VARIABILITY OF CROP COEFFICIENTS IN SPACE AND TIME — EXAMPLES FROM CALIFORNIA

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ABSTRACT

Crop coefficients are calculated for almonds, citrus, and grapes in California based on a combination of remote sensing of actual crop evapotranspiration from the Surface Energy Balance Algorithm for Land (SEBAL®) and ground-based reference evapotranspiration from the California Irrigation Management Information System (CIMIS). Crop coefficients are calculated at the field scale, and the apparent variability in crop coefficients among fields and over time is examined. Crop coefficients derived from remote sensing are compared to published values used with reference evapotranspiration for estimation of crop water use. The opportunity to refine crop coefficients for irrigation management and water resources planning through improved understanding of the variability in crop water use via remotely sensed crop evapotranspiration estimates is discussed.

BACKGROUND

Increasing demand on limited fresh water supplies to satisfy multiple demands necessitates improved water management at all levels. Competition for fresh water supplies will continue to increase due to population growth, environmental requirements, and climate change. Improved tools are needed to quantify water use and enable planning that maximizes water use efficiency.

The consumptive use of water by crops (evapotranspiration, or ET) represents a major component of total water use in California. The California Department of Water Resources (DWR) estimates that in a typical year, 41% of the developed water supply is applied to agricultural lands. Of the water applied for irrigation, approximately 69% is consumed as crop ET. (DWR 2005a)

Crop water use is predicted to estimate water needs by water managers at field, farm, district, and regional scales. Because crop ET represents approximately two-thirds of the total water needed for irrigation, inaccuracies in predicted ET can have a substantial impact on projected water needs. Further, resource planners often estimate crop ET retroactively. Water balances ranging from small areas within irrigation districts to the entire State are performed to quantify flow paths such as consumptive use, surface runoff, and deep percolation. Based on the results,

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water management evaluations are made, and opportunities to increase water use efficiency through improved management are identified. Accurate characterization of actual crop ET is needed to accurately estimate water balance components and potential improvements to water use efficiency. Relatively small uncertainties in crop ET can translate into large uncertainties in other, lesser water balance components such as deep percolation.

THEORY

ET Estimation methods: K_c x ET_o

Crop ET is estimated from a variety of methods at multiple spatial and temporal scales. Among the most common ET estimation procedures employed by water managers is the K_c x ET_o approach, in which crop ET (ET_c) is estimated as the product of a crop and time specific crop coefficient (K_c) with consumptive use by a grass reference crop estimated for the period of interest using weather observations (reference ET, ET_o). Additionally, a stress coefficient, K_s, may be introduced to account for the effects of moisture or other stresses ($ET_c = K_c \times K_s \times ET_o$). Procedures for applying the K_c x ET_o approach have been documented extensively. Examples include Doorenbos and Pruitt (1977), Snyder et al. (1989), Jensen et al. (1990), and Allen et al. (1998).

In California, ET_o estimates are provided by the California Irrigation Management Information System (CIMIS). The CIMIS program began in 1982 and has established a state-wide network of more than 120 weather stations. For each weather station hourly, daily, and monthly ET_o estimates are available. CIMIS ET_o values are calculated using a modified version of the Penman equation as described by Pruitt and Doorenbos (1977). The CIMIS Penman additionally employs a wind function developed at the UC Davis (DWR 2005b). Calculations are performed on an hourly time step, and hourly values are summed to provide daily ET_o estimates.

Crop coefficients for use with CIMIS ET_o are available from a variety of sources including those listed above. Additionally, researchers, farm advisors, irrigation consultants, and growers have developed crop coefficients specific to their crops and fields based on observation of their specific field conditions.

Advantages of the K_c x ET_o approach include continuous water use estimates across time (typically hourly or daily time steps), estimates of ET for virtually any crop and stage of growth, and relatively lesser cost for small areas (e.g., a single farm or field). Disadvantages include inability to estimate ET variability within or among fields of the same crop in an area without detailed information describing actual field conditions, large uncertainty in the accuracy of crop coefficients, and relatively greater cost for detailed application to large areas.

