management for green water in several ways. First, not all farms are in control of their water supply. Lack of flexibility at the district or 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, farms are typically divided into irrigation blocks, meaning that when crop water is needed, the whole farm cannot be irrigated simultaneously. It may take days to several weeks for an irrigation system to cover the whole farm or crop, complicating timing decisions with respect to crop water stress. In other words, if the system has an 8 day return interval, then the system may need to be started 8 days before the onset of stress in 1/8 of the area covered by the irrigation system and so on, to avoid crop water stress in all parts of the field. These complications, paired with inherent climatic variability in California that makes rainfall uncertain, mean that optimizing green water use in irrigated agriculture is a formidable adaptive management challenge.

Nevertheless, managing for green water is an attractive strategy for climate change adaptation to a warmer, likely more water-limited future, especially where snowmelt fed regions are challenged by more severe droughts, warmer temperatures and declining snowpacks, such as in California and the western United States (Stewart *et al.*, 2005; AghaKouchak *et al.*, 2014).

A green water resource management endeavor practiced at the farm-scale is in sharp contrast to the large-scale, water resource management focus as currently practiced in California. To utilize green water, thousands of soil reservoirs must be effectively managed by thousands of farmer-operators. 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 4; 5A-C). 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). Thus, the green water resource shows both spatial and temporal concentration, demonstrating the need for adaptive management that varies by region, crop, soil, and year.

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 to 80% for each rooting depth, the growing season ET is reduced by 17-19% 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 line 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).

Our study assumed different surface wetting fractions for different crops based on common irrigation systems for different 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 partial surface wetting likely does not actually 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.

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 for crops. Average dormant season evaporative losses of 1.4 km3 yr-1 precipitation from bare soil under perennials show that green water is also available for growing cover crops during the winter. While there is only an estimated 7.7 cm yr-1 in dormant evaporation for early blooming almonds, there is 14.0-15.4 cm yr-1 dormant evaporation for bare soil in the later blooming grapes, pistachios, and walnuts. Cover crops in these perennial crops 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 health (Brennan and Acosta-Martinez, 2017; Mitchell *et al.*, 2017), through protecting the soil surface from crusting and maintaining infiltration rates, providing a possible positive feedback to the green water resource.

Our study assumed no limitation to precipitation infiltration or percolation when the soil is below field capacity during rainfall. Due to ignoring a possibility of overland flow loss, this 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. The bucket soil hydrology model used by the FAO-56 dual Kc approach assumes that all rainfall in excess of field capacity is immediately lost to deep percolation. So, in some cases, the reported green water availabilities could actually be underestimated by neglecting water periodically available to crops between saturation and field capacity from more slowly draining soil.

One of the more interesting and 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 a function only 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 km3 yr-1 when comparing the shallow and moderate scenarios, compared to a gain in green water of 0.6 km3 yr-1. In this comparison, the irrigation frequency was reduced from 59 irrigations yr-1 to 19 irrigations yr-1 across all crops.  To put this into context of crops like almonds and pistachios, current microirrigation depths are most similar to the depths applied in our study’s shallow scenario (mean application of 21 mm, Table 2). In the southern California Central Valley, microsprinkler systems are commonly managed to apply 25-40 mm per application, but drip systems are managed to apply as little as 3-9 mm per set or as frequently as 1-3 times per day (B. Sanden, personal communication, June 1, 2018).​ When the average irrigation frequency was reduced further in a deep scenario to just 10 irrigations yr-1, the additional savings in soil surface evaporation was 0.8 km3 yr-1, compared to an additional 0.4 km3 yr-1 gain in use of green water. 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, 21% of growing season ET was surface soil evaporation, compared to 12% and 9% in the moderate and deep scenarios, respectively. This demonstrates how irrigation frequency is directly tied to the proportion of irrigation water lost to soil evaporation in these major perennial crops. While this 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 only 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. Similarly, evaporation losses of 7-17% were estimated from a drip-irrigated desert vineyard (Kool *et al.*, 2014b). In contrast, a study of micro-sprinkler irrigation in California almond orchard found evaporative losses of 21-27% when irrigating in 25 mm sets every 2-3 days (Koumanov *et al.*, 1997), very similar to our shallow scenario results. The FAO-56 dual Kc model approach considers how the irrigation system surface coverage and vegetative canopy coverage combine to create a certain proportion of the surface both wetted and exposed to evaporative energy (Allen *et al.*, 1998; Allen *et al.*, 2005a) and has been validated as technique to estimate water demands in orchards, vineyards, and alfalfa (Hunsaker *et al.*, 2002; Fandino *et al.*, 2012; Paco *et al.*, 2012; Paco *et al.*, 2014; Cancela *et al.*, 2015). Future work and field validations are needed to explore to what extent surface coverage and microclimates control evaporative losses in perennial crops, as different assumptions were made for different crops in this study (Table 1). 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. The transition from low-frequency, surface and sprinkler irrigation systems to high-frequency, micro-irrigation systems across California the past several decades (Tindula *et al.*, 2013) may have reduced crop water stress and helped increase crop yields like in almonds (Sanden, 2007) but come at a cost of increased evaporative water consumption. In their review of evaporation research, Burt *et al.* (2005) noted that Westlands Water District had collected 15 years of data that suggested ET in high-frequency, drip-irrigated almonds is 10-15% higher than almonds irrigated by other methods. Burt *et al.* (2005) suggested it was at least partly due to evaporative losses, supporting the findings of this modeling study, and they concluded that evaporation in irrigated agriculture deserved further research.

