Changes in Evapotranspiration of Agricultural Crops in Kern County during the 2014-2015 Drought Years

Masters Report

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Abstract

The 2012-2015 drought in California has major impacts for agricultural water users in Kern County. Farmers shifted crop planting patterns and irrigation scheduling to minimize profit loss with water shortage. This report models the changes in crop evapotranspiration from 2011 to 2014 and 2015 using the remote-sensing-based METRIC model developed by the University of Idaho. Results show that rather than universal losses of acreage and productivity, farmers reduced acreage on annual crops while increasing acreage on low-water-use new orchards. Productivity increased on the annual crops that remained in production, perhaps due to fallowing less productive land. High-value crops such as citrus and grapes saw increases in both acreage and productivity. Remote-sensing-based evapotranspiration mapping provides an important tool to policymakers by providing field-based estimates of a wide range of farmer responses to drought including planting, fallowing, under-irrigation, and, if combined with productivity models, changes in revenue.

Introduction

The 2014-2015 drought years had major implications for water users across California. Multiple studies and reports examined the impact of the drought and flexibility with which environmental, municipal, and agricultural water users responded to shortages and curtailments (Hanak et al., 2017; Howitt, Lund, & Sumner, 2015; Medellín-Azuara, MacEwan, Howitt, Sumner, & Lund, 2016). This report examines the impact of the drought on crop evapotranspiration in Kern County. At the state and irrigation district level, a large amount of public data is published on annual water allocations and expected deliveries. At the level of individual farms, data is not generally available on whether farmers respond to the drought by maintaining irrigation through water transfers or groundwater extraction or decrease irrigation through increases in plant stress or fallowing. This report uses the remote-sensing-based METRIC (Mapping Evapo Transpiration at high Resolution with Internalized Calibration) model to analyze changes in crop evapotranspiration (ETc) for Kern County from 2011 to 2014 and 2015. Cumulative seasonal ETc was estimated for the Kern cropland area and crop coefficient (Kc) and ETc estimates were analyzed for many of the major Kern crops. The crop coefficient from METRIC is the actual, “observed” (estimated) crop coefficient, rather than a potential research-based crop coefficient, and is therefore directly proportional to the estimated vigor and water demand of the crop. The analysis shows a significant decrease in ETc from 2011 to 2015, concentrated along the western edge of the Kern cropped area. There was a significant negative shift in Kc for most permanent crops analyzed, the result of a combination of water stress and an increase in newly planted orchards. This decrease in Kc was reflected in the Kern County reported decreases in bearing-acre productivity for these crop groups. The annual crops analyzed showed a steady Kc, inline with reported improved productivity per acre (which coincided with a significant decrease in acreage). The results of this study show that ET mapping can provide important information on crop stress during a drought, which can help bridge our understanding of agricultural water shortages between fallowing and declines in productivity.

Background

The METRIC model was first developed by Dr. Richard Allen of the University of Idaho in 2000, on a foundation of earlier work on the SEBAL (Surface Energy Balance Algorithm for Land) model by Dr. Allen and Dr. Wim Bastiaanssen of Delft University of the Netherlands (R. G. Allen, Tasumi, & Trezza, 2007; Bastiaanssen, Menenti, Feddes, & Holtslag, 1998; Marcos, 2004; Roerink, Bastiaanssen, Chambouleyron, & Menenti, 1997). The fundamental theory of remote-sensing ET modeling is a surface energy balance – computing ET as the residual energy remaining when the soil and air heat fluxes are subtracted from the energy of incoming solar radiation (Equation 1) (Bastiaanssen, Pelgrum, et al., 1998; Castellví & Snyder, 2009; Shapland, Snyder, & Martínez-cob, 2014).

(1) $$Latent\ Heat\ Flux = Surface\ Net\ Radiation\ Flux - Soil\ Heat\ Flux - Sensible\ Heat\ Flux\ to\ Air$$

The latent heat flux is then converted to a rate of evapotranspiration using the latent heat of vaporization. METRIC uses images taken by NASA’s Landsat satellites to measure long- and short-wave radiation at the atmospheric surface on a 30-meter by 30-meter resolution for the visible spectrum and a 100-meter by 100-meter resolution for the thermal spectrum. The METRIC algorithm combines these measurements with local weather data to anchor the atmospheric estimates to field measurement. The model is calibrated to local conditions using METRIC’s unique hot and cold pixel calibration, which uses fully-irrigated alfalfa fields and fallowed agricultural fields as pixels of known ETc that can be used to create linear relationships to all other agricultural pixels.

The surface energy balance in METRIC calculates the instantaneous ETc directly and then uses the reference evapotranspiration (ETref) to calculate instantaneous Kc for each pixel (Equation 2).

(2) $$ET_c = ET_{ref} \times K_C$$

with

ETref	reference evapotranspiration, either ETo for grass or ETr for alfalfa
Kc	crop coefficient
ETc	crop evapotranspiration

The value of Kc is assumed to be constant for a 24-hour period, so the instantaneous Kc is multiplied by the daily ETref to calculate the final output, daily ETc. Kc is based on the crop type and growth stage, and can be adjusted for site-specific stresses that may influence plant transpiration. The base crop coefficient is considered a universal value, empirically-determined, which represents that crop in any region or under any conditions. It is not truly universal because crops can transpire significantly differently in different environments – such as a tropical environment and a desert environment –different Kc factors may exist for those two regions. Kc is *not* tied to temperature or humidity conditions, which are embedded in the reference evapotranspiration. If Kc is different between two regions, that means that the crop will evapotranspirate differently given the *same* air temperature, solar radiation, humidity, and water availability. Kc represents the potential crop coefficient for a well-watered crop under optimal agronomic conditions. If a plant is subject to water or environmental stress, the Kc factor will be adjusted for stress (Figure 1). A typical Kc curve is shown below in Figure 2.

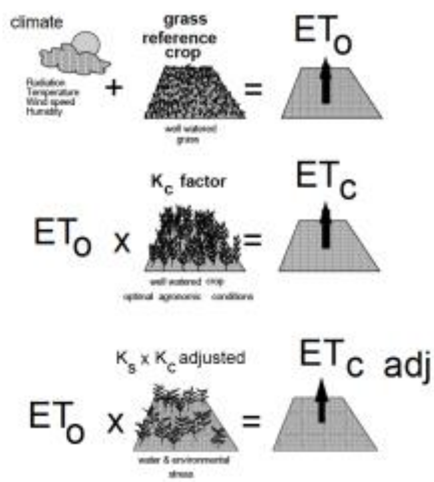

Figure 1. Reference (ET_o), standard crop evapotranspiration and (ET_c) and non-standard crop evapotranspiration (ET_{cadj}) (R. Allen, 1998)**.**

