Characterizing the green water resource in California irrigated perennial agriculture

*Abstract*

Agriculture in Mediterranean climates relies on irrigation (blue water) to produce high-yielding, high-quality crops, but blue water supplies for agriculture are challenged by climate change, urban demand, and environmental uses. Green water, the soil stored water from in situ rainfall potentially available to crops, can reduce agricultural reliance on blue water, especially for deeply rooted perennial crops that have access to relatively large soil volumes.

To quantify and characterize the green water resource in California perennial irrigated agriculture, the FAO-56 dual crop coefficient modeling approach was used to simulate daily soil water balances and irrigation from 2003-2018 for five perennial crops in California, including alfalfa, almonds, grapes, pistachios, and walnuts, covering 1.46 million irrigated hectares. In addition to considering the effects of climate and soil variability, we explored 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 of total plant available water in the root zone) to see how varying the size of the soil water reservoir accessible to crop roots affects 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, which represents 6-18% of growing season evapotranspiration. Thus, in the world of green water for perennial crops, the glass is only marginally full at best. However, 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. Surprisingly, by enlarging the soil reservoir, blue water demand was reduced substantially more than the increase in green water utilization. This is because larger soil water reservoirs allow for less frequent but deeper irrigations, which reduces the number of required irrigations, the surface soil evaporative loss, and the demand for blue water. Assuming the entire study area’s irrigation was managed shallowly with a 30% allowable depletion, 0.5 m rooting depth, and an average of 59 irrigations yr-1, then a transition to a moderate depth irrigation management scenario (50% allowable depletion, 1.0 m rooting depth, and 19 irrigations yr-1) would bring a 30 km3 reduction in soil surface evaporation through 13 years versus a gain of 7 km3 in green water; a deepening to 2.0 m rooting depth in the management scheme would bring an additional 11 km3 cumulative savings in evaporation by reducing irrigations to just 10 applications yr-1 with 5 km3 more green water utilized. In conclusion, managing irrigated perennial agriculture by 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. An open question is whether or not regular, effective soil water use through 1-2 m of soil can be accomplished without introducing harmful perennial crop stress and risk to farmers.

* 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) that accounts for 70% of global blue water use by humans (FAO, 2015). In Mediterranean climates like in California, the reliance on irrigation in agriculture 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 driven by warming, especially in the western US (Dettinger *et al.*, 2015). These hydroclimate change effects include expansion of Hadley cells that could particularly affect precipitation in regions between 30 and 40 degrees latitude (Seidel *et al.*, 2008), warming driven increases in watershed evapotranspiration that reduces downstream water supply (Goulden and Bales, 2014), loss of seasonal snow water storage important to the reliability of human water supply systems in snow and ice-dominated watersheds (Stewart *et al.*, 2005), and increasing frequency of wet and dry extremes (Berg and Hall, 2015; Swain *et al.*, 2018) with droughts expected to be more severe due to higher temperatures, such as the example of the 2012-14 California drought (AghaKouchak *et al.*, 2014).

Given the above challenges to water resource management, solutions are needed. So far, water resource professionals and scientists have focused almost entirely on blue water resources and infrastructure, such as these ongoing examples in California: (1) $2.7B of the $6.5B California Proposition 1 water bond funding is appropriated for water storage projects such as new dams (Jezdimirovic and Hanak, 2016); (2) on-going analysis of a multi-billion dollar plan called California WaterFix to re-route north to south regional water transfers under the Sacramento-San Joaquin delta to meet environmental regulations (CDWR, 2018); and (3) since new dam capacity and regional water transfers are limited, groundwater banking on agricultural land with local flood flows is an active area of research to expand blue water storage capacity in wet years via groundwater storage (Kocis and Dahlke, 2017). However, as part of an integrated water resource management strategy, there may not only be better or more clever ways to manage blue water but also opportunities related to green water, the soil stored rainfall potentially available to plants for transpiration (Rockstrom *et al.*, 2010).