Applying the FAO-56 dual Kc methodology across five major California perennial crops showed that irrigation management strategies that emphasize full use of soil water storage in the root zone to make use of green water and minimize irrigation frequency is a strategy to curtail demand for blue water. Such a soil storage based strategy would require less blue water diversion, pumping, and consumption, on the order of tens of km3 over decadal scales spread over 1.46 million hectares. 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. Nevertheless, 13-year evaporative savings between a shallow and moderate scenario approached 30 km3, showing that an irrigation program that applied an average 67 mm (moderate scenario) vs. 21 mm (shallow scenario) per irrigation, would keep the surface wetted less often and lose much less water to evaporation.

**1.5 Conclusion**

The cumulative green water resource in California perennial crops was enough to fill California’s largest reservoir, Shasta Lake, 3-5+ times over 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 across the landscape, 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. Surprisingly, shifts from high- to low-frequency irrigation management scheme with more reliance on the soil water reservoir resulted in evaporative savings larger than the gain in green water use. This is very relevant to how current microirrigation systems are managed, since they now dominate orchard and vineyards in California, where irrigation depths are commonly < 40 mm in microsprinklers and <25 mm in drip systems per application. Moving from a “business-as-usual” shallow irrigation management scheme to a moderate strategy saved 30 km3 blue water evaporation and increased green water use by 7 km3 cumulatively.

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 irrigations in California. This study assumed no limitations on infiltration or soil permeability, so soil and residue management to maintain soil hydrologic function may be necessary to achieve this study’s results in some locations. 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 one-third of precipitation evaporated from bare soil under dormant perennials in the scenarios. Finally, breeding of rootstocks capable of growth in deep soil and water uptake 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.

**Table 1.** Modeled crop area, soil features by crop, and seasonal crop growth assumptions. For the basal crop coefficient values (Kcb), 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 horizon3 | Lithic / Paralithic | End dormancy | Peak  growth/  cuttings | Senescence | Dormancy | Kcb, ini | Kcb, mid | Kcb, end |
|  | *------------ ha -----------* | | |  |  |  |  |  |  |  |
| Alfalfa, Central Valley1,2 | 206,690 | 29,804 | 1,896 | NA | 7 | NA | NA | 0.3 | 1.15 | 1.1 |
| Alfalfa, Imperial Valley2 | 80,214 | 0 | 0 | NA | 10 | NA | NA | 0.3 | 1.15 | 1.1 |
| Alfalfa, Intermountain2 | 64,888 | 22,580 | 9,269 | Apr 1 | 3 | Oct 16 | Nov 23 | 0.3 | 1.15 | 1.1 |
| Almonds | 455,970 | 80,470 | 30,348 | Feb 15 | Jun 1 | Sep 4 | Nov 11 | 0.2 | 0.95 | 0.65 |
| Grapes, Central Valley | 248,866 | 63,138 | 3,133 | Mar 15 | Jun 15 | Aug 17 | Oct 22 | 0.2 | 1.05 | 0.8 |
| Grapes, Coast and Foothills | 111,634 | 3,317 | 32,526 | Mar 15 | Jun 15 | Aug 17 | Oct 22 | 0.2 | 0.7 | 0.55 |
| Pistachios | 137,590 | 21,289 | 4,337 | Apr 25 | Jun 15 | Sep 4 | Nov 15 | 0.3 | 0.95 | 0.65 |
| Walnuts | 149,352 | 27,170 | 9,495 | Apr 1 | Jul 7 | Sep 4 | Nov 11 | 0.4 | 1.05 | 0.6 |

1 Peak growth assumed to resume Feb 14th with irrigation first considered on Feb 7th 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.