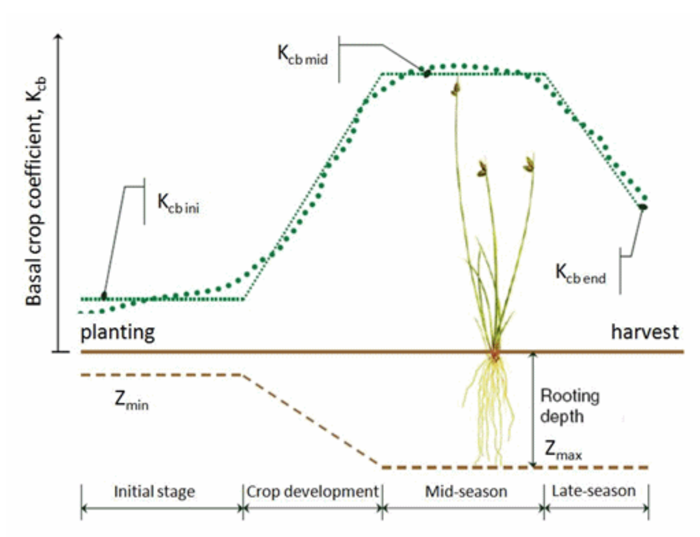

Figure 2. Seasonal Kc Curve (Stockholm Environmental Institute, 2001)**.**

In the METRIC model the ETc and Kc are estimates of the “actual” rather than “potential” values; the Kc multiplier includes field conditions such as water stress, since the algorithm is not based on a historical potential ET curve but the energy balance of the field. METRIC uses an alfalfa reference ETr. The California Department of Water Resources, which manages California's network of weather stations, CIMIS (California Irrigation Management Information System), uses a grass reference ETo. To provide Kc values appropriate to the California-standard grass reference ETo, the ETc rasters from METRIC, calculated using the alfalfa ETr, are then divided by the CIMIS Penman-Monteith ETo. All Kc values reported here are for grass reference ETo.

Penman-Monteith Equation for Evapotranspiration

The computation of reference ET is universal and transferrable, based on one of the standard evapotranspiration equations, such as the Penman-Monteith equation, the Hargreaves equation, or the ASCE-equation. METRIC utilizes the Penman-Monteith equation, as outlined in the global standard Food and Agriculture Organization's Irrigation and Drainage Paper No. 56 (R. Allen, 1998) and in the American Society of Civil Engineers' Standardized Reference Evapotranspiration Equation (Walter et al., 2005). This equation uses daily or hourly weather data from a well-designed weather station to calculate local ETref. The calculation of the reference ET is done outside of the METRIC model, using either the DOS-based Ref-ET tool built by the University of Idaho or the R-based ASCE Penman-Monteith script written as part of this project. The R-based script was created to ease analysis of intermediate outputs and sensitivity. The core Penman-Monteith Reference Evapotranspiration equation is outlined in Walter et al. (2005) (Equation 3):

(3) $$ET_{ref} = \frac{0.408\Delta(R_n - G) + \gamma \frac{C_n}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)}$$

with

ETref	reference evapotranspiration [mm/day]
Rn	net radiation at the crop surface [MJ/m^2 /day]
G	soil heat flux density [MJ/m^2 /day]
T	mean daily air temperature at 2 m of height [C]
Cn	numerator constant based on timestep and reference type
Cd	denominator constant based on timestep and reference type
U_2	wind speed at 2 m height [m/s]
e_s	saturation vapor pressure [kPa]
e_s-e_a	saturation vapor pressure deficit [kPa]
Δ	slope vapor pressure curve [kPa/C]
γ	psychrometric constant [kPa / C]

This equation is primarily driven by the incoming solar radiation, in combination with local climate and aerodynamic parameters, and outputs the reference ET for the given daily or hourly interval. The data obtained from CIMIS is cross-referenced for quality control against adjacent CIMIS stations, relation to maximum potential solar radiation for the given day, and spikes from one interval to another. ET generally peaks during midday, when solar radiation is at its maximum. ET depends on sufficient water *availability*; the CIMIS station data is standardized through specific design and maintenance parameters, including a well-watered footprint around the climate-sensing instruments.

Crop Coefficient

As shown above in Figure 1, reference evapotranspiration is converted to crop evapotranspiration with a crop coefficient (Kc) multiplier. Kc is defined as (R. Allen, Pereira, Raes, & Smith, 1998) (Equation 4).

(4) $$K_c = K_s \times K_{cb} + K_e$$

with

Kc	Adjusted crop coefficient for water stress and soil evaporation
Kcb	Basal crop coefficient for maximum potential transpiration without water as a limiting factor
Ks	Water stress reduction to the basal crop coefficient
Ke	Coefficient for soil evaporation

Kcb is the primary driver of Kc, and like the Penman-Monteith equation, it can be universally applied. Kcb is based on the crop type and crop cover / stage of growth. This estimation is based on empirical measurements from the research (R. Allen, 1998; Ayars & Hutmacher, 1994; Irrigation Training and Research Center, 2003). The other adjustments to Kcb are based on local conditions and their effect on plant stress, including the depth of the root zone, the amount of water available to the roots, the evaporation at the soil surface, and other factors. This calculation is much more nuanced and difficult to accurately estimate over multiple fields or a large region. METRIC estimates the Kc values of the field, so this value is a fully adjusted Kc that includes any soil evaporation or water stress. For this reason, the Kc values of the METRIC model will be more broadly distributed and vary from published potential Kc values.

ETr versus ETo

Alfalfa evapotranspirates at a higher rate than grass, so the alfalfa-based reference ET will have a larger range of values. Alfalfa is also taller than grass, and so its surface roughness and relationship between vegetation indices and temperature reflects many field crops better than grass. In California, however, the network of CIMIS stations uses a grass-based reference ET. In general, ETr is about 25% higher than ETo, but the relationship is not fixed nor is it linear based on input variables. Considering Equation 3, the parameters that change for grass versus alfalfa reference are G, Cd, and Cn. G only changes for hourly calculations; on a daily timestep G is considered to be zero. Since Cd and Cn are direct multipliers of the wind speed, the changes in the ETr/ETo ratio track most closely with the wind speed input. Figure 3 below shows the ratio of ETr/ETo and wind speed for July 2015 (Figure 3).