ET Estimation Methods: Remote Sensing Energy Balance

Conservation of energy at the Earth's surface denotes a balance between net radiation reaching the Earth's surface from the Sun with combined soil, sensible, and latent heat fluxes. Latent heat flux (energy per unit area per unit time) can be easily converted into ET flux (volume of water per unit area per unit time) based on the latent heat of vaporization and density of water. ET flux can be estimated as a closure term from estimates of the remaining fluxes (Equation 1).

$$ET_a = \frac{1}{\lambda \rho_w}\left[R_n - (G + H)\right] \qquad [1]$$

where λ is the latent heat of vaporization of water, ρ_w is the density of water, ET_a is the actual crop ET, Rn is the net radiation flux at the Earth's surface, G is the soil heat flux, and H is the sensible heat flux.

Description of SEBAL. The SEBAL model applies radiative, aerodynamic, and energy balance physics in a series of 25 computational steps to estimate actual crop ET (ET_a) from the energy balance. ET_a is calculated at the pixel-scale using multispectral satellite imagery with a thermal band. The key input data consist of radiances in the visible, near infrared, and thermal infrared regions sensed by earth observing satellites; ground based weather data from agricultural or other weather stations; and land use data describing general vegetation types, when available. Knowledge of specific crop types is not needed to solve the energy balance. SEBAL is internally calibrated for each image to estimate sensible heat flux between the surface and the atmosphere, avoiding the need for absolute calibration of the surface temperature of each pixel. A detailed explanation of the algorithm is provided by Bastiaanssen et al. (1998).

Validation of SEBAL. SEBAL has been developed through 19 years of research and validation. Validation is ongoing as a means of quality control due to periodic refinements, sensitivity of model results to analyst judgments related to internal calibration, and interest in further quantifying the accuracy of the approach. The algorithm has been applied on more than 150 projects in 15 countries, including 19 projects in the United States (seven in California). Comparisons have been made to six different ET estimation methods for a variety of landscapes including irrigated pasture, sugar beets, riparian vegetation, playas, olives, rice, palm trees, cotton, wheat, sunflower, bare soil, grassland and forest. Seasonal ET_a estimates from SEBAL (multiple satellite images processed and integrated over time) compare well to seasonal ET_a from ground based measurements, falling within 5%. The deviation of ET_a values from ground-based measurements for shorter periods (instantaneous and up to 10 days) may be as much as 15 to 20%. The validation of SEBAL is summarized in detail by Bastiaanssen et al. (2005).

Recent SEBAL Validations in California. In addition to the numerous validation studies conducted world-wide, two validations have recently been conducted in California. Comparisons of SEBAL ET_a to ground-based estimates were conducted by Cassel (2006) for peaches, almonds, and alfalfa in the Southern San Joaquin Valley. It was found that SEBAL ET_a values fell within 5% of lysimeter and neutron probe estimates across a series of images processed for the 2002 growing season (April – October). Additionally, SEBAL estimates of district-wide ET_a for the Imperial Irrigation District were compared to an independent water balance (Soppe et al. 2006). Annual ET_a was calculated for the 1998 water year (October 1997 – September 1998) based on measured inflows and outflows. Total consumptive use from SEBAL was found to agree with the annual water balance within 1%.

Advantages and Disadvantages. Advantages of remotely sensed ET include the ability to estimate ET_a for any crop and stage of growth, ability to evaluate the variability within and among fields of similar types, ability to incorporate all environmental stresses into the ET estimate, ability to estimate ET across large landscapes using a single set of calculations for each image, and relatively low cost for large areas (e.g. a watershed or basin). Disadvantages include limitations in the frequency of ET estimates determined by the return interval of the satellite and relatively greater cost for estimating ET for small areas (e.g. a single farm or field).

Remote Sensing ET_a with Ground-Based ET_o to Estimate Crop Coefficients

The combination of continuous weather monitoring with periodic but spatially rich estimates of ET_a provides the opportunity to refine crop ET estimates by quantifying and explaining the spatial variability in crop coefficients. Once the variability in crop coefficients is spatially mapped, it is possible to examine factors that contribute to variability such as crop age, soil types, soil or water salinity, irrigation methods, shallow groundwater levels, or other spatial aspects of the irrigated landscape.

