Quantifying the green water resource in California irrigated perennial agriculture

*Abstract*

Agriculture in Mediterranean climates relies on irrigation stored surface water and pumped groundwater (blue water) to produce abundant, high quality crops. Green water, the soil stored water from rainfall potentially available to crops, has the potential to reduce agricultural reliance on blue water, especially for deeply rooted crops that have access to relatively large soil volumes. The growth of the mostly high-value perennials from X to Y% of the irrigated landscape has transformed California irrigated agriculture from one of principly annuals, flexibly planted based on cyclical drought, to one of more and more orchards and vineyards and their hardened irrigation demand, even in droughts.

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 irrigation for five major perennial crops in CA (alfalfa, almonds, grapes, pistachios, and walnuts), using daily, publicly available data from 2003-2018, covering 1.46 million irrigated hectares. In addition to considering the effects of natural weather and soil variability, we tested 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 explore how varying the size of the soil water reservoir 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 163-263 km3 in cumulative blue water demand, which represents 6-17% of growing season evapotranspiration across the scenarios. Thus, in the world of green water for perennial crops, the glass is only 10-15% full in aggregate, though a strong spatial gradient in the resource exists. Due to a well-defined north-to-south precipitation gradient, 16-20% of the landscape with perennial crops can annually meet, on average, 20% or more of its crop water demand with green water when rooted 1-2 m and with minimal crop water stress. 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 was managed 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 soil 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 further deepening to 2.0 m rooting depth would bring a further 11 km3 cumulative savings in evaporation by reducing irrigations to just 10 applications yr-1 with a smaller gain in green water of 5 km3. 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 utilization of green water, but also by reducing evaporation of blue water at the soil surface by irrigating less frequently and more deeply. An open question is to what extent full utilization of the soil reservoir can be accomplished without introducing detrimental crop stress or risk to farmers who may not know the true size of the easily accessible soil reservoir for optimal irrigation timing.

**1.1 Introduction**

Irrigated agriculture, climate change, and environmental concerns are forcing Mediterranean societies to reconsider how water is managed, allocated, and planned for, in order to meet human and ecosystem needs reliably. Globally, irrigated agriculture is responsible for 40% of food production (FAO, 2015). This production relies on a 2,700 km3 freshwater input aka blue water, accounting for 70% of global blue water use by humans. In Mediterranean climates like in California, the reliance on irrigation in agriculture is a matter of necessity to meet crop water demands, especially in high-value crops. 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 (NASS, 2015) depends on large annual inputs of blue water: on average, 80% of California’s annual 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 streamflow from CA’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 CA 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 (ET) 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/or increasing frequency of wet and dry extremes (Berg and Hall, 2015; Swain *et al.*, 2018) with droughts predicted to be markedly 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 to adapt to climate change. So far, water resource professionals and scientists have focused almost entirely on blue water resources and infrastructure, such as these several ongoing examples: (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 using short-term, 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. This soil stored moisture fraction is available to crops later during the growing season, plus any growing season precipitation, and less any growing season deep percolation. Soils are able to temporarily store a volume of water equal to their total pore space, commonly 40-60% of the soil’s total volume. But since the larger pores rapidly drain due to gravity, only some part of the total soil porosity is effectively storing water between storms. The soil’s field capacity is the water content at which the larger soil pores have been drained by gravity but is available to uptake by roots or evaporation at the surface. At the other end of the spectrum, the water held in the smallest soil pores is not plant available, because the suction required to extract water from these pores is more than what crop roots can typically exert. This volume of unavailable soil held water is called the wilting point.The difference between field capacity and wilting pointis called the plant available water. This soil stored rainfall potentially available to plants comprises green water and is the conceptual underpinning of a green water resource analysis for five major irrigated perennial crops in California, spanning 1.45 million hectares.