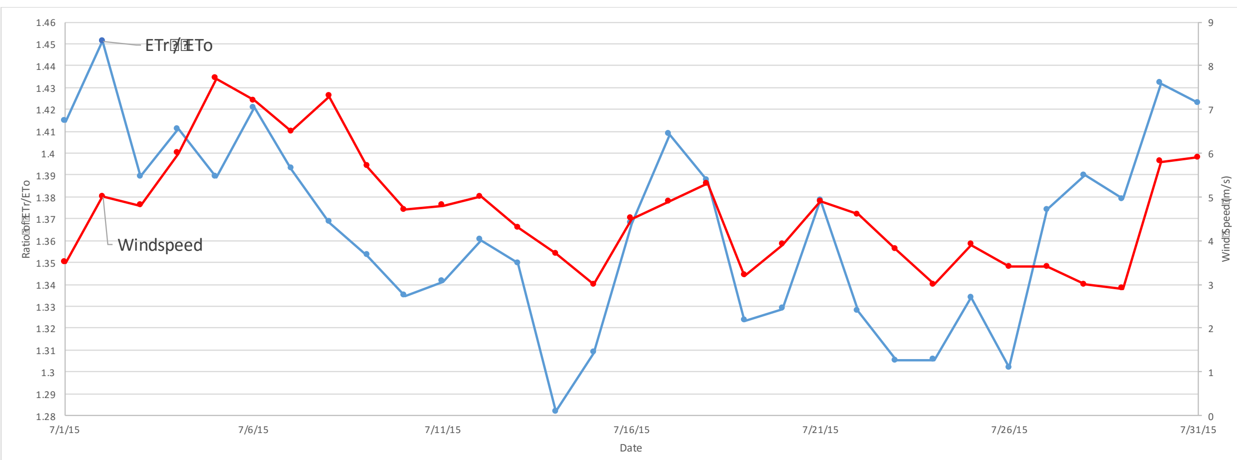

Figure 3. How the ETr/ETo ratio is affected by wind speed (July 2015, Shafter CIMIS Station).

Additional consequences to the difference occur in the Cd and Cn multipliers. METRIC calculates the instantaneous Kc at the time of the Landsat image using the hourly reference ET values and then holds that Kc constant to calculate the daily crop evapotranspiration. The ratio of hourly/daily Cd and Cn values are not identical between grass and alfalfa. If the model is run using ETr, but then analyzed using ETo, differences in this scaling will affect the results. Table 1 and Table 2 show the ETr/ETo ratio for daily and hourly time steps for 2015. The ratio of ETr to ETo is 10-15% higher for the daily time step than for the hourly time step.

Table 1. Daily ETr and ETo for 2015 Landsat Dates (Shafter CIMIS Station).

Date	ETr	ETo	ETr/ETo
3/5/15	2.82	2.24	1.26
3/21/15	4.93	3.66	1.35
4/22/15	4.78	3.90	1.23
5/8/15	5.01	4.20	1.19
5/24/15	6.67	5.08	1.31
6/25/15	13.74	9.70	1.42
7/11/15	7.39	5.66	1.30
7/27/15	11.49	8.25	1.39
8/12/15	8.01	5.96	1.34
10/31/15	3.92	2.70	1.46

Table 2. Hourly ETr and ETo for 2015 Landsat dates (value at 11 am, satellite image time) (Shafter CIMIS Station).

Date	ETr	ETo	ETr/ETo
3/5/15	0.41	0.35	1.17
3/21/15	0.50	0.41	1.20
4/22/15	0.53	0.47	1.13
5/8/15	0.49	0.50	0.98
5/24/15	0.58	0.58	1.00
6/25/15	0.87	0.72	1.20
7/11/15	0.71	0.58	1.24
7/27/15	0.86	0.69	1.25
8/12/15	0.78	0.61	1.27
10/31/15	0.51	0.40	1.29

Table 3 shows the impact of this difference on the estimate of Kc. The algorithm is designed so daily and hourly values of Kcr are identical. However, when ETo is used to back-calculate daily and hourly Kc, the hourly Kc values are more than 10% lower than the daily Kc values. These differences are important when moving between grass- and alfalfa-referenced ET.

Table 3. Comparison of Daily and Hourly Kc and Kcr (Shafter CIMIS Station).

Date	Mean ETc (mm/day)	ETr (mm/day)	Daily Kcr	Hourly Kcr	ETo (mm/day)	Daily Kc	Hourly Kc
3/5/15	2.80	3.48	0.80	0.80	2.59	1.08	0.94
3/21/15	3.43	5.68	0.60	0.60	4.09	0.84	0.72
4/22/15	3.91	5.61	0.70	0.70	4.39	0.89	0.79
5/8/15	2.24	5.48	0.41	0.41	4.5	0.50	0.47
5/24/15	4.82	7.88	0.61	0.61	5.83	0.83	0.73
6/25/15	8.00	12.70	0.63	0.63	9.11	0.88	0.74
7/11/15	5.51	8.49	0.65	0.65	6.33	0.87	0.79
7/27/15	6.74	10.80	0.62	0.62	7.86	0.86	0.76
8/12/15	5.80	8.91	0.65	0.65	6.49	0.89	0.82

Methods : METRIC Model

The inputs and major outputs of METRIC are shown in Table 4.

Table 4. METRIC Inputs and Outputs

Inputs	Intermediate Outputs	Outputs
Landsat Satellite Images (NASA)	Surface Temperature	Daily ETc
Weather Data (CIMIS)	Vegetation Indices NDVI, LAI, NDWI	Instantaneous Kcr
Digital Elevation Map (USGS)	Surface Energy (Rn, G, H)	
Reference ET (CIMIS data, RefET model)		

Normalized Difference Vegetation Index

The final output of METRIC is an ET raster, but several intermediate outputs can be used to analyze agricultural regions including albedo, reflectance, Kcr, Leaf Area Index and the Normalized Difference Vegetation Index (NDVI). METRIC calculates NDVI on a pixel-by-pixel basis using the at-satellite reflectance values. NDVI is an index that compares the near-infrared radiation to the visible radiation, also known as “greenness”. In the METRIC model, Landsat spectral bands 4 and 5 are used in the following equation

(5) $$NDVI = \frac{\rho_{t,5} - \rho_{t,4}}{\rho_{t,5} + \rho_{t,4}}$$

This equation takes the normalized difference of the 4 (red) and 5 (near-infrared) spectral bands to calculate a measure of the amount of green vegetation (or canopy cover) present in the spectral image. For Landsat 7 images, the new coastal band 1 had not yet been implemented, so bands 3 and 4 correspond to approximately the same wavelengths as Landsat 8's 4 and 5. Testing of the METRIC model by its developers showed a minor difference in NDVI results depending on if at-satellite or at-surface reflectance is used. The difference in the spectral band assignments between Landsat 7 and Landsat 8 is shown below.

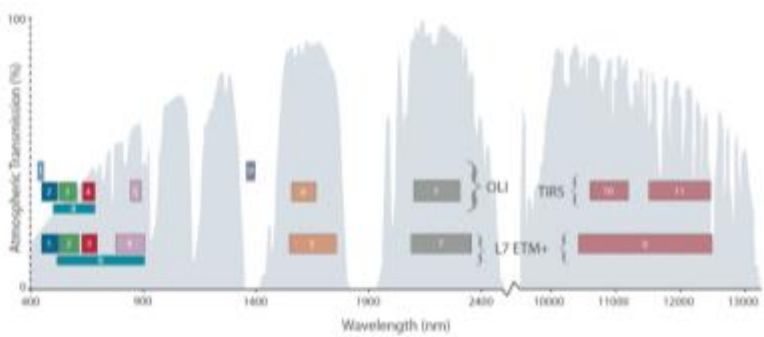

Figure 4. Landsat 7 and 8 Bands (NASA, 2017)

Cloud Cover

Several algorithms exist for cloud-masking of Landsat projects. A common tool used to mask clouds and/or cloud shadows is Fmask, an open-source software developed by Dr. Zhe Zhu at Texas Tech University (Zhu & Woodcock, 2012). Fmask only creates a mask of clouds or cloud-shadows, it does not extrapolate to fill cloud gaps. Gap-filling is typically done by using either lower-resolution temporally adjacent data from a source such as Modis, or doing an interpolation of previous and subsequent images. In this study of Kern County, gaps were filled using linear interpolation of adjacent images.