Because most precipitation falls during the dormant season of high-value perennial crops in Mediterranean climates, for much of the Mediterranean irrigated landscape, green water is provided through soil storage of winter precipitation along with some growing season rainfall. Each particular soil has a particular plant available storage capacity defined as the difference between water retained against drainage by gravity (field capacity) and the water retained in soil when plants suffer water stress (wilting point). The soil’s plant available water storage provides green water. How the size of the soil reservoir is defined is the conceptual underpinning of this study’s green water resource analysis for five major irrigated perennial crops in California, spanning 1.46 million hectares, using a water-balance based, simulation approach.

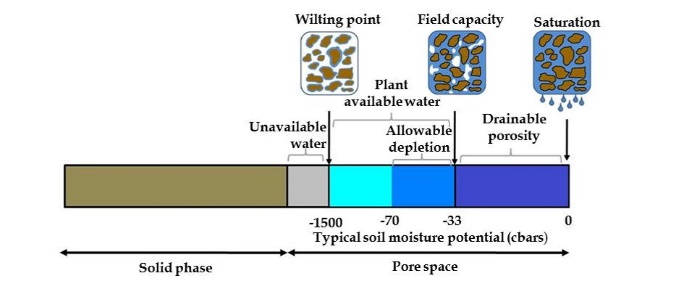
One technique for utilizing green water in irrigated agriculture in California is to withhold irrigation at the beginning of the growing season until soil-stored water has been depleted to just before the onset of plant water stress. This proportion of plant available water is called the allowable depletion 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 and utilization of the green water resource is expected to result in several benefits: (1) reduced 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 is twofold. First, I characterize the green water resource within a water balance framework across five major irrigated perennial crops in California: alfalfa, almonds, grapes, pistachios, and walnuts. These crops comprise approximately half of the irrigated acreage in CA and represent an expanding agricultural sector (Tindula *et al.*, 2013) with “hardened” water demands. Due to their perennial nature and high establishment costs, fallowing during droughts is impractical, except for alfalfa. Thus a green water resource analysis is of interest to helping reduce consistent irrigation water reliance.

Second, as part of the resource analysis, we sought to quantify 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. Examining how the size of the soil reservoir used in the irrigation management scheme affects irrigation water demand is a unique contribution to the literature on regional irrigation water demand analyses.

In quantifying the green waterresource, we consider how over 1.2 million different unique combinations of full root zone soil water storage capacity (0.5-3.0 m depth), surface soil characteristics (10-15 cm depth), irrigation decisions (30, 50, and 80% allowable depletion of total plant available water), crop, and climate (precipitation and potential evapotranspiration) combine to produce different possibilities of the resource across space and time. Although provision of green water is a soil ecosystem service that can have multiple downstream benefits, 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). This study quantifies green water availability at the scale of available data: soil map unit and crop combinations at the scale of the field with climate data provided by publicly available 2-4 km raster resolution datasets.

In conclusion, the broad goal of this study is to map the green water resource, improve understanding of overall water balance implications of managing for green water, and to better understand to what extent the green water resource depends on the size of the soil reservoir used to provide crop water. Better understanding the resource’s spatial gradient can lead to improved, place-based, and well-timed irrigation strategies that reduce reliance on blue water by making use of green water.