Tasumi et al. (2005) applied the surface energy balance algorithm METRIC^{TM} to examine the variation in crop coefficients within crop populations for eight crops in Idaho. METRIC was developed based on SEBAL and modified for use specifically in Idaho and the Western U.S. (Tasumi et al. 2000, 2003; Allen et al. 2002, 2003). Field-scale crop coefficients were calculated and used to estimate relationships with the Normalized Difference Vegetation Index (NDVI), which provides an index of green vegetation. Additionally, crop coefficients from the energy balance were compared to standard values used for the K_c x ET_o approach.

METHODS

Three general data sources were utilized in this study. Existing SEBAL datasets providing ET_a estimates at the pixel scale derived from Landsat imagery were compiled. Cropped fields were identified using cropping data from DWR land use surveys and Kern County. ET_o was estimated from reported CIMIS values.

Field-scale crop coefficients were calculated for each image date. Existing SEBAL datasets and cropping data were compiled for each region. Field boundaries were buffered inward to identify areas in which ET_a estimates were not affected by heat transfer processes occurring outside of the field (thermal contamination). Then, ET_a and NDVI for each pixel within each field of interest were averaged to estimate field-scale ET_a and NDVI. Field values were filtered to remove fields with low NDVI during critical growth periods and to group fields based on estimates of fractional ground cover. Finally, field crop coefficients were calculated based on ET_o values from nearby CIMIS weather stations.

SEBAL Datasets

Three existing SEBAL datasets from California were selected as summarized in Table 1. The extent of each analysis area is shown in Figure 1.

Crop Classification

Land use data were obtained for each of three growing areas within the Landsat coverage areas of Figure 1. For the Southern San Joaquin Valley, almond, grape, and orange fields were identified based on 2002 cropping data provided by Kern County GIS (www.co.kern.ca.us/gis). For the Sacramento Valley, almond fields were identified based on 1998 and 2003 crop surveys for Colusa County and for 1998 and 2004 crop surveys for Sutter County from the DWR Division of Planning and Local Assistance (www.dpla2.water.ca.gov). For the Coachella Valley, citrus and grape fields were identified based on a combination of draft 2003 DWR cropping data (NRCS 2006) and 1996 digital orthoquad imagery from the California Spatial Information Library (CASIL, at gis.ca.gov).

Table 1. SEBAL Datasets Used for Crop Coefficient Analysis

Region	Satellite Platform	Row/ Path	Thermal Resolution[1]	Image Dates	Images
Southern San Joaquin Valley (2002 season)	Landsat 7 ETM	42/35	60 m	4/12, 5/14, 6/15, 7/17, 8/2, 9/3, 10/5/2002	7
Sacramento Valley (2001 season)	Landsat 7 ETM	44/33	60 m	4/23, 5/25, 6/10, 7/12, 7/28, 8/13, 8/29, 9/14/01	8
Colorado River (1998 season)	Landsat 5 TM	39/37	120 m	10/26, 11/27, 12/13/97; 1/14, 3/3, 4/4, 5/22, 7/9, 8/26, 9/27/98	10

1. 30 m resolution for visible and near infrared bands.

Figure 1. Landsat Scene Extents for SEBAL Analysis.

Buffering of Field Boundaries

Field boundaries were buffered inward to identify cropped areas that were not affected by thermal contamination. Thermal contamination of within field pixels occurs when lower resolution thermal pixels cross the field boundary and are affected by heat transfer processes outside of the field. For such pixels, the thermal radiance represents a weighted average of the radiance of the pixel area outside the field with the radiance of the pixel area inside the field.

Minimum buffering distances were estimated based on the pixel resolutions of the Landsat thermal band relative to the SEBAL outputs (30 meters). Based on the assumption that fields are generally rectangular in shape and oriented similarly to the Landsat pixels, a minimum inner buffer distance of 45 meters was estimated for Landsat 7, and an inner buffer distance of 105 meters was estimated for Landsat 5-based SEBAL outputs (Figure 2) The buffer distance was estimated so that only pixels containing a thermal pixel that was fully within the field boundaries are used. The buffer distances are somewhat conservative because the influence of heat transfer process occurring outside of the field increases as the thermal pixel area outside of the field increases.