Temperature

The METRIC algorithm inputs temperature from the Landsat's band 10, a thermal band. The TIRS data is recorded at 100-meter resolution and is downscaled automatically by NASA to a 30-meter-by-30-meter product (United States Geological Survey, 2016). NASA recommends a conversion of the DN to TOA brightness temperature, under the assumption of unity emissivity, as given using equation 6:

(6)
$$T = \frac{K2}{ln\left(\frac{K1}{L_\lambda}+1\right)}$$

with

T TOA Brightness Temperature (Kelvin)
L_λ Spectral Radiance (W/(m^2*sr*µm)
K1 Thermal conversion constant
K2 Thermal conversion constant

Hot and Cold Pixel Selection

The METRIC method is centered around the selection of the "hot" and "cold" calibration pixels. These two pixels are chosen to represent the two extremes of the agricultural fields in the image. The hot pixel is a bare agricultural soil pixel, representing a field that is generally under production (i.e., not fallowed and overgrown with weeds or grass), but does not have any crop growing. The ET of this field will be close to zero. The cold pixel is a fully-irrigated alfalfa field, with excellent crop uniformity and assumed evapotranspiration near the maximum expected for alfalfa. These pixels, along with the CIMIS station, are used to scale the Landsat satellite data. Although the Landsat data has excellent spatial resolution, several simplifying assumptions are used to convert the measured value (top of atmosphere radiance and temperature) to estimates of field-level heat fluxes and vegetation indices. The core assumption of the hot/cold pixel method is that the impact of these assumptions on the results is a consistent bias correctable through linear scaling. The Kc of the hot pixel is set as 0.1 and the Kc of the cold pixel is set as 1.05 based on standard values for alfalfa and soil (R. Allen et al., 2011). These values are converted to ET estimates using the ETref from the CIMIS station. The relationship between the ET values of these pixels and the temperature and NDVI rasters from the Landsat data is then used to calculate a linear scaling factor for all other pixels in the image. This scaling factor removes biases introduced in calculations upstream of the hot/cold selection by scaling the agricultural fields to grounded data. Choosing the right pixel is based on both qualitative and quantitative parameters. Quantitative parameters include temperature, NDVI, LAI, and albedo within certain ranges, a field within 20 km of the weather station, and the correct landuse type. Qualitative parameters include choosing from a field with even crop development, surrounded by similar fields, and choosing a pixel from the center of the field. The UC Davis hot/cold pixel selection process consists of creating a mask layer of pixels based on the quantitative parameters. The qualitative parameters are then applied within this masked area.

Methods : Kern Study

Comparison between Crops

In additional to the aggregated ET data, several individual crop groups were selected for analysis. Crops that were the largest economic commodities over the past fifteen years were chosen, using the rankings of the annual Kern County Agricultural Report. From Table 5 below, alfalfa, almonds, carrots, citrus, grapes, and pistachios were chosen for the crop coefficient analysis.

Table 5. Top Grossing Agricultural Commodities (Kern County Ag Commissioner's Report)

	Top Commodities (by Revenue)									
Year	1	2	3	4	5	6	7	8	9	10
2000	Grapes	Citrus	Cotton	Milk	Almonds	Pistachios	Nursery	Alfalfa	Potatoes	Cattle
2001	Grapes	Citrus	Milk	Cotton	Almonds	Alfalfa	Nursery	Potatoes	Pistachios	Cattle
2002	Grapes	Citrus	Carrots	Almonds	Milk	Cotton	Pistachios	Nursery	Alfalfa	Potatoes
2003	Grapes	Almonds	Citrus	Carrots	Milk	Cotton	Alfalfa	Nursery	Potatoes	Cattle
2004	Grapes	Almonds	Milk	Citrus	Cotton	Carrots	Pistachios	Alfalfa	Potatoes	Cattle
2005	Almonds	Grapes	Milk	Citrus	Pistachios	Carrots	Cattle	Alfalfa	Cotton	Potatoes
2006	Almonds	Grapes	Milk	Carrots	Citrus	Cattle	Pistachios	Alfalfa	Cotton	Potatoes
2007	Milk	Grapes	Citrus	Almonds	Carrots	Pistachios	Alfalfa	Cattle	Cotton	Silage & Forage
2008	Milk	Grapes	Citrus	Almonds	Carrots	Alfalfa	Cattle	Pistachios	Potatoes	Silage & Forage
2009	Grapes	Milk	Almonds	Carrots	Citrus	Pistachios	Cattle	Alfalfa	Pomegranates	Potatoes
2010	Grapes	Almonds	Pistachios	Milk	Citrus	Carrots	Cattle	Cotton	Potatoes	Pomegranates
2011	Milk	Almonds	Grapes	Citrus	Carrots	Pistachios	Cattle	Alfalfa	Cherries	Cotton
2012	Grapes	Almonds	Milk	Citrus	Pistachios	Cattle	Carrots	Alfalfa	Cotton	Potatoes
2013	Grapes	Almonds	Milk	Citrus	Cattle	Pistachios	Carrots	Alfalfa	Cotton	Potatoes
2014	Grapes	Almonds	Milk	Citrus	Cattle	Pistachios	Carrots	Alfalfa	Cotton	Pomegranates

Although alfalfa is a top-ten rather than top-five commodity, as a key input to the cattle and milk industries it was considered a major crop. Grapes was used as an aggregate grouping for wine, table, and raisin grapes. Citrus was also used as an aggregate grouping for oranges, lemons, grapefruit, tangerines, and tangelos.

Bounds of Evapotranspiration Calculations

For the scope of this study, the evapotranspiration data was calculated from May 7th through September 12th. The estimates are *not* meant to represent total evapotranspiration for the year, only of the designated agricultural fields during this timeframe. The total water use for the area will be significantly *higher* than these estimates because of the growing season of many crops extends beyond this timeframe, as seen in Table 6, which lists the planting and harvest dates for some of the major Kern County commodities.

Table 6. Kern County Planting and Harvest Dates (Kern County Department of Agriculture and Measurements and Standards)

Crop	Planting Dates	Harvest Dates
Alfalfa Hay	09/01-10/31	03/20-10/31
Almonds	January - February	08/04-10/15
Carrots	11/15-3/20 and July - August	4/1-7/15 and 10/15-3/15
Grapes, wine and raisin	3/15-4/15	08/15-10/25
Grapes, table	5/1-6/15	06/25-11/24
Oranges	March - June	10/15-09/30
Pistachios	January - February	09/05-10/05

Further, estimates of evapotranspiration are not estimates of applied water – evapotranspiration is the fraction of applied water that is considered consumptive use, but this is only one part of the total applied irrigation water. The METRIC model does not estimate conveyance losses, changes in soil moisture, deep percolation to groundwater, run-off, or any other component of agricultural water use.