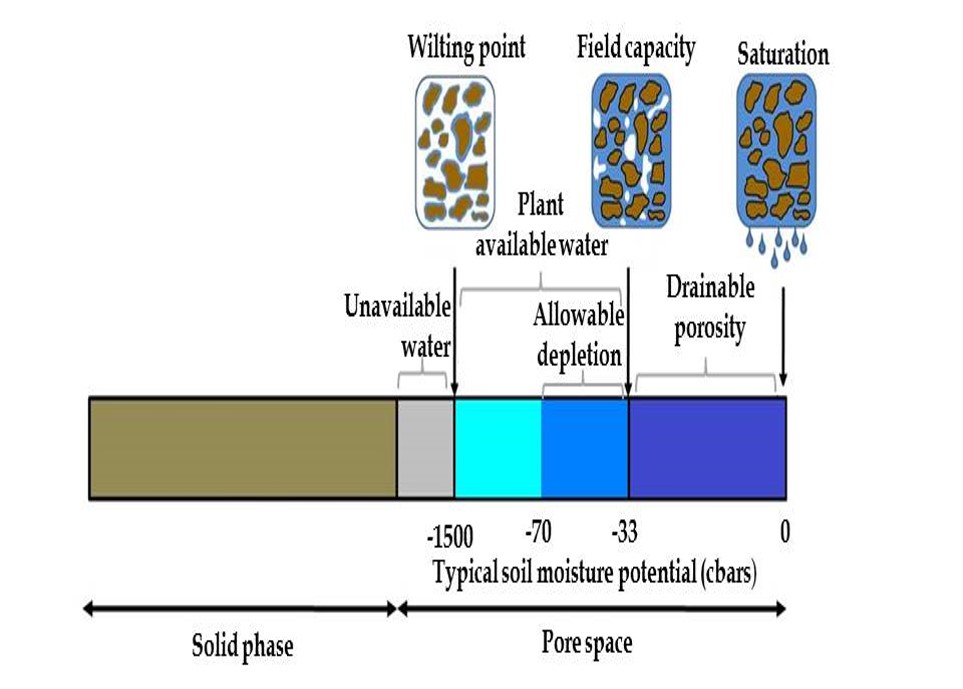
Although provision of green water is a soil ecosystem service that can have multiple downstream benefits, the green water resource has not been quantified or analyzed in detail in California, despite implicit assumption of its use in California agricultural water demand models that estimate irrigation 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.

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, so as to minimize risk to crop health. This proportion of plant available water is called the allowable depletion in irrigation management and is commonly found to be 50% of the plant available water (Figure 1) (Hanson *et al.*, 1999). 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 to make room for winter precipitation storage in soils, depending on a 14 year mean climate water balance.

The objective of this study is twofold. First, I attempt to quantify and characterize the green water resource in several major irrigated perennial crops in California, including 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 for the farmer. Thus a resource analysis of green water is of interest to reducing or optimizing blue water resources.

Second, as part of the resource analysis, we sought to quantify how varying the rooting depth or level of allowable depletion in irrigation management, both of which change the size of the soil water storage capacity available to crops, would affect the available green waterresource but also potentially affect crop water stress and deep percolation as a result of managing the soil reservoir for green water. 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 California and is accomplished at a finer scale than other available irrigation demand studies in California.

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 a spatial gradient in the green water resource that is temporally variable across this 1.46 million hectare study area. This chapter focuses on the overall water balance implications of managing for green water and pictures of the resource’s spatial gradient that emerge from the analysis. Better understanding this gradient can lead to improved, place-based, and well-timed irrigation strategies that reduce reliance on blue water by making use of green water.



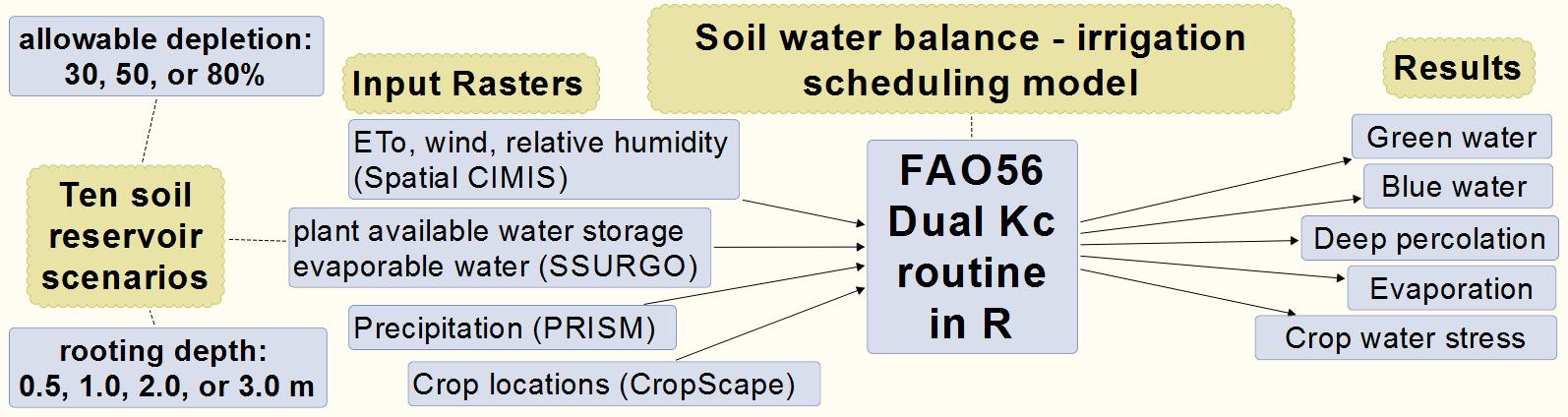
**Figure 1**. Three allowable depletion levels of plant available water (30, 50, and 80%) are used in the scenarios to determine when to irrigate, not wilting point

**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 (CA) (alfalfa, almonds, grapes, pistachios, and walnuts) covering 1.46 million hectares, using publicly available weather, soils, and crop distribution data. These disparate data sources of varying spatial resolutions are integrated into an algorithm coded in R that closely follows the FAO-56 reference ET, dual crop coefficient (dual Kc) approach (Allen *et al.*, 1998; Allen *et al.*, 2005a), to determine when to irrigate based on meeting initial crop water demand with the green water resource. 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 cropping variability at the scale of available data, we tested twelve different 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 (Figures 1 and 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 based on a Penman-Monteith reference ET (ETo). This allows for explicit 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). In essence, a single crop coefficient (Kc act) is derived from three coefficients: first, a basal crop coefficient (Kcb), fundamentally 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, depending on mean particle size diameter, see Methods). The daily water balance procedure for the root zone and surface soil 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 crop transpiration*

(1)

(2)

Ke is determined in surface soil water depletion accounting. See section 1.2.3 for details.