**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

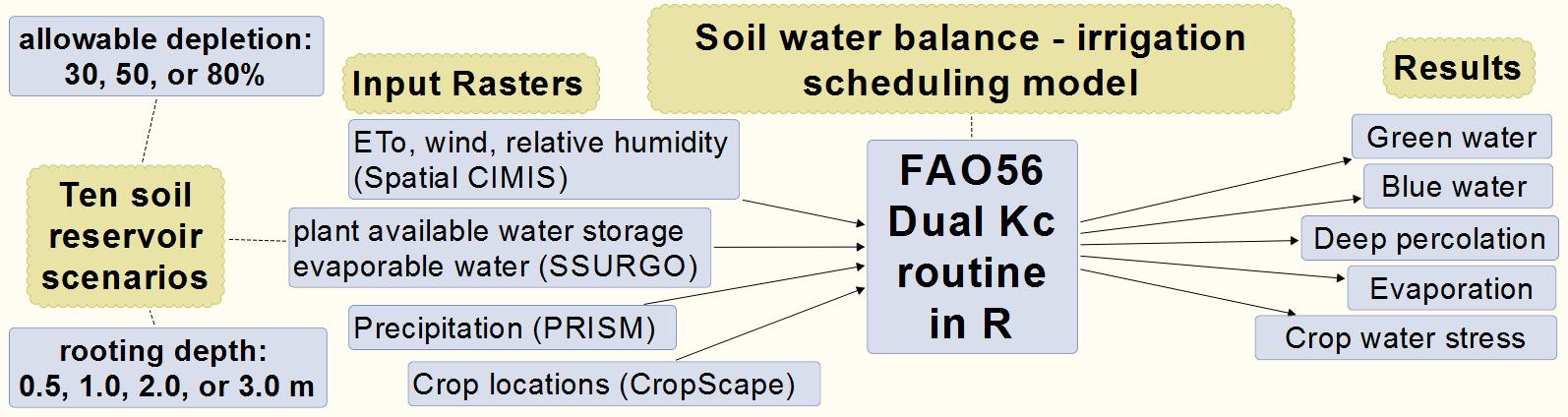
**1.2 Materials and Methods**

*1.2.1 Overview*

We use a 14+ year, daily simulation to model irrigation of the major perennial crops in California (alfalfa, almonds, grapes, pistachios, and walnuts), using publicly available climate, soils, and crop distribution data. These disparate data sources of varying spatial resolutions are 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 are 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, and crop (Figure 2).

In addition to considering the effects of climate, soil, and crop combinations, we tested twelve different soil reservoir scenarios 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 of total plant available water storage in the root zone) to explore how varying the size of the soil water reservoir affects the

green water resource and, consequently, blue water demand (Figure 2).



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

The FAO-56 dual Kc approach estimates actual crop evapotranspiration (ETc act) 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). This allows for consideration of interactive drivers of soil evaporation, such as frequency and depth of precipitation and irrigation, surface soil properties, and crop canopy cover, rather than assuming static evaporation-transpiration partitioning ratios which are built into the single Kc approach (Pereira *et al.*, 2015). Thus, the dual Kc is better suited to the subtleties of a green water resource analysis than the more simplifying, single Kc approach. In the dual Kc approach, a single crop coefficient (Kc act) is actually derived from three coefficients: first, a basal crop coefficient (Kcb), conceptually based on canopy cover and leaf characteristics and adjusted by a location’s daily minimum relative humidity (RHmin) and average daily wind speed at 2 m height (*u2*) according to Allen *et al.* (2005a); second, a soil water stress coefficient (Ks), derived from a daily root zone soil water balance (0.5-3.0 m depth, depending on the assumed soil reservoir scenario); and, third, a soil surface evaporation coefficient (Ke), derived from a daily surface soil water balance (0.1-0.15 m depth) and dependent on how much of the surface is wetted by irrigation and how much is exposed to evaporative energy. The daily water balance procedure for the root zone and surface soil in this study is summarized as follows with a few modifications to the approach detailed in Allen *et al.* (1998) and Allen *et al.* (2005a)**.**

1.2.2 *Root zone water depletion (Dr) accounting by day (i) to estimate actual crop evapotranspiration (ETc act)*

(1)

(2)

The evaporation coefficient (Ke) is determined in surface soil water depletion accounting (see section 1.2.3). Climatic adjustment of basal crop coefficients (Kcb adj) was done using daily values for wind (u2) and minimum relative humidity (RHmin), an option suggested by Allen *et al.* (2005a):

(3)

Sources for standard basal crop coefficients (Kcb std) are covered in section 1.2.8.

(4) when *AWS > Dr, i-1 > stress point*

For all crops and soils, the stress point was assumed when the soil water depletion (Dr) reached 50% of total plant available water storage (*AWS*) for the entire root zone. If *Dr, i-1 ≤ stress point*, then *Ks = 1*. If *Dr, i-1 ≥ AWS*, then *Ks = 0*. *Dr = 0* means that the root zone is at field capacity. *Dr = AWS* means that the root zone is at wilting point. Daily water balance tracking in the root zone was as follows:

(5)

(6)

This water balance approach means that any surface runoff is incorporated into the root zone deep percolation term (*DPr*) when precipitation (P) inputs occur at the root zone’s field capacity. This approach assumes that soils will not produce surface runoff or deep percolation when the root zone is below field capacity. Irrigations (Ir) are applied the following day, as detailed in equation 5 above, and are estimated as follows from a sub-daily soil water depletion estimate that assumes daily P inputs occur early in the morning:

(7)

(8) when during the crop’s growing season.