Comparison Methods

This report considers three parameters – crop coefficients (Kc; grass-reference ETo indexed), crop evapotranspiration (ETc), and acreage. The benefit of comparing crop coefficients is that they are independent of changes in ET due to climate factors such as solar radiation and wind; the Kc value is the full representation of the vigor of the crop. Crop coefficients for six key commodities (alfalfa, almonds, carrots, citrus, grapes, and pistachios) are analyzed in this report. To calculate seasonal ETc, the Kc values were linearly interpolated between image dates.

Results

Crop Coefficients of Key Crops

The Kc values for the six key crops are shown below in Figure 5. The key crops chosen are a mix of permanent and annual crops, and they show several important trends. The distribution of Kc varies across the crops; it is consistently on the higher end for the annual crops of alfalfa and carrots. A larger distribution can be representative of spatially distributed water stress, but it is also heavily affected by differences in planting and harvesting dates across the image. Carrots clearly show a drop-off in Kc during the June – July harvest time and then an increase as the second crop comes in. The Kc for grapes and citrus remained fairly constant across the three years, but there is a significant decrease in Kc from 2011 to 2014/2015 for almonds and pistachios. These Kc values represent the quartiles across all almond and pistachio fields, so the changes in Kc reflect a combination of planting and harvesting dates, changes in ETc due to water stress, and changes in Kc due to the fractions of fully established and immature orchards.

Figure 5. Seasonal Crop Kc from Landsat Images (available images not evenly distributed in time)

(a) Alfalfa

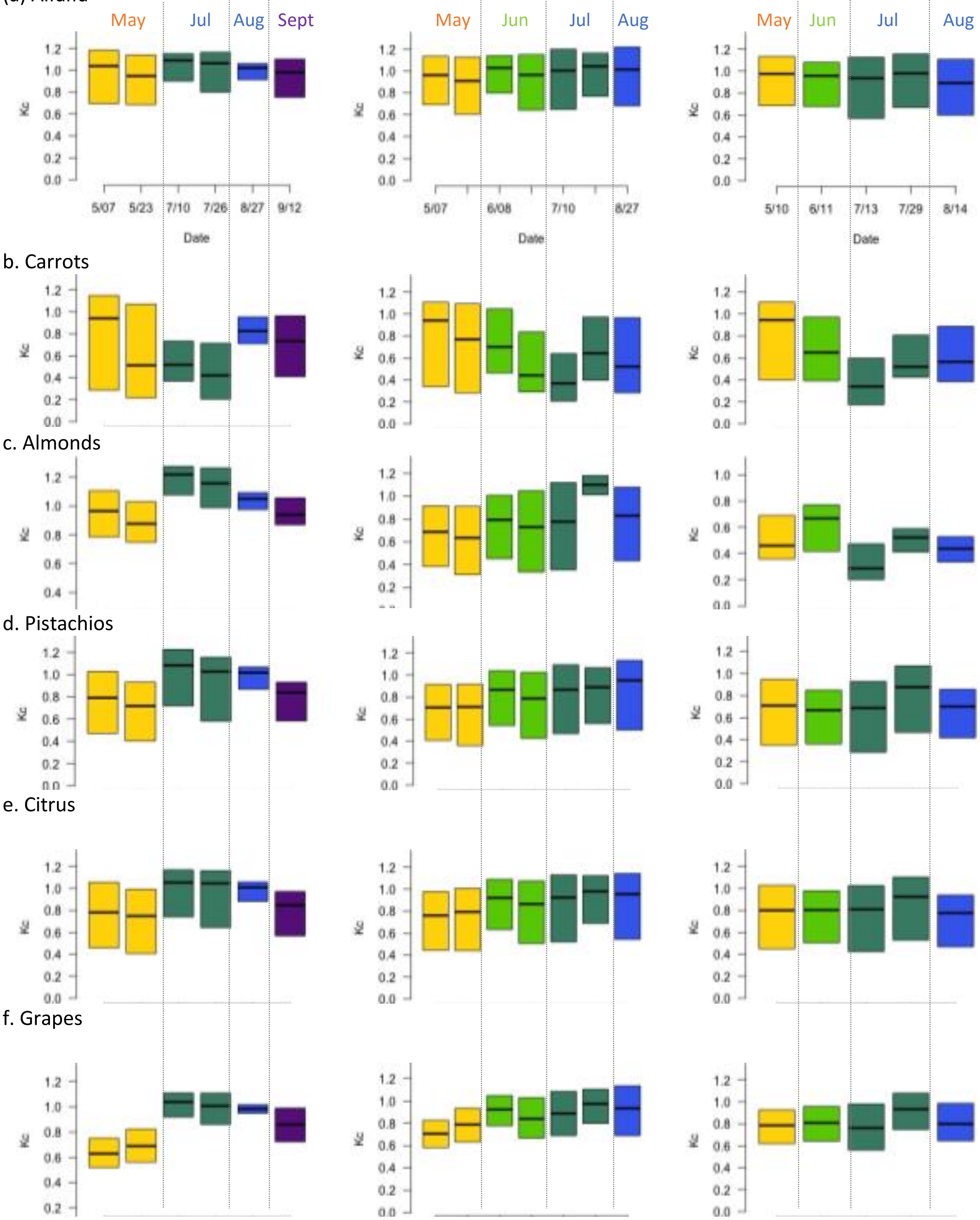

Table 7 shows the quartile values of the key crops along with the mean for each year. The mean is almost always less than the median, indicating some degree of left-skewed distribution, which is what would be expected for crop growth. There is a steady and dramatic decrease in Kc for the orchard crops between 2011 and 2015 – over 50% for almonds, 20% for pistachios, and 10% for pistachios. Grapes maintain a fairly constant Kc. For the annual crops, we see a 10% decrease in alfalfa Kc and a 5% decrease in carrot Kc. This pattern makes a lot of sense when compared to the acreage analysis in section 4.3 below. Although total acreage under production decreased during the drought due to fallowing, there were both significant gains and losses in acreage for different crops in Kern County. The Kern County Agricultural Crop Report for 2015 has not been released yet, but the 2014 report shows significant increases in acreage for permanent crops such as almonds, pistachios, citrus, and grapes along with significant decreases in acreage for most annual crops such as alfalfa, vegetables, cotton, wheat, and other hay (Table 9).

This shift in cropping pattern accomplishes several things. Fallowing annual crops is a more flexible response to drought for farmers and also does not result in the multi-year productivity slump seen after stresses for permanent crops such as almonds. Kc values for the annual crops were fairly constant, indicating that farmers were likely fully irrigating the non-fallowed acreage of those crops. This finding is supported by the Kern County Agricultural Crop Report, which shows productivity per acre increasing from 2011 to 2014 (Table 9). Planting new orchards during a drought, as seen by the increase in permanent crop acreage, allows farmers to make a future investment while minimizing their water use – immature almonds, pistachios, and citrus use about 60% of the water of a fully established crop.