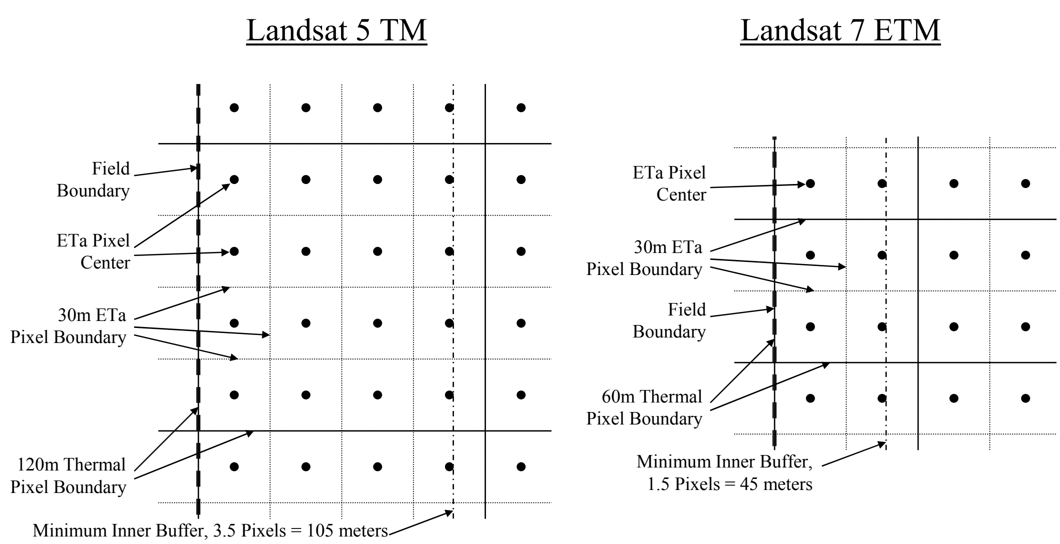

Figure 2. Inner Buffer Distance for Landsat Derived SEBAL Outputs

ET_a and NDVI values for each pixel within the buffered areas were extracted for each image and imported to a Microsoft Access database for calculation of field averages.

Filtering of Field Data Based on NDVI

Field ET_a values were filtered prior to the calculation of crop coefficients based on NDVI. Filters were applied in order to remove fields from analysis for which the land use data may be incorrect or the crop was poorly developed.

Threshold NDVI values for the filters were estimated based on a relationship estimating fractional canopy cover from NDVI (Equation 2) after the form of Choudhury et al. (1994):

$$f_c = 1 - \left(\frac{0.8 - NDVI}{0.8 - 0.125} \right)^{0.7} \qquad [2]$$

Threshold NDVI values corresponding to 10 percent incremental changes in fractional cover (f_c) were derived from Equation 2 and are given in Table 2. In addition to applying filters to remove suspect fields from analysis, fields for tree and vine crops were separated into fractional cover classes based on NDVI. NDVI criteria applied to each crop-region combination are summarized in Table 3. These criteria were selected qualitatively based on estimates of when crops in a region would be at maximum cover.

NDVI values were converted to fractional cover estimates to provide insight into the effect of varying ground shading on crop ET. Growers may not have access to NDVI measurements for their fields during the irrigation season, but can easily estimate fractional cover based on measurements of tree or vine shading relative to the total field area per plant (row spacing x plant spacing). NDVI may vary for reasons other than fractional cover such as crop type or other factors.

Table 2. Threshold NDVI Values Corresponding to Estimated 10 Percent Fractional Cover Increments from Equation 2.

f_c	*NDVI*
0.20	0.310
0.30	0.395
0.40	0.475

f_c	*NDVI*
0.50	0.550
0.60	0.618
0.70	0.680

Table 3. NDVI Criteria to Delineate Crop Canopy Cover Classes and Filter Field Records.