(9)

Percent allowable depletion is 30, 50, or 80%, depending on the model scenario.

(10)

*1.2.3. Surface soil (0.1-0.15 m depth) water balance accounting for estimation of soil evaporation*

This study also included the update to FAO-56 equations to separately estimate evaporation for soil wetted by precipitation only and soil wetted by both precipitation and irrigation (Allen *et al.*, 2005a). This is relevant to many California perennial crops now irrigated by micro-irrigation systems that wet only a fraction of the soil surface (Tindula *et al.*, 2013) but much more frequently (Hanson *et al.*, 1999). In estimating the overall soil evaporation coefficient (Ke), this is taken as the sum of the evaporation coefficient for thesurface wetted by precipitation alone (Kep) and that wetted by both evaporation and irrigation (Kei) (equations 11-13).

(11)

(12)

(13)

(14)

(15)

For equations 12 and 13, a limit was placed on the daily soil evaporation coefficient estimates to ensure that surface soil water depletion did not exceed total evaporable water (TEW) for the given soil, which did occasionally occur for some coarse textured soils with high daily reference ET. The fraction of soil surface wetted by irrigation (*fw*) and fraction of cover (*fc*) control how much of the soil wetted by precipitation is exposed to evaporative energy (*fewp*) and the fraction of soil wetted by both precipitation and irrigation exposed to evaporative energy (*fewi*).

(16)

(17)

For equations 16 and 17, *fc* is specific to the crop growth curve, paralleling the respective basal crop coefficient curve for dates specific to California (Goldhamer and Snyder, 1989). An upper limit on evaporation is estimated as follows and applied in equations 12 and 13:

(18)

(19)

In equation 19 for the weighting coefficient (W), limits are imposed such that TEW – Dep initial ≥ 0.001 and TEW – Dei initial ≥ 0.001, for situations where the initial surface soil water depletion estimate exceeds TEW. The evaporation reduction coefficients (Krp and Kri) are used to reduce evaporation when readily evaporable water (REW) is exhausted but deeper or more tightly held evaporable water remains:

(20) for *TEW > Dep end, j-1 > REW*

(21) for *TEW > Dei end, j-1 > REW*

If *Dep, j-1 < REW*, then *Krp = 1*. If *Dep, j-1 = TEW*, then *Krp = 0*. The same rules are applied to the *Kri* calculation. As implied above, separate surficial soil water depletion accounting in the zone wetted by both precipitation and irrigation (*Dei*) and the zone wetted by precipitation only (*Dep*) are needed to estimate evaporation (E). Transpiration is ignored in the surface layer, following the recommendation for modeling crops rooted deeper than 30 cm (Allen *et al.*, 2005a).

(22)

(23)

(24)

(25)

(26)

(27)

*1.2.4 Estimating green water use*

Green wateruse is quantified as the cumulative difference between growing season actual evapotranspiration (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 ET includes soil surface evaporation, utilization of green water includes soil surface evaporation of precipitation but only during the growing season. This approach also assumes that all irrigation water is meeting crop ET demand, so that any growing season deep percolation 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.

*1.2.5* *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) 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 are 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 outlined in sections 1.2.2 and 1.2.3 above. During the simulation, water balance results were aggregated to annual, seasonal, and monthly time scales to save hard disk write time except for 1% of soil-climate-crop systems where detailed daily water balances and intermediate calculations were saved for quality control inspection. A desktop computer with a 4-core Intel Xeon 3.80 Ghz CPU and 64 GB of RAM was used to run the simulations and aggregate results. Model runs took approximately 0.75 days for all soil-climate-crop systems for a given root depth and allowable depletion scenario. Thus, nearly 1.3 million simulations were performed in total for the 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://www.github.com/smdevine/GreenWater>.