Table 7. Crop Coefficient (Kc) Statistics for Selected Crops

Statistic	Alfalfa			Carrots			Grapes		
	2011	2014	2015	2011	2014	2015	2011	2014	2015
First Quartile	0.79	0.69	0.64	0.37	0.32	0.35	0.76	0.69	0.64
Second Quartile	1.02	0.99	0.95	0.66	0.63	0.60	0.87	0.87	0.82
Third Quartile	1.13	1.16	1.12	0.93	0.95	0.87	0.97	1.02	0.99
Mean	0.95	0.91	0.86	0.65	0.64	0.62	0.84	0.84	0.80

Statistic	Almonds			Pistachios			Citrus		
	2011	2014	2015	2011	2014	2015	2011	2014	2015
First Quartile	0.91	0.47	0.34	0.60	0.47	0.38	0.62	0.54	0.48
Second Quartile	1.03	0.79	0.47	0.91	0.83	0.73	0.92	0.89	0.82
Third Quartile	1.14	1.04	0.61	1.06	1.03	0.93	1.07	1.08	1.02
Mean	1.01	0.76	0.48	0.82	0.74	0.66	0.83	0.80	0.75

Evapotranspiration

Figure 6 below shows the cumulative (seasonal) evapotranspiration for Kern County for 2011, 2014, and 2015. The seasonal values are, consistent with all calculations, for the May 7th through September 12th dates. There is an overall decrease in ET across the county with a concentration along the western edge of the cropped area. Given the increased reliance on groundwater pumping in response to the enormous cuts in surface water allocation, it is expected that areas with weaker groundwater supplies would have been impacted more significantly by the drought.

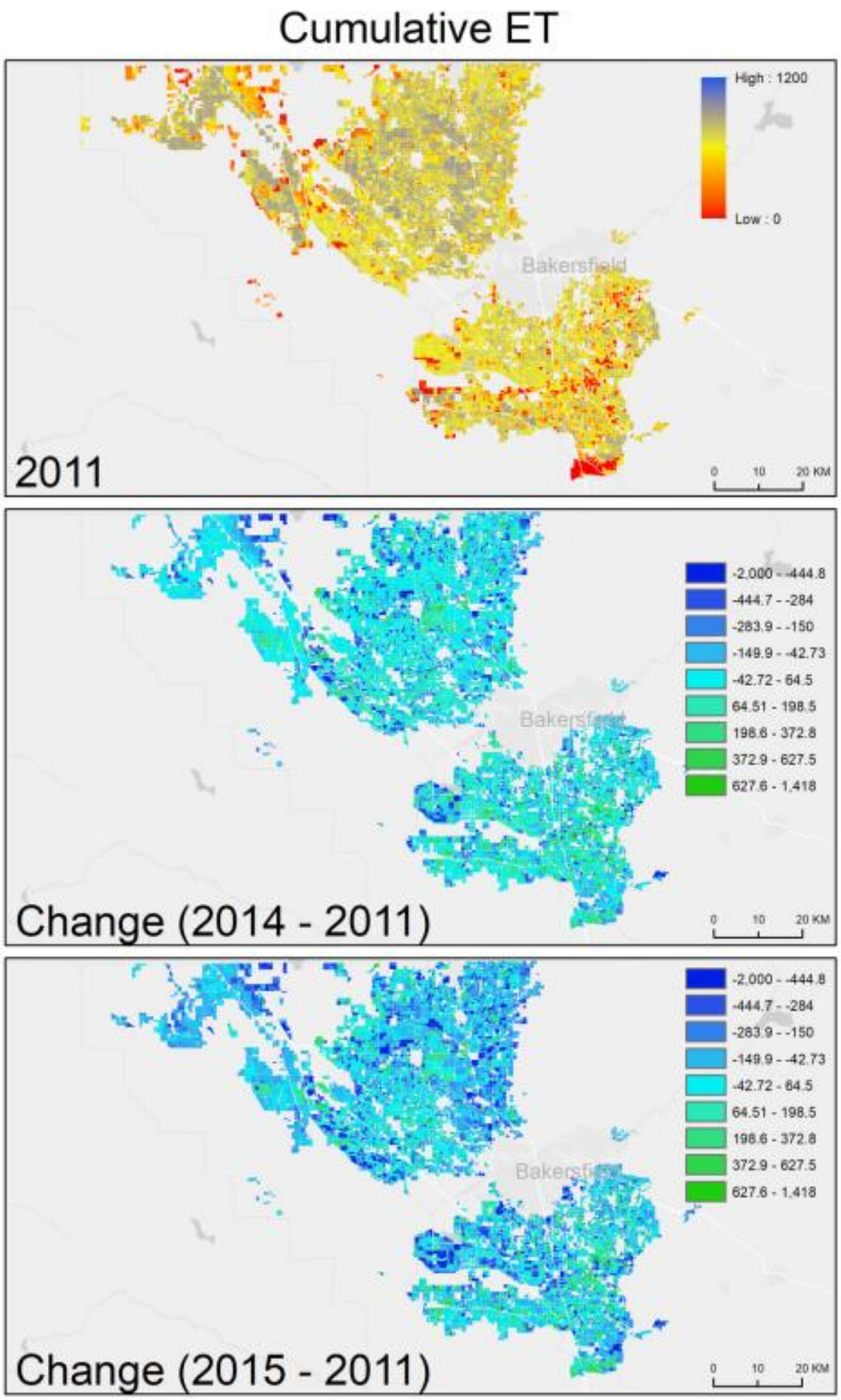

Figure 6. Kern County Agricultural Evapotranspiration for 2011, 2014, and 2015 (in mm/season)

Changes in ETc are a combined response to changes in cropping patterns, irrigation management, and climate; differences in climatic values like solar radiation, humidity, surface temperature, and wind speed are the drivers of reference ETo. Figure 7 below shows the differences in seasonal ETo for 2011, 2014, and 2015. Although for a given Julian day any of the three years might be the minimum or maximum ETo, overall 2014 was 7% higher than 2011 and 2015 was 2% higher than 2011. Since ETc is directly proportional to ETo, this means that approximately 7% of the change in ETc for 2014 and 2% of the change in ETc for 2015 is driven by ETo.