Region	Crop	Critical Time Period	Fractional Cover Class	NDVI Range
San Joaquin Valley	Almonds	5/14/02	> 0.6	> 0.618
			0.5 - 0.6	0.550 - 0.618
			0.4 - 0.5	0.475 - 0.550
			0.3 - 0.4	0.395 - 0.475
	Citrus	6/15/02	> 0.5	> 0.550
			0.4 - 0.5	0.475 - 0.550
			0.3 - 0.4	0.395 - 0.475
	Grapes	6/15/02	> 0.7	> 0.680
			0.6 - 0.7	0.618 - 0.680
			0.5 - 0.6	0.550 - 0.618
			0.4 - 0.5	0.475 - 0.550
			0.3 - 0.4	0.395 - 0.475
Sacramento Valley	Almonds	7/12/01	>0.7	> 0.680
			0.6 - 0.7	0.618 - 0.680
			0.5 - 0.6	0.550 - 0.618
			0.4 - 0.5	0.475 - 0.550
Coachella Valley	Citrus	4/4/98	> 0.5	> 0.550
			0.4 - 0.5	0.475 - 0.550
			0.3 - 0.4	0.395 - 0.475
	Grapes	5/22/98	> 0.7	> 0.680
			0.6 - 0.7	0.618 - 0.680
			0.5 - 0.6	0.550 - 0.618

Reference Evapotranspiration

Daily ET_o estimates for each region were obtained from CIMIS (wwwcimis.water.ca.gov). For each region and crop of interest, a single ET_o was calculated for each image date based on the area-weighted average of nearby stations using Thiessen polygons. Selected stations are listed in Table 4.

Table 4. Selected CIMIS Stations.

Region	Station ID	Station Name	Latitude	Longitude	Elevation (ft)	Start Date	Status
Southern San Joaquin	21	Kettleman	35.869	-119.894	340	11/19/1982	Active
	54	Blackwells Corner	35.650	-119.958	705	10/19/1986	Active
	125	Arvin-Edison	35.206	-118.778	500	3/22/1995	Active
	138	Famoso	35.604	-119.213	415	4/9/1997	Active
	146	Belridge	35.505	-119.690	410	10/9/1998	Active
	182	Delano	35.833	-119.256	300	3/21/2002	Active
Sacramento Valley	27	Zamora	38.808	-121.908	50	12/5/1982	Ended 1/20/06
	30	Nicolaus	38.871	-121.545	32	1/3/1983	Active
	32	Colusa	39.226	-122.024	35	1/13/1983	Active
Coachella Valley	50	Thermal	33.646	-116.242	-30	7/22/1986	Ended 1/11/1999
	141	Mecca	33.538	-115.992	-180	5/5/1998	Active

For the Coachella Valley, data for station 141 were not available until after the first six image dates. For the first six image dates, only the ET_o values for station 50 were used. For the Sacramento Valley, data for stations 30 and 32 were not available for the final three image dates. ET_o values for these dates were estimated from station 27.

Calculation of K_{cs}

Lumped crop coefficients representing combined evaporation, transpiration, and the effects of stresses were calculated from ET_a and ET_o for each field according to Equation 3.

$$K_{cs} = \frac{ET_a}{ET_o} \qquad [3]$$

where K_{cs} is the lumped crop coefficient combining soil surface evaporation, crop transpiration, and stresses (i.e., $K_{cs} = K_c \times K_s$), ET_a is the field average SEBAL ET_a, and ET_o is the average CIMIS ET_o. The notation "K_{cs}" has been defined as a means of differentiating between crop coefficients based on optimum growing conditions (K_c) and crop coefficients based on actual growing conditions (K_{cs}).

Comparison to Published Crop Coefficients

Calculated K_{cs} values were compared to crop coefficients published for use with CIMIS ET_o. Sources of published crop coefficients selected for comparison were Snyder et al. (1989) and Consoli et al. (2006).

RESULTS AND DISCUSSION

Citrus

Southern San Joaquin. Average ET_a for each image date for 117 orange fields in Kern County with estimated f_c greater than 0.3 are presented in Figure 3 along with CIMIS ET_o. The relative frequency distribution of ET_a for the 117 fields are shown vertically along the axis of each image date as a means of visualizing the variability in ET_a (and K_{cs}) similar to Tasumi et al. (2005).