*1.2.6 Soils – plant available and evaporable water*

The FAO-56 approach assumes a bucket-based soil hydrology model that relies on the concept of field capacityto simplify soil water movement, such that when a root zone is at field capacity, additional precipitation is assumed to drain instantaneously. Drainage from root zones at or below field capacity is considered to be negligible. For finely textured soils with more limited infiltration and percolation capacities, deep percolation could be overestimated during wet periods, since this water may exit the crop root zone as overland flow even before field capacity is reached in the root zone (see section 1.2.2, equation 6). However, we assume that daily estimates of plant available water generated by the model are mostly resilient to errors of allocating excess soil moisture to either deep percolation or overland flow. In some cases, the reported green water availabilities are likely underestimated by neglecting some water periodically available to crops between saturation and field capacity from more slowly draining soil.

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 SSURGO soil map units in California was accessed from the California Soil Resource Lab at the University of California, Davis. The soil mapunit shapefile was intersected with the crops shapefile to identify the necessary soil survey area symbols for downloading assoicated 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’s representative available water capacity for each horizon in the rooting zone. Available water capacity is the ‘awc\_r’ variable (column 86) in SSURGO’s *chorizon.txt* table. 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 (eg. 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 (eg. 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):

(30) ,

Where is the plant available soil water storage, is the soil water content at wilting point, and is the depth of the surface layer subject to evaporation.

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). Following this logic, a set of equations were developed to estimate a continuous function of from the weighted mean particle size diameter (WMPD) of the detailed SSURGO particle size fraction data for the surficial layer:

(31) ,

Where each term is a weight percentage of the total fine fraction, thereby ignoring coarse fragments. is 1-2 mm diameter, is 0.5-1 mm diameter, is 0.25-0.5 mm diameter, is 0.1-0.25 mm diameter, is 0.05-0.1 mm diameter, silt is 0.002-0.05 mm diameter, and clay is < 0.002 mm. The WMPD data was then re-scaled to an evaporative layer depth of 10-15 cm using its median and standard deviation (sd) with a correction in the denominator for fine textured soils so that the finest textured soils would have an evaporative depth equaling 15 cm:

(32)

for WMPD ≤ WMPDmedian

(33)

for WMPD > WMPDmedian

The surface depth thickness of each soil component in SSURGO was estimated from multiple horizons when the bottom of the SSURGO surface horizon was shallower than the estimated of that horizon. Specifically, a weighted depth mean was calculated from those horizons spanning the surface 10-15 cm of soil through an iterative process to reach a stable estimate for for that soil.

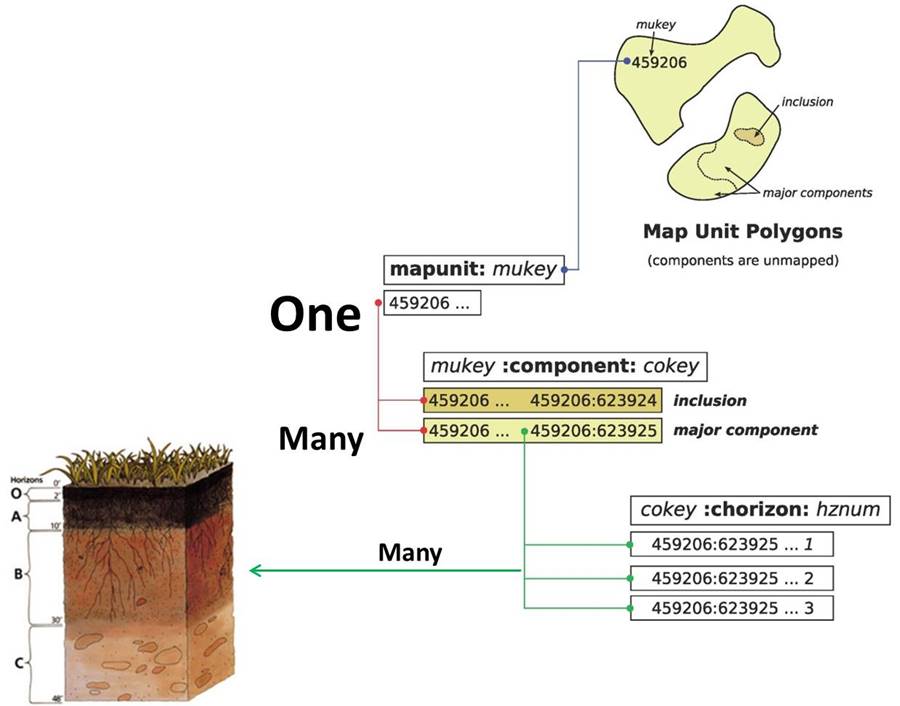
Next, the readily evaporable water (*REW*) was calculated based on the fraction of sand, clay, and > 2mm fragments (*fragvol*) in each surface horizon, following the equations published in Allen *et al.* (2005b), using the Ze values calculated above:

(34) for sand ≥ 80%

(35) for clay ≥ 50%

(36) for sand < 80% and clay < 50%

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). Spatially, 88.5% of soils have only 1 major component that requires no component percent weighting results scheme; 11.1% have 2 major components; and 0.4% have 3 major components in this study area.



**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.

*1.2.7 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). Data from 10/1/2003 - 8/31/2017 was considered “stable,” data from 9/1/2017-2/28/2018 was considered “provisional,” and data from 3/1-3/8/2018 was considered “early,” based on the download date and PRISM’s data classification scheme (Figure 4A).

Daily reference ETo (Figure 4B-C), 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:

(37)

(38)

(39)

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. These corrections were based on multi-year means for that location and date.

*1.2.8 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). 140,819 fields were identified as alfalfa, almonds, grapes, pistachios, or walnuts in this dataset, totaling 1,487,535 ha. A total of 1,455,204 ha were modeled, excluding some grapes and alfalfa located outside of the major growing regions or for fields where soils data was unavailable (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, assumed to take place generally outside the Central Valley in coastal or foothill locations (Table 1). Kcb std for almonds, grapes in the Central Valley, pistachios, and walnuts were taken from high-density orchard and table grape values in Table 3 in Allen and Pereira (2009). 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. Grapes located in coastal California and foothills, including Sonoma and Napa Valleys, were assumed to be for higher quality wine production and Kcb values were taken from Table 3 in Allen and Pereira (2009) for wine grapes. 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 cover (*fc*) values for almonds, grapes, pistachios, and walnuts were taken from Table 2 and 3 in Allen and Pereira (2009). 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).

*1.2.9 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 typically 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 in the fall when precipitation is below average.

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 continued growth.

We also included a different irrigation strategy for each 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 for high quality wine production. Soil moisture levels were managed 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; in the 50% allowable depletion scenario irrigation was applied to restore soil back to 50% plant available water when Ks reached 0.5; and in the 80% allowable depletion scenario irrigation was applied to restore soil back to 50% plant available water when Ks reached 0.2. Then, the target end-of-season soil water content was equal to either 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.

1.2.10 *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 the polygon features in the spatial dataset. 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 and irrigation assumptions were used in the simulation. The major grape growing region is in the Central Valley. A second region called the Foothills and Coastal Mountains grape region, included farms across the state but excluded some grapes in the southern desert. For alfalfa, the considered regions were (1) Central Valley (including alfalfa in surrounding foothills); (2) Imperial Valley (in the ecoregion called the Sonoran Basin and Range); and the (3) Intermountain region, which excluded some alfalfa farms near the coast.

**1.3 Results**

*1.3.1 Green water availability*

The results section focuses on 3 of the 12 soil storage scenarios to compare the green water resource for different crops as a function of the size of the soil reservoir: a shallow (0.5 m root depth and 30% allowable depletion); a moderate (1.0 m root depth and 50% allowable depletion); and a deep scenario (2.0 m and 50% allowable depletion).

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 comprises 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 ET can be supplied by green water, there are substantial portions of the landscape where green water availability is 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 meets only 11% of its annual crop water needs on average with green water. The highest green water availability is north of the Sacramento-San Joaquin Delta, where 24% of annual crop water demand can be met in a deep scenario, compared to 12% south of the Delta (Table 3). Greater variability exists across the landscape in a deep compared to a shallow scenario (Figure 5A-C; Table 3).

A well-defined north-to-south precipitation gradient (Figure 4A) meant that the green water resource follows this trend (Figure 5A-C). However, the general green water resource trend is 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 is also temporal concentration: a handful of wet years supply much of the green water resource. In the moderate scenario, the wettest 6 of 13 years provide 62% of the cumulative resource, all years with 2.1-2.9 km3yr-1 green water available. In the deep scenario, the annual availability increases to 2.6-3.6 km3 yr-1 for the same years, providing 64% of the cumulative resource.