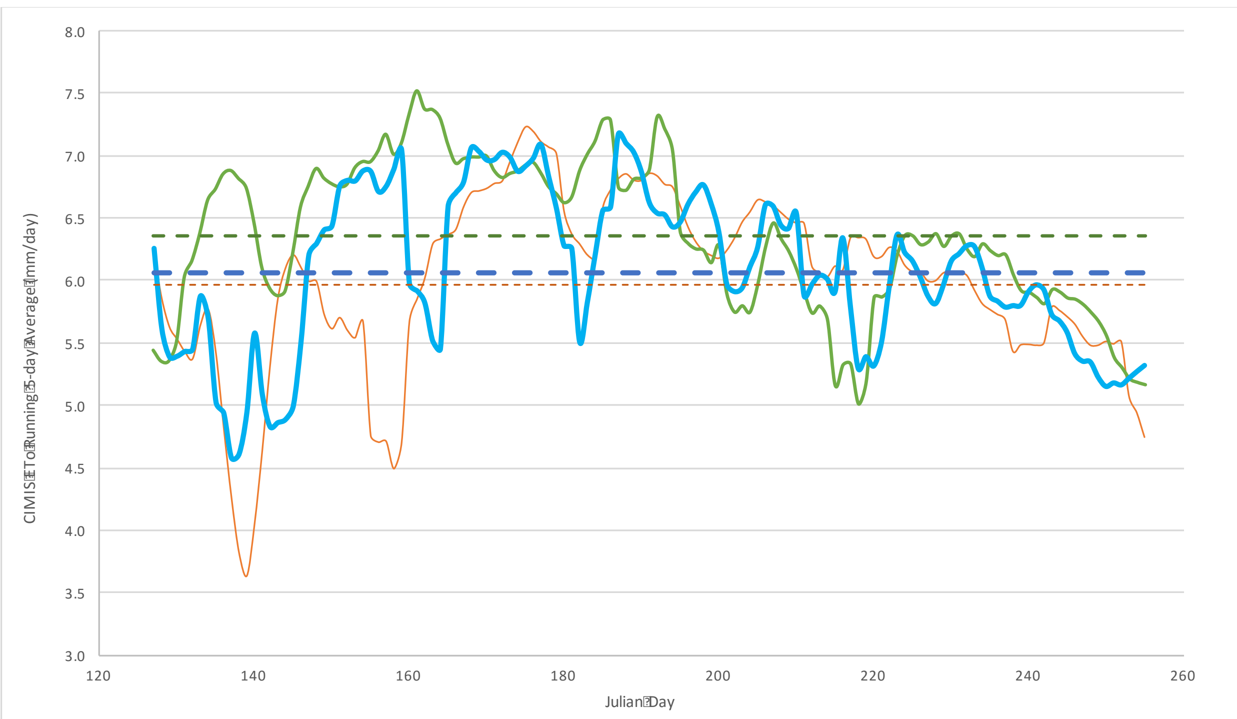

Figure 7. Daily ETo for Shafter CIMIS Station

Figure 8 shows the distribution of seasonal ETc for the three years. This analysis is by pixel in the METRIC raster, so the frequency is a count of 30-meter by 30-meter pixels. We see a drop-off in the two- to three-foot range from 2011 to 2014, along with a slight increase in the below-two-foot range. 2015 has an even more dramatic shift in ETc, with far fewer pixels in the upper range and a big shift of area to around the one-foot mark.

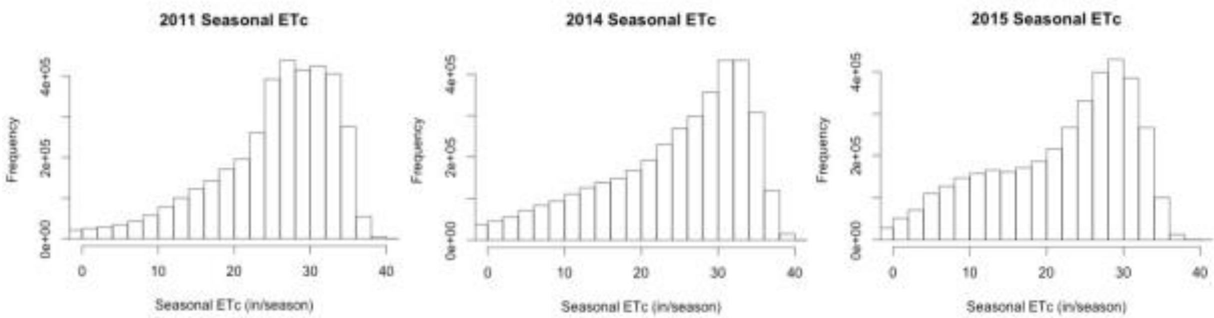

Figure 8. Cumulative Evapotranspiration Distribution of Pixels

Table 8 shows results parallel to our Kc analysis above; a fairly steady ETc for annual crops and grapes along with a decrease for almonds, pistachios, and citrus. Despite the ETo for 2014 and 2015 being 7% and 2% higher than in 2011, we see a decrease in mean ETc of 12% for almonds, 24% for pistachios, and 9% for citrus. This suggests that these permanent crops were under-irrigated in 2014 and 2015 and had lower ETc values due to crop stress.

Table 8. Evapotranspiration Statistics (Inches / Season) for Key Crops

	Alfalfa			Carrots			Grapes		
Year	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**
Acres	72,796	72,428	67,423	23,140	24,418	21,962	100,488	106,441	104,805
Mean ETc	28.6	27.6	25.6	17.3	18.2	17.7	25.9	26.1	24.0
ETc Std. Dev.	5.3	6.8	7.6	8.7	6.8	5.4	5.4	6.4	6.5

	Almonds			Pistachios			Citrus		
Year	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**
Acres	186,931	206,592	213,276	79,587	102,944	117,136	61,494	62,139	62,231
Mean ETc	31.1	30.2	27.4	25.3	22.4	19.3	26.2	25.7	23.9
ETc Std. Dev.	5.4	6.7	6.3	9.0	10.4	9.0	5.5	5.8	6.0

	Cotton			Tomatoes (Processing)			Corn		
Year	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**	**2011**	**2014**	**2015**
Acres	68,290	39,004	27,725	11,103	12,064	14,240	68,290	39,004	27,725
Mean ETc	24.4	27.2	22.9	21.4	22.8	20.0	25.4	26.0	21.4
ETc Std. Dev.	4.6	7.4	9.1	5.3	3.8	4.2	3.9	4.5	5.7

Changes in Crop Acreage and Productivity

The differences in the Kc and ETc values must be considered in relationship to changes in crop acreage and productivity. Table 9 below shows the official acreages reported by the Kern County Agricultural Commissioner for 2011 and 2014. These numbers will not be exactly the same as the values extracted from the Kern County crop GIS files, partly because of temporal changes in the exact acreage and partly because the aggregation and classification differs between the two data sets (the most significant difference being that the data below is presented for bearing acreage only for orchard crops).

The data here is for the crops considered in the Kc and ETc analysis above, as well as for some additional field and pasture crops with significant acreage. The table has been highlighted to show the positive (yellow) and negative (blue) changes in acreage and productivity. This data supports the conclusions in sections 4.1 and 4.2 above – acreage for orchard and vineyard crops is up, but productivity for orchard crops is down. Acreage for most field, vegetable, pasture, and hay crops is down, while productivity is up. The production figures for orchards are for bearing acreage only, so the drop in Kc due to immature non-bearing orchards is outside of this aggregation, it covers only decreases in productivity due to water stress or other factors.