(3)

Sources for basal crop coefficients are covered in section 1.2.7. Equation 3 was applied using daily values for wind (u2) and minimum relative humidity (RHmin), an option suggested by Allen *et al.* (2005a), as opposed to modifying using site-specific climatic averages.

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

For all crops, the stress point was assumed to occur at 50% 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 or that plant available water is exhausted.

(5)

(6)

This water balance approach means that any surface runoff is incorporated into the root zone deep percolation term (*DPr*). This assumes that soils will not produce surface runoff when the root zone is below field capacity. See section 1.2.5 for more details regarding soils data and assumptions. Irrigations are applied the following day as detailed in equation 5 above. See section 1.2.8 for additional details regarding irrigation decisions and assumptions for different crops and end-of-season irrigation depth determination.

(7)

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

(9)

(10)

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

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

(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. Equations 14 and 15 estimate daily evaporation from the soil wetted by both precipitation and irrigation (Ei) and precipitation only (Ep), respectively, as determined by the fraction of soil surface wetted by irrigation (*fw*). See section 1.2.8 for more details regarding irrigation assumptions.

(16)

(17)

For equations 14 and 15, fraction of cover (*fc*) is specific to the crop growth curve, paralleling the respective basal crop coefficient curve for dates specific to California (Goldhamer and Snyder, 1989). *fc* values for almonds, grapes, pistachios, and walnuts were taken from Table 2 and 3 in Allen and Pereira (2009).

(18)

(19)

In this equation 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.

(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:

(22)

(23)

(24)

(25)

(26)

(27)

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

As an error check, total model water balance was checked:

Where and precipitation (), irrigation (Ir), deep percolation (), and evapotranspiration (ETc) are all the cumulative terms from beginning to end of the model.

*1.2.4* *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. Of these several hundred thousand units across California, 107,561 represented unique combinations of soil major component, climate, and crop, given the varying resolutions of the input datasets detailed above. 313,573 polygons were successfully modeled, representing 94,868 unique combinations of soil map unit, climate, and crop.

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. 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 common in microirrigation systems that wet a fraction of the soil surface (Allen *et al.*, 2005a). 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 model and aggregate results. Model runs took approximately 0.75 days for all 107,561 soil-climate-crop systems for a given root depth and allowable depletion scenario. Thus, 1,290,732 simulations were performed in total for the twelve scenarios of rooting depth and allowable depletion. The set of R scripts used to download data, integrate the data into a common model framework, run the dual crop coefficient model, and aggregate, explore, and analyze results are available at <https://www.github.com/smdevine/GreenWater>.

*1.2.5 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. This simplifying model assumption has the effect of producing conservative estimates of plant available water, since any water content between field capacity and saturation becomes instantaneously unavailable as a loss to deep percolation. However, for finely textured soils with more limited infiltration and percolation capacities, deep percolation may be overestimated during wet periods, since this water may exit the crop root zone as overland flow (see section 1.2.2, equation 5). However, we assume that daily estimates of plant available water generated by the model are resilient to errors of allocating wet periods’ excess soil moisture to either deep percolation or overland flow. In fact, the reported green water availabilities are likely underestimated in places by neglecting some water periodically available to crops between saturation and field capacity from more slowly draining soil. This study assumes instantaneous drainage even in these scenarios.

Several steps were needed to estimate root zone plant available water from the Soil Survey Geographic Database’s (SSURGO) tabular data for crops where deep tillage is common during establishment in California. The 2017 updated shapefile for SSURGO soil map units 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 relevant tabular data. Downloading mapunit, component, and horizon level data (Figure 3) was done with the “SDA\_query” function from the SoilDB package in R. This function submits a SQL query to the Soil Data Access website and returns the query as a dataframe for each level of the database[[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, weighting by relative thickness of the soil profile. 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 cropped to alfalfa noted below. To populate available water capacity for soils with paralithic or lithic contacts (typically denoted by a Cr or R horizon in SSURGO horizon nomenclature but not always), 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, which is common practice in California. 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 routine for each soil across the study domain, 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). We defined TEW using the widely implemented equation (Allen *et al.*, 1998):

(30) ,

Where is the plant available soil water water storage defined as the ‘awc\_r’ variable (column 86) in SSURGO’s *chorizon.txt* table, is the soil water content at wilting point, and is the depth of the surface layer subject to evaporation.

is typically 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:

(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 the horizons spanning the surface 10-15 cm of soil through an iterative process to reach a stable estimate for .