2 Alfalfa Kcb is reduced to 0.3 (Kcb, ini) after each cutting

3 Pedogenic restrictive horizons constraining to root growth were identified in SSURGO’s component restrictions table and were mostly duripans and claypans

Table 2. Cumulative water balance component totals from modeling the different soil storage scenarios from 2005-2017. 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 km3 through 13 years.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RD | AD | | GW | Ir | E | DP | CS | ET | DPa | ΔS | Ir freq | First ir | Last ir |
| *-m-* | *-%-* | *-mm-* | *13 yr total, growing season cubic kilometers (km3)* | | | | | | | *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; Irr = irrigation (blue water); E = evaporation; DP = deep percolation; CS = crop stress; ET = evapotranspiration; DPa = annual deep percolation**;** ΔS = change in soil storage; Irr freq = irrigation frequency, average number of irrigations applied per year; First irr = average first day of irrigation; Last irr = average last day of irrigation; DOY = day of year

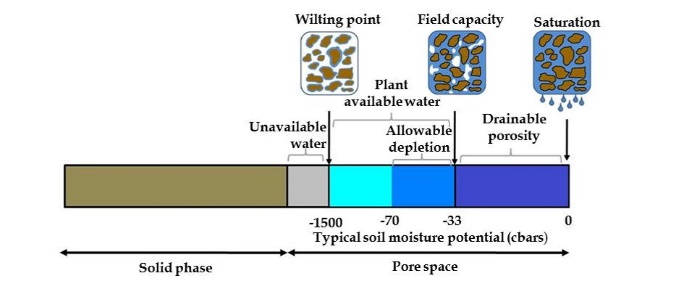
**Table 3**. Summary of green water (GW) availability by California Department of Water Resources’ hydrologic region and soil reservoir scenario (shallow, moderate, and deep). The top half of the table summarizes perennial crops north of the Sacramento-San Joaquin Delta. The bottom half summarizes perennial crops south of the Delta. The South Coast and South Lahontan regions are not included, where only 1,500 hectares of perennials were modeled.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Shallow1 | Mod2. | Deep3 | Shallow | Mod. | Deep | Shallow | Mod. | Deep |
| Region | Perennials | Cumulative GW | | | Crop water use met by GW | | | Mean annual GW availability | | |
| *North of Delta* | --ha-- | -----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* | **1,124,438** | **11.1** | **15.8** | **18.7** | **5%** | **8%** | **10%** | **76** | **108** | **128** |
|  |  |  |  |  |  |  |  |  |  |  |
| *TOTAL* | **1,453,690** | **17.4** | **24.6** | **29.6** | **6%** | **10%** | **12%** | **92** | **130** | **157** |

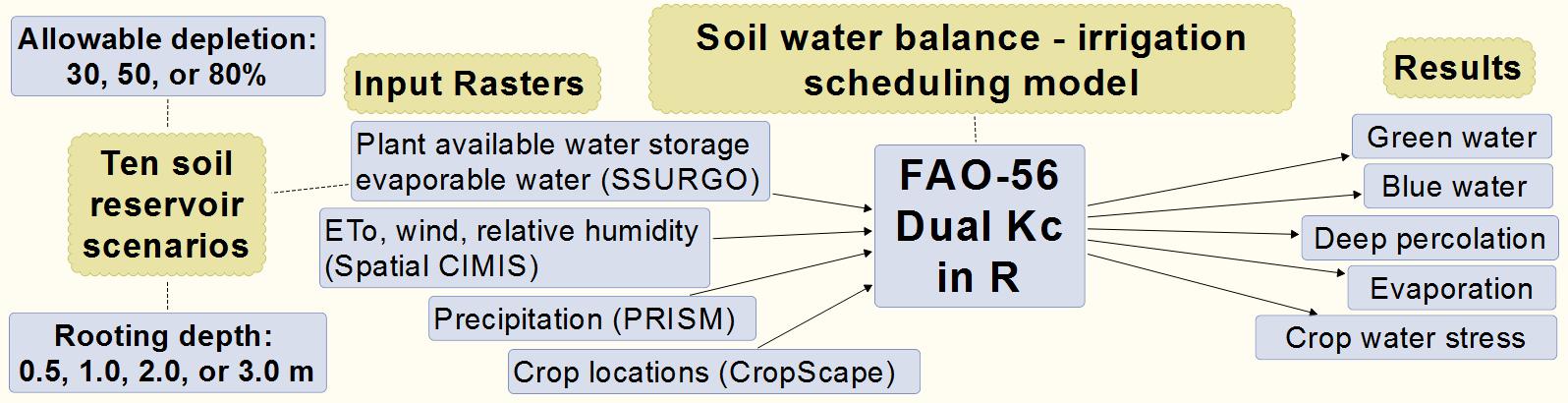
1 The shallow scenario is 0.5 m rooting depth and 30% allowable depletion.