Table 9. Kern County Crop Acreage and Per-acre Production (Kern County Ag Commissioner's Reported Data)

Permanent Crops			
Crop	Year	(Bearing) Acreage	Production (ton/acre)
Almonds	2011	147,000	1.28
	2014	199,000	1.01
	Change	52,000	-0.27
	Change(%)	35%	-21%
Citrus	2011	53,990	16.1
	2014	64,234	14.79
	Change	10,244	-1.31
	Change(%)	19%	-8%
Grapes	2011	79,500	10.13
	2014	106,200	12.26
	Change	26,700	2.13
	Change(%)	34%	21%
Pistachios	2011	62,800	1.57
	2014	102,900	0.78
	Change	40,100	-0.79
	Change(%)	64%	-50%

Field Crops and Vegetables			
Crop	Year	(Bearing) Acreage	Production (ton/acre)
Tomatoes	2011	13,000	50.23
	2014	14,000	52.86
	Change	1,000	2.63
	Change(%)	8%	5%
Cotton Lint	2011	67,295	1,470
	2014	34,435	1,760
	Change	-32,860	290.00
	Change(%)	-49%	20%
Wheat	2011	64,000	2.55
	2014	27,600	3.37
	Change	-36,400	0.82
	Change(%)	-57%	32%
Potatoes	2011	17,810	22.08
	2014	13,470	27.71
	Change	-4,340	5.63
	Change(%)	-24%	25%
Vegetable Crops (Incl. Carrots and Sweet Corn)	2011	40,600	
	2014	36,600	
	Change	-4,000	
	Change(%)	-10%	

Pasture, Hay, and Silage			
Crop	Year	(Bearing) Acreage	Production (ton/acre)
Hay, Alfalfa	2011	125,000	8.18
	2014	109,000	8.46
	Change	-16,000	0.28
	Change(%)	-13%	3%
Hay, Grain	2011	24,000	3.09
	2014	9,210	5.19
	Change	-14,790	2.10
	Change(%)	-62%	68%
Hay, Other	2011	14,000	3.6
	2014	7,400	3.41
	Change	-6,600	-0.19
	Change(%)	-47%	-5%
Pasture, Rangeland	2011	1,480,000	
	2014	1,450,000	
	Change	-30,000	
	Change(%)	-2%	
Silage and Forage	2011	90,000	21.26
	2014	85,000	19.2
	Change	-5,000	-2.06
	Change(%)	-6%	-10%

Comparing Kern County's analysis of changes in acreage to the National Agricultural Statistics Services (NASS) dataset, we see very consistent results for 2011 and 2014 (Table 10). The NASS acreage is for California as a whole, rather than just Kern County, so it is not a direct comparison, but the magnitude and direction of the shift is consistent across all the crop groups. It is likely that the 2015 Kern County data, when published later this year, will correspond to the trends seen in the 2015 NASS dataset. In 2015 NASS estimates continuing decreases in the field, vegetable, and hay crops shown below and continuing increases in the orchard and vineyard crops.

Table 10. California Crop Acreage (National Agricultural Statistics Services Data)

Crops	Year	Thousand Acres
Almonds, All	2011	875,000
	2014	1,020,000
	2015	1,110,000
Almonds, Bearing	2011	800,000
	2014	870,000
	2015	890,000
Almonds, Non-Bearing	2011	75,000
	2014	150,000
	2015	220,000
Oranges, Grapefruit, Tangerines (Bearing Only)	2011	222,600
	2014	221,800
	2015	224,800
Grapes, All (excluding rootstock)	2011	767,524
	2014	771,480
	2015	755,718
Grapes, Bearing	2011	737,137
	2014	731,966
	2015	715,674
Grapes, Non-Bearing	2011	30,387
	2014	39,514
	2015	40,044
Pistachios (Bearing Only)	2011	153,000
	2014	221,000
	2015	

Crops	Year	Thousand Acres
Tomatoes, All	2011	291,500
	2014	321,800
	2015	
Cotton	2011	456
	2014	212
	2015	161
Durum Wheat	2011	120
	2014	35
	2015	70
Potato	2011	36
	2014	34
	2015	32
Corn	2011	630
	2014	520
	2015	430
Rice (all)	2011	585
	2014	434
	2015	385

Crops	Year	Thousand Acres
Alfalfa Hay Harvested	2011	880
	2014	875
	2015	820
Other Hay Harvested	2011	510
	2014	500
	2015	455

These results differ from the California Statewide Agriculture Production Model (SWAP) drought model predictions reported by UC Davis (Medellín-Azuara et al., 2016). SWAP estimated across-the-board reductions in acreage for the Tulare Lake Basin region. This region encompasses part of Kern County as well as part of Kings, Tulare, Fresno, Madera, and Merced counties. The SWAP model grouped agricultural commodities into vegetables, orchards and vines, feed crops, field crops, and grain, and estimated acreage reductions ranging from 1,600 acres for orchards and vines to 33,000 acres for field crops with a total reduction of 77,000 acres. These numbers cannot be directly compared to the numbers for Kern County, partly because the regions and crop groupings are different, but also because the Kern County data does not represent *fallowing* only reductions in crop acreage that may represent a switch to a different crop. Nonetheless, what we see in Kern is a departure from the predictions of the SWAP model in that we do not see reductions across the board but rather transitioning from annual crops to new permanent orchards and vineyards as discussed above combined with shifts in productivity that will have economic impacts beyond what is represented by simple fallowing.

Conclusions

The UC Davis and NASS fallowed land estimates for the Sacramento-San Joaquin Valley line up closely with the trends reported by Kern. These trends reflect of farmers conserving water during the drought through a demand management portfolio – combining fallowing of predominantly annual crops with conversion of acreage to immature orchards and what appears to be stress-irrigation of mature bearing orchards. It appears that citrus and grapes were managed more carefully than almonds and pistachios – citrus had a relatively small reduction in productivity and vineyard productivity increased (in keeping with the trends seen in the Kc analysis). Kern reported a 21% decrease in productivity for almonds from 2011 to 2014 and a 50% decrease in productivity for pistachios. The productivity per acre-foot of water would be impacted even more significantly, since the Kern County analysis only includes bearing acreage and not the significant increase in immature orchards. The decrease in the Kc values for almonds and pistachios from 2011 to 2014 to 2015 is a combination of both plant stress and the increase in new orchards; immature orchards use about 60% of the water of mature orchards (as well as much less than many other crops, including alfalfa cotton, etc.), so replacing more water-intensive acreage with new trees allows farmers to invest in future harvests while reducing immediate water demand. The downside of this adaptation is that it reduces fallowing flexibility in the future, if the orchards are replacing annual crops, and there is an element of one-time opportunity, relative to the life-cycle of the new trees. The annual crops analyzed showed a steady Kc, similar to the reported improved productivity per acre, but a significant decrease in acreage and therefore total consumptive water use.

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