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) for 10 cm thick surface layers:

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

*1.2.6 Climate data*

Daily, 4 km resolution precipitation rasters from October 1, 2003 – March 8, 2018 covering the contiguous United States were downloaded from the PRISM Climate Group (<http://www.prism.oregonstate.edu/>) using the *prism* R library’s “get\_prism\_dailys” function starting on 8/17/17 and updated several times through 3/9/18 for more recent or more stable data. 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

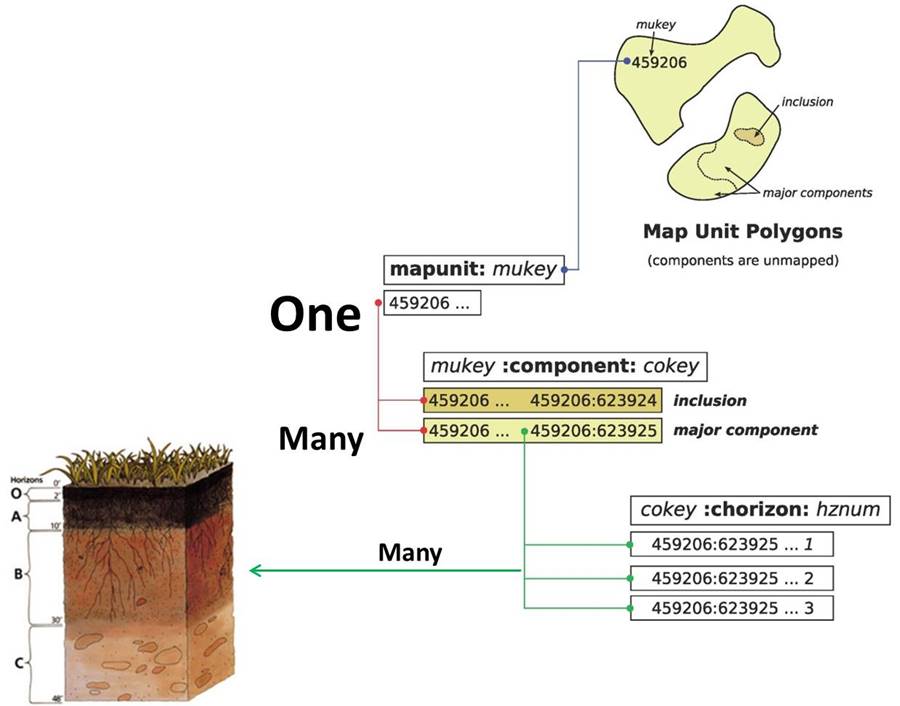


Figure 3. SSURGO is a many-to-one relational database. A number of steps were needed to make the information in the database usable by the FAO-56 dual crop coefficient model and then aggregated to the map unit scale.

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.

*1.2.7 Crops*

Perennial crop distribution was assumed from the 2014 Department of Water Resources land use classification and irrigated lands’ crops map produced by LandIQ (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 (Table 1). A total of 1,455,204 ha were modeled, excluding some grapes and alfalfa located outside of the major growing regions for which irrigation strategies and growth curves were assumed in this study or for fields where soils data was unavailable (Table 1).

Basal crop coefficients (Kcb std) were assumed from several sources and chosen to reflect high density production with the exception of wine grapes grown for high quality through regulated deficit irrigation management (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).

*1.2.8 Irrigation decisions*

There are two fundamental irrigation related parameters relative that need to be determined for the dual Kc model. First, the proportion of the soil surface wetted. 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 and was considered to have potential green water and to be able to absorb irrigation water.

Second, factors need to be defined regarding irrigation timing. In this study, irrigation was applied the day following when a given crop-soil-climate system reached its specific allowable depletion during the given crop’s growing season (Table 1). The irrigation event then brought the system back to field capacity.

An exception to this irrigation timing rule was followed at the end of the growing season for all crops except alfalfa in the Imperial Valley. In the late summer and fall, a 14-year climatic average was calculated for each unique scenario 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 on the day of leaf-drop after this set number of irrigation-free days. In other words, a fall season irrigation free period is calculated for each system based on its specific climate input and its soil water storage capacity and assumed vegetative characteristics 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 region of California: (1) alfalfa in the Imperial Valley where there is year-round production and irrigation in 10 cutting cycles; (2) alfalfa in the northern California intermountain region, where alfalfa is dormant from late November to late March each year with 3 cuttings through September followed by fall regrowth, during which the fall irrigation rules outlined above are applied before winter induced dormancy; or (3) alfalfa in the Central Valley, where there is a break from irrigation and cutting from Nov-Jan but with continued photosynthetic activity. Thus, assuming still mostly ‘green’, transpiring fields, this means dry winters produce fields with soil water contents depleted below their allowable depletion and implies occasional to frequent winter crop water stress, depending on location.