2 The moderate scenario is 1 m rooting depth and 50% allowable depletion.

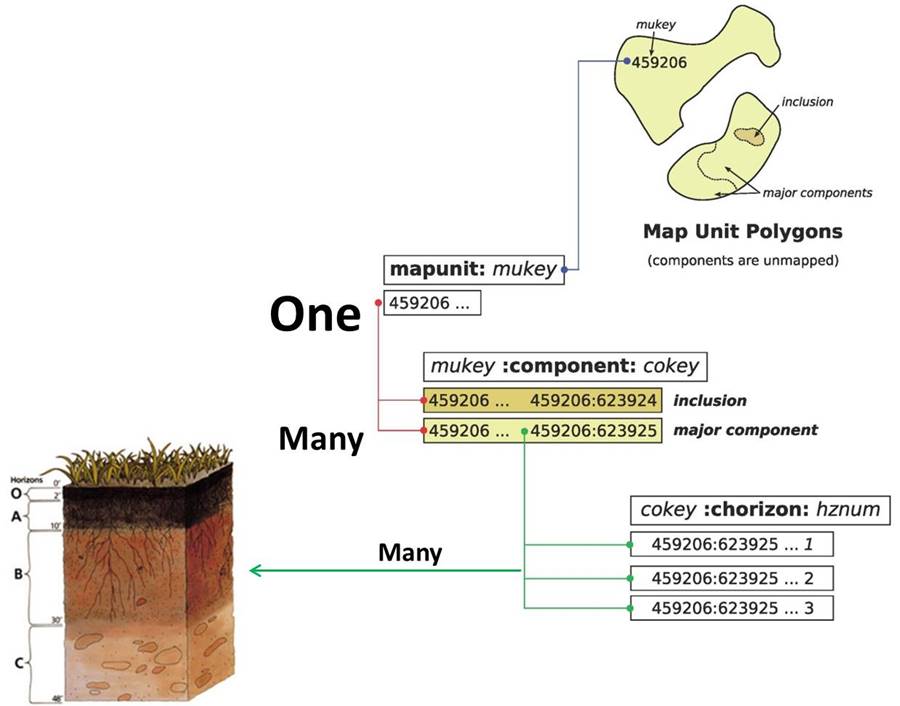
3 The deep scenario is 2 m rooting depth and 50% allowable depletion



**Figure 1**. Three allowable depletion levels of plant available water (30, 50, and 80%) are used in the scenarios to determine when to irrigate, not wilting point



**Figure 2**. Overview of modeling approach, 14-year simulation (Oct 2003-Mar 2018)



**Figure 3**. SSURGO is a many-to-one relational database. A number of steps were needed to make the information in the database usable by the FAO-56 dual crop coefficient model and then aggregated to the map unit scale



**Figure 4A-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 (see Methods).



**Figure 5A-C**. Mean annual green water 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 6A-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 7A-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 and 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.



**Figure 8A-C**. Maximum annual deep percolation via precipitation from 2005-2017. 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.

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1. See <https://github.com/smdevine/GreenWater/blob/master/GetData/download_SSURGO_allCA.R> [↑](#footnote-ref-1)
2. See R script: <https://github.com/smdevine/GreenWater/blob/master/GetData/download_PRISM.R> [↑](#footnote-ref-2)
3. See R script: <https://github.com/smdevine/GreenWater/blob/master/GetData/spatialCIMIS.R> [↑](#footnote-ref-3)