Allowing for substantial crop water stress (80% allowable depletion level) does increase the amount of green water utilized for a given rooting depth, but the effect on cumulative crop water stress is an order of magnitude larger than the increase in green water utilization (Table 2).

In all of these scenarios, we assumed bare soil conditions during dormancy, so wintertime evaporation is substantial. Even in the deep scenario, the annual green water resource is only 52% of precipitation, even though deep percolation has been reduced to just 19% of precipitation. This is 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, effective precipitation is 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, decreases in 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 directly helped drive 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. In short, larger soil reservoirs enhanced inter-annual variability in blue water demand while reducing the annual average demand. Wet years tended also to have lower potential evapotranspiration conditions, such that the annual blue waterdemand was reduced even more. An increasing north-to-south potential evapotranspiration gradient (Figure 4B-C) further meant that when combined with consideration of available green water, an even steeper blue waterdemand gradient exists from north-to-south for all crops (Figure 6A-C). The gradient becomes steeper when the soil reservoir is 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 has the most benefits for green water availability when going from the shallowest soil storage scenario to a moderate soil storage scenario with equally proportional gains in the northern and southern DWR regions (Table 3). Using this comparison, the landscape shows a mean increase in green water availability of 0.66 mm green water mm-1 increase in allowable depletion (Figure 7A). When going from a moderate to deep scenario, the landscape sees a lower mean increase of 0.57 mm green water mm-1 increase in allowable depletion, since a large area cropped to perennials is already precipitation, not storage limited at 1.0 m depth (Figure 7D). This P 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 climate across this landscape is precipitation not soil water storage limited at 2.0 m depth.

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. The effect is a progressively shorter irrigation season length and lower irrigation frequency as the allowable depletion is increased (Figures 7C and E). Increasing the allowable depletion as an irrigation management strategy also has the side effect of slightly more fall crop water stress. Utilizing additional green waterin deeper rooting or higher allowable depletion threshold scenarios has the effect of decreasing cumulative annual deep percolation (Figures 8A-C; Table 2).

When the soil water storage capacity is increased, blue water demand is 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). Thus, using more soil water storage decreases the frequency of surface wetting and reduces 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 (see equation 27, Methods 1.2.3). Episodic dry and wet years create fluctuations in soil moisture recharge and storage during the fall and winter with some annual carryover of irrigation water and obscure annual accuracy of green water 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 range from 1.1-2.9 km3 yr-1 in the moderate scenario, annual results are susceptible to this soil moisture change error. Since the change in soil water from one year to the next could have been either precipitation or irrigation sourced, this complicates green water accounting.

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.

**Table 1.** Modeled crop area, soil features by crop, and seasonal crop growth assumptions

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Crop | Total  Area | Hardpan | Lithic / Paralithic | End dormancy | Peak  growth/  cuttings | Senescence | Dormancy | Kcb, ini | Kcb, mid | Kcb, end |
| 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

Table 2. Cumulative water balance component totals from modeling the different soil storage scenarios from 2005-2017. Columns sorted by area-weighted mean 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 | Irr | E | DP | CS | ET | DPa | ΔS | Irr freq | First irr | Last irr |
| *-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

**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, while 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 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.



**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**. Figures (top) show the difference between the moderate and shallow scenarios, in terms of (A) green water, (B) blue water, and (C) additional days to first irrigation. Figures (bottom) show the difference between the deep and moderate scenarios. 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.

*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 14-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% crop water demand, depending on rooting depth and allowable depletion (Table 2).

Like the results, several of the soil reservoir scenarios are highlighted in the discussion: a shallow (0.5 m root depth and 30% allowable depletion); a moderate (1.0 m root depth and 50% allowable depletion); and a deep scenario (2.0 m and 50% allowable depletion). The resource is spatially concentrated, so in some areas the proportion of crop water demand met by green water is much larger (Figure 5A-C; Table 3). For instance, in the deep scenario, the 80th percentile on the landscape can provide 20% of crop water needs with green water, while the 20th percentile can provide 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 is 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 accounts for 70% of the green water resource.