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, regulated deficit irrigation (RDI) was assumed for high quality wine production, such that a minimum RDI irrigation trigger at 0.8 was practiced for the 30% allowable depletion scenario, a minimum RDI irrigation trigger at 0.5 was practiced for the 50% allowable depletion scenario, and a min RDI irrigation trigger at 0.2 was practiced for the 80% allowable depletion scenario with target soil water content equal to allowable depletion at leaf-drop. For Central Valley grapes, irrigation was practiced the same as for Central Valley alfalfa and tree crops, outlined above.

1.2.9 *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 California Department of Water Resources 2014 crops shapefile 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. Of these, there were 94,868 unique combinations of soil map unit, crop, and climate covering 1.46 million hectares successfully modeled, which expanded to 106,998 combinations at the major soil component level (Figure 3). To get the appropriate climate data, centroids were calculated for each of these polygon features in the spatial dataset. Then these field centroids were tagged with each of the climate datasets’ raster number with the *cellFromXY* function in the *raster* R package. For the PRISM data, the field polygon centroids were projected to geographic coordinates before identifying the PRISM raster cell number. Scenarios involving grapes and alfalfa were further identified as to their growing region using the EPA level 4 ecoregion shapefile. The major grape growing region is in the Central Valley. A second region called the Foothills and Coastal Mountains grape region, included multiple ecoregions: (1) the Cascades; (2) Central California Foothills and Coastal Mountains ecoregion units; (3) Coast Range; (4) Eastern Cascades Slopes and Foothills; (5) Klamath Mountains/California High North Coast Range; (6) Sierra Nevada; (7) Southern California Mountains; and (8) Southern California/Northern Baja Coast. For alfalfa, the considered regions were (1) Central Valley; (2) Imperial Valley (in the ecoregion called the Sonoran Basin and Range); and the (3) Intermountain region, which included multiple ecoregions: (1) the Cascades; (2) Eastern Cascades Slopes and Foothills; (3) Klamath Mountains/California High North Coast Range; (4) Sierra Nevada; (5) Northern Basin and Range; and (6) Central Basin and Range. Scenarios were tagged with this location information to determine which region specific growing and irrigation assumptions were used in the simulation.

Table 1. Modeled crop area, soil features by crop, and seasonal crop growth assumptions [move to Chp 2]

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Crop | Total  Area | Hardpan | Lithic / Paralithic | End dormancy | Peak  growth/  cuttings | Senescence | Dormancy | Kcb, ini | Kcb, mid | Kcb, end |
| Alfalfa, Central Valley[[4]](#footnote-4) | 206,690 | 29,804 | 1,896 | NA | 7 | NA | NA | 0.3 | 1.15 | 1.1 |
| Alfalfa, Imperial Valley | 80,214 | 0 | 0 | NA | 11 | NA | NA | 0.3 | 1.15 | 1.1 |
| Alfalfa, Intermountain | 64,888 | 22,580 | 9,269 | Apr 1 | 3 |  | Nov 23 | 0.3 | 1.15 | 1.1 |
| Almonds | 455,970 | 80,470 | 30,348 | Feb 15 | Jun 1 |  | Nov 11 | 0.2 | 0.95 | 0.65 |
| Grapes, Central Valley | 248,866 | 63,138 | 3,133 | Mar 15 | Jun 15 |  | Oct 22 | 0.2 | 1.05 | 0.8 |
| Grapes, Coast and Foothills | 111,634 | 3,317 | 32,526 | Mar 15 | Jun 15 |  | Oct 22 | 0.2 | 0.7 | 0.55 |
| Pistachios | 137,590 | 21,289 | 4,337 | Apr 25 | Jun 15 |  | Nov 27 | 0.3 | 0.95 | 0.65 |
| Walnuts | 149,352 | 27,170 | 9,495 | Apr 1 | Jul 7 |  | Nov 11 | 0.4 | 1.05 | 0.6 |

**Results**

*Green water availability*

The results focus 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% AD); a moderate (1.0 m root depth and 50% AD); and a deep scenario (2.0 m and 50% AD).

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 (Table 2).

Although a relatively small portion of growing season ET is met by green water, there are substantial portions of the landscape where green water availability is much greater (Figure 5A-C). On average, assuming the moderate to deep scenarios, 20% of the landscape can meet 16-20% or more of its crop water needs with green water. A well-defined north-to-south precipitation gradient (Figure 4A) meant that the green water resource follows this general north-to-south 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 variability 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 deepest scenario, the annual green water resource is only 63% of precipitation, even though deep percolation has been reduced to just 9% of precipitation. This is because of dormant season soil evaporation, which was constant at 1.1-1.65 km3 yr-1 (30-33% cumulative) of precipitation across all scenarios (Table 2). This begs the question as to whether cover crops could make use of this evaporated water and improve soil surface conditions without negatively affecting green water availability to perennial crops.

Finally, in quantifying green water, we used an operational definition to estimate, for the sake of practicality and simplicity:

Where each term is a cumulative amount for 13 years (2005-2017). Since crop ET includes soil surface evaporation, utilization of green water includes soil surface evaporation of precipitation but only during the growing season. For annual accuracy in quantifying green water, all soil storage supplied ET must come from that preceding winter’s or in-season rainfall. In reality, episodic dry and wet years create fluctuations in soil moisture recharge and storage during the fall and winter and obscure annual accuracy of this simplistic approach. In 3.5% of simulations in all scenarios, the irrigation water applied is greater than the growing season ET for a given year. This means that the green water resource is calculated as negative for that year. Interannual ΔS is substantial at several critical times of the year. For instance, in the moderate scenario, interannual ΔS ranged from 0.3 to -0.6 km3 at the end of the growing season (eg. 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. Given the annual green water results range from 1.1-2.9 km3 yr-1 for this scenario, they are prone to this soil moisture change error. However, our results have focused on 13 year cumulative amounts to avoid this year-to-year 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, from the shallow to deepest scenarios. This means that the overall model simulation change in soil water storage provided at most 1-3% of the green water.

**How much of the total green water resource is in different regions? Get shapefiles for different DWR regions or ecozones to do this summary as a Table**

*Blue (irrigation) water demand*

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 differences in irrigation 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 irrigation water demand while reducing the annual average demand, since greater capacity to store precipitation in wet years reduced subsequent irrigation needs that same year. Wet years tended also to have lower potential evapotranspiration conditions, such that the annual blue waterdemand was reduced more than the increase in available green water. Moreover, this reduced the required number of irrigations and the surface soil evaporative loss of irrigation water those years (Table 2). 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 ???).

Cumulatively, 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 decreases in soil surface evaporation explained about 75% of this cumulative, reduced irrigation water demand. Thus, larger allowable depletions allowed for greater intervals between irrigations. This led to a reduction in the frequency of surface wetting and the amount of time the soil surface was wet, cutting overall soil evaporation.

**insert figure showing blue water demand variability (range) maps for each of the 3 scenarios**

*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 (0.5 m root depth x 30% allowable depletion) to a moderate soil storage scenario (1.0 m root depth x 50% allowable depletion), where the landscape experiences a mean increase in green water availability of 0.66 mm GW mm AD-1 increase (Figure 7A). When the rooting depth increased from 1.0 to 2.0 m with 50% allowable depletion, the landscape sees a lower mean increase of 0.57 mm GW mm AD-1 increase, since more of the area cropped to perennials becomes precipitation, not storage limited in this moderate-to-deep scenario comparison (Figure 7D). 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 3.0 m depth and provides a target for root stock breeders looking to target green water utilization. The effects of each of these increases in the theoretical soil storage capacity can also be considered in terms of the overall, cumulative water balance. In the shallowest soil storage scenario (0.5 m root depth x 30% allowable depletion), the 80th percentile in the green water resource is 11% of its annual crop water needs on average. Extending the crop rooting depth to 2.0 m and increasing the allowable depletion to 50% increases the 80th percentile to meeting 20% of its crop water needs with green water on average annually. So, while increases in available green water are widely limited by precipitation as the soil water storage capacity is increased, a relatively small proportional area that remains storage limited at each different combination of rooting depth and allowable depletion explains most of the increase in the green water resource (Table 2).

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 offset early season irrigation needs so as to spread out early season irrigations, and ending irrigation at a specified date in the fall to make room in the soil reservoir for capture of winter precipitation. The effect is a progressively shorter irrigation season length as the allowable depletion is increased (Figures 7C and E). This strategy also has the side effect of slightly more fall crop water stress but reduces fall deep percolation to a greater extent.

Utilizing additional green waterin deeper rooting or higher allowable depletion threshold scenarios has the effect of decreasing cumulative annual deep percolation (Figures 6A-C; Table 2). While decreased deep percolation, especially early in the growing season when fertilizer applications are common, would be expected to reduce non-point source pollution, lack of natural deep percolation could eventually lead to problematic soil salinity unless leaching by irrigation water is practiced. Therefore, in some ways, management for green water is at odds with management for soil salinity, especially in the drier climates of the southern half of the study area. However, this region only has X% of the green water resource.

As mentioned above in the section on irrigation water demand, when the soil water storage capacity is increased, blue water demand is reduced more than the increase in green water availability (Figure 9B and E); this holds true after correcting for the effect of crop water stress on blue water demand (Table 2). The results show that more soil water storage allowed for less frequent, deeper irrigations, since more plant available irrigation water can be stored in the soil to sustain deep rooting crops between irrigations. Thus, additional 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 22.3 km3 in the deep scenario (Figure ???). **Insert fact about median number of irrigations across the scenarios**.