As a whole, given the reality of California’s dry, warm climate, green water can at best fill a glass 10-20% full for even perennial crops rooted to 1-2 m. Nevertheless, given the magnitude 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 recently. 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, this hardened irrigation demand is of concern for groundwater resources, especially during drought, and highlights the relevance of green water to meeting perennial crop water demand.

Availability of green water can be substantial even in a shallow soil reservoir scenario but is enhanced by deeper rooting or higher allowable depletions (Table 2). Though the San Joaquin and Tulare regions are considered as relatively dry climates, nearly 60% of the green water resource is in this region that has 68% of the perennial crops (Table 3). This shows the importance of timely shallow soil reservoir management and precipitation tracking in optimizing green water use, 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 strategy could complement current, multi-billion dollar efforts to adapt blue water management in California to climate change and increasing urban and environmental uses of water (Jezdimirovic and Hanak, 2016; Kocis and Dahlke, 2017; CDWR, 2018) and help farmers comply with the Sustainable Groundwater Management Act in California.

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 are delayed to allow for crop use of green water. For instance, deep percolation is reduced from 1.7 to 1.2 to 0.9 km3 yr-1 on average when 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 (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 [see Methods]. 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. 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 reservoirs are challenged by warmer temperatures and declining snowpacks, such as in California and the western United States (Stewart *et al.*, 2005). 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 is increased to 80% for each rooting depth, the growing season ET is reduced by 17-19%, increasing the amount of green water utilized (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, a brief meta-analysis of deficit irrigation studies showed that almond growers could get away with 10-15% less applied water than full ET with only minor reductions in yield (Steduto *et al.*, 2012).

This study assumed different surface wetting fractions for different crops based on standard assumed irrigation systems for different crops but assumed that the entire soil volume was still utilized for green water and irrigation applications. In practice, we may have underestimated needed irrigation frequency for grapes. Because a drip irrigation system with 0.35 fractional surface wetting may not actually wet the entire field’s soil volume, the wetting “bulbs” from each dripper may not overlap. So, a 2 m rooting depth scenario may actually be wetting to 3 m under the drippers 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 limits 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 follow-up question is how winter annual cover crops would affect the water balance and green water for crops. Dormant season evaporative losses of 1.4 km3 yr-1 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 ET for early blooming almonds, there is 14.0-15.4 cm yr-1 dormant ET 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. Research into the water balance of cover crop versus bare soil in Mediterranean perennial crops is needed. 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.

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 frequency is also a driver of evapotranspiration. When irrigations are less frequent and more deeply applied, the model shows 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 is reduced from 59 irrigations yr-1 to 19 irrigations yr-1 across all crops. When the average irrigation frequency is reduced further in a deep scenario to just 10 irrigations yr-1, the additional savings in soil surface evaporation is 0.8 km3 yr-1, compared to an additional 0.4 km3 yr-1 gain in use of green water. 21% of growing season ET is surface soil evaporation in the shallowest scenario, compared to 12% and 9% in the moderate and deep scenarios, respectively, demonstrating 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 is 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). The FAO-56 dual Kc model approach used in the study does consider 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 is needed to explore to what extent surface coverage drives evaporative losses in the simulation, as different assumptions were made for different crops in this study, along with field validations (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 shows 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 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 approach 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 green water resource is substantial in California perennial crops but amounts to only a 6-12% contribution to meeting total perennial crop water demand across the landscape, depending on the depth to which crops can effectively extract soil water and 50% allowable depletion. A surprising result was to see the possible evaporative savings when a farm shifts from a high- to low-frequency irrigation management with more reliance on the soil water reservoir. Future work is needed to validate the FAO-56 dual Kc method for predicting full season soil water balance under perennial crops and the extent to which deep soil moisture can be utilized without crop stress. There is a clear need for practical applications to enhance green water utilization by advising time-to-first and time-to-last irrigations in California. This could be accomplished using a combination of monitoring and modeling approaches: soil moisture and crop stress sensors and/or a water balance modeling approach such as the FAO-56 dual Kc used in this study. If fall crop water stress can be tolerated, then soils can be drawn down to a greater extent to store winter rainfall. If practiced along with early season precipitation tracking, soil management for hydrologic function, and selection or breeding of perennial crops that can make use of 0.5-2 m deep soil water in the wetter regions, then green water will be well utilized in California.

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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)