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.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RD | AD | | GW | Irr | E | DP | CS | ET | DP | ΔS |
| *--m--* | *--%--* | *--mm--* | *--------13 yr total, growing season cubic kilometers (km3)--------* | | | | | | *--annual--* | *-model run-* |
| *0.5* | *30* | *21* | 17.4 | 263 | 63.1 | 4.3 | 3.1 | 280 | 22.3 | 0.6 |
| *0.5* | *50* | *34* | 20.1 | 245 | 51.8 | 2.4 | 6.6 | 265 | 20.1 | 0.7 |
| *1* | *30* | *40* | 21.2 | 244 | 46.1 | 2.0 | 1.2 | 265 | 18.4 | 1.0 |
| *0.5* | *80* | *55* | 22.3 | 199 | 37.1 | 0.8 | 35.9 | 221 | 18.3 | 0.7 |
| *1* | *50* | *67* | 24.6 | 225 | 33.4 | 0.9 | 4.2 | 249 | 15.6 | 1.1 |
| *2* | *30* | *76* | 25.4 | 224 | 30.3 | 0.9 | 0.6 | 250 | 14.4 | 1.4 |
| *1* | *80* | *107* | 27.5 | 179 | 23.5 | 0.3 | 37.2 | 206 | 13.4 | 1.2 |
| *3* | *30* | *113* | 28.3 | 215 | 24.1 | 0.8 | 0.4 | 244 | 11.7 | 1.7 |
| *2* | *50* | *127* | 29.6 | 210 | 22.3 | 0.6 | 3.0 | 239 | 10.7 | 1.6 |
| *3* | *50* | *188* | 32.5 | 204 | 18.6 | 0.5 | 2.6 | 236 | 7.9 | 1.7 |
| *2* | *80* | *203* | 33.1 | 167 | 16.7 | 0.2 | 36.9 | 200 | 8.0 | 1.5 |
| *3* | *80* | *300* | 35.9 | 162 | 14.7 | 0.1 | 36.4 | 198 | 5.4 | 1.6 |



**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.



**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.



**Figure 6A-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.



Figure 7A-F. Figures (top) show the difference between the moderate (1.0 m root depth and 50% allowable depletion) and shallow (0.5 m root depth and 30% allowable depletion) scenarios, in terms of green water (A), blue water (B), and additional days to first irrigation (c). Figures (bottom) show the difference between the deep (2.0 m root depth and 50% allowable depletion) and moderate scenarios. Class breaks are at the 20th, 40th, 60th, and 80th percentiles by area.

*Discussion*

The FAO-56 dual crop coefficient water balance methodology was used to quantify and investigate the soil stored rainfall (green water) available to five of California’s major perennial crops (alfalfa, almonds, grapes, pistachios, and walnuts). The results show a relatively modest green water opportunity for California water resource management to use soil water storage and in-field rainfall to help meet 6-18% crop water demand, depending on the size of the soil reservoir and allowable depletion in irrigation management. On average, 1.9 km3 green water yr-1 for 1.46 million hectares of perennials is available for crops rooted 1 m, given a 50% allowable depletion of available soil water. Even in the shallowest soil reservoir scenario considered (0.5 m and 30% allowable depletion), 1.3 km3 green water yr-1 is still available on average, showing the importance of even optimum shallow soil reservoir management in optimizing green water use. However, the reality of California’s dry, warm climate is that green water is at best a glass 10-15% full for even deeply rooted perennial crops. Nevertheless, given the magnitude of irrigated land in California, this small relative annual contribution of green water to crop ET is a 13 year cumulative that could fill California’s largest manmade reservoir, Shasta Lake with a capacity of 4.5 MAF, 5+ times over. This demonstrates the magnitude of hardened irrigation water demand for perennial crops in California.

If utilized, less deep percolation and reductions in non-point source pollution would follow. For instance, deep percolation is reduced from 1.7 to 1.2 to 0.9 km3 yr-1 when going from the shallowest to moderate to deep soil reservoir scenarios modeled. 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 6A-C). 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 environmental concerns [citation from PPIC].

One of the more interesting findings of this study was that full use of soil water storage can reduce reliance on blue water, not only by substituting green water for blue water, but through evaporative savings. When irrigations are less frequent and more deeply applied, the model shows evaporative savings of 2.3 km3 yr-1 when comparing the shallowest (0.5 m and 30% allowable depletion) and a moderate (1.0 m and 50% allowable depletion) scenario, compared to a gain in green water of 0.6 km3 yr-1. In the shallow to moderate scenario 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 (2.0 m and 50% allowable depletion) 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 quantity of blue water lost to soil evaporation in these major perennial crops. In fact, 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. The FAO-56 dual Kc model attempts to represent, where the surface exposed and wetted is tied both to the irrigation system surface and the vegetative canopy coverage. For instance, Bonachela *et al.* (2001) used drip irrigation experimental data in olive orchards to model evaporation and estimated losses of 4-12% of ET as evaporation from a mature olive orchard compared to losses of 14-42% of ET for a young orchard but details on irrigation frequency were not provided. Similarly, evaporation losses of 7-17% were estimate from a drip-irrigated desert vineyard (Kool *et al.*, 2014b). **In contrast, such and such found higher evaporative losses of …** 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 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 increased crop yields 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 drip-irrigated almonds is 10-15% higher than almonds irrigated by other methods, supporting the findings of this modeling study. Such empirical evidence of irrigation frequency driven increases in blue water consumption may also be evident in the amplification of the almond Kc curve the past several decades (Figure X). Acknowledging that this amplification is at least partially due to management that promotes now denser canopies, it may also be explained by increased frequency of water application in drip irrigated systems used in the irrigation trials. Unfortunately, specifications of the irrigation systems used in crop coefficient studies are typically not documented, revealing the lack of interest in how irrigation system and practices also affect the observed evapotranspiration. Applying the FAO-56 dual Kc methodology across five major California perennials shows that irrigation management strategies that emphasize full use of soil water storage in the root zone to both make use of green water and minimize irrigation frequency has major implications. 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.

Allowing for crop water stress is another way to increase the size of the utilizable soil moisture reservoir and enhance green water utilization. When the allowable depletion is increased to 80%, the growing season ET is reduced by 17-19%, increasing the share of growing season ET met by green water (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. Besides their wetter climate, the main reason that the highest proportion of growing season ET is met by green water in wine grapes is due to assumed intentional crop water stress to increase crop quality at the expense of some yield.

This study assumed different surface wetting fractions for different crops based on standard assumed irrigation systems for different crops (microspray for orchards at fw=0.65), drip for grapes at fw=0.35, and flood/sprinkler of alfalfa at fw=1) but assumed that the entire soil volume was still utilized for green water and irrigation applications. This 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 non-productive blue water consumption. In practice, we may have underestimated irrigation frequency for grapes, because a drip irrigation system with 0.35 surface wetting may not actually use the entire field volume for irrigation applied, since the wetting bulbs from each dripper may not actually overlap. So, a 2 m scenario may actually be wetting to 3 m in some soils for the given irrigation assumptions and the irrigation depth and frequency would need to be revised to match the wetting depth to 2 m.

Utilizing green waterthrough a program of well-timed irrigation management based on water balance tracking or field based monitoring is not trivial. While a number of water-balance based, irrigation management applications 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 tools are tailored to optimize use of green water or emphasize how different irrigation frequency strategies are tied to evaporative losses. Multiple data streams are needed to accomplish the green water utilization goal based on water balance tracking [see Methods]. These data streams have to be integrated to produce metrics for complex decisions throughout the growing season: to adaptively delay irrigation at the beginning of the season, delay irrigation when growing season precipitation occurs, and also adaptively end irrigation before the beginning of crop dormancy to make room in the soil reservoir for capture of winter rainfall. Moreover, farms are divided into irrigation blocks, meaning that when crop water is needed, the whole irrigation system cannot typically be turned on at once. Rather, it may take days to several weeks for an irrigation system to cover the whole farm or an entire orchard, 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. These multiple needed operative steps paired with inherent climatic variability in California means that optimizing green water use in irrigated agriculture is a formidable adaptive management challenge. In spite of this, managing for green water is an attractive strategy to climate change adaptation to a warmer, possibly more water-limited future, at least where snow melt fed reservoirs are less reliable in California. Such a water resources management endeavor is in sharp contrast to the large-scale management focus as currently practiced in California based on enormous blue water reservoirs. 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 20% or more of crop water needs in the wetter regions, down to less than 6% of crop water needs in the driest 20% of California’s major perennial landscape (Figure 5A-C).

Since our study assumes bare soils during winter except for alfalfa, a next step could be consideration of winter annual cover crops. Dormant season evaporative losses of 1.4 km3 yr-1 from bare soil under perennials show that precipitation is also available for growing cover crops. 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 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. There is an open question as to what the true water balance is or would be in areas where cover crops typically are not used. Cover crops may provide other hydrologic and environmental benefits, such as protecting the soil surface from crusting and maintaining infiltration rates, reducing soil leaching losses, and possibly promoting better soil health and fertility [citation?]. Future work on the green water resource in California needs to validate FAO-56 methods for predicting full season soil water balance under perennial crops and developing practical strategies for green water utilization using soil moisture and crop stress sensors, a water balance modeling approach such as the FAO-56 dual Kc used in this study, a more advanced hydrologic model that also considers unsaturated flow and crop water use above field capacity, or some combination of all of these.

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1. See <https://github.com/smdevine/GreenWater/blob/master/GetData/download_SSURGO_allCA.R> for details [↑](#footnote-ref-1)
2. See R script for details: <https://github.com/smdevine/GreenWater/blob/master/GetData/download_PRISM.R> [↑](#footnote-ref-2)
3. See R script for details: <https://github.com/smdevine/GreenWater/blob/master/GetData/spatialCIMIS.R> [↑](#footnote-ref-3)
4. Peak growth resumes 2/14 with irrigation first considered on 2/7 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. [↑](#footnote-ref-4)