Calculated K_{cs} values for estimated f_c classes are presented in Figure 4 along with published values from Snyder et al. and Consoli et al. "K_{cs} (0.5)" denotes fields with fractional cover greater than 0.5, "K_{cs} (0.4)" denotes fields with fractional cover from 0.4 to 0.5, and "K_{cs} (0.4)" denotes fields with fractional cover from 0.3 to 0.4. This naming convention for estimated f_c classes is used through the remainder of this paper. Summary statistics of ET_a and K_{cs} for each fractional cover class are presented in Table 5.

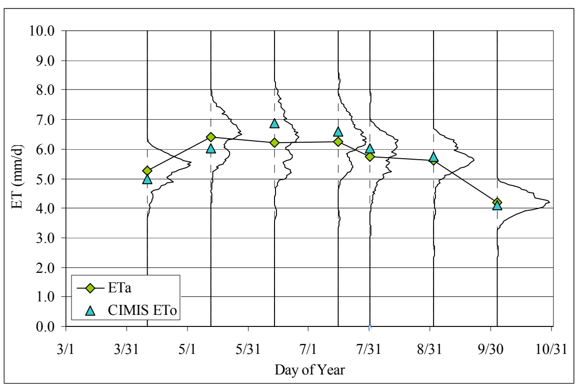

Figure 3. Kern County Orange ET_a and ET_o.

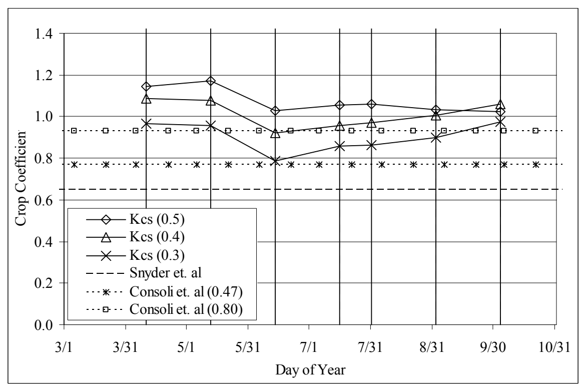

Figure 4. Kern County Orange Crop Coefficients from Remote Sensing, Snyder et al. (1989), and Consoli et al. (2006).

Orange ET was similar to reported ET_o throughout the images, with differences in ET_a (and K_{cs}) among fields explained, in part, by differences in NDVI. It is hypothesized that much of the variability in NDVI is due to differences in fractional cover, although the presence of cover crops or other factors could influence NDVI.

Calculated K_{cs} across the range of estimated f_c classes evaluated were generally greater than other reported values. Consoli et al. evaluated crop coefficients in navel orange orchards near Lindsay, California in the Southern San Joaquin Valley and found seasonal average K_{cs} values of 0.77 and 0.93 for fractional cover of 0.47 and 0.80, respectively. Higher crop coefficients estimated in this study may be due to underestimation of ET_o, limitations of the assumed f_c(NDVI) relationship, or inaccuracies in the ET_a estimates. K_{cs} values greater than those reported by Snyder et al. are consistent with the findings of Consoli et al. Variability in calculated K_{cs} across image dates is not unexpected due to uncertainties in ET_a values for individual images, however the average seasonal K_{cs} is expected to be within 5% of the actual value, provided that the ET_o values are accurate.

Table 5. ET_a and K_{cs} Summary Statistics for Kern County Oranges.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date 4/12/02	5/14/02	6/15/02	7/17/02	8/2/02	9/3/02	10/5/02
> 0.5	34	ET_a (mm/d)	Mean	5.70	7.04	7.09	6.96	6.33	5.95	4.27
			Std. Dev.	0.20	0.32	0.47	0.47	0.39	0.47	0.26
		K_{cs}	Mean	1.15	1.17	1.03	1.05	1.06	1.03	1.02
			Std. Dev.	0.04	0.05	0.07	0.07	0.07	0.08	0.06
0.4 - 0.5	40	ET_a (mm/d)	Mean	5.41	6.54	6.30	6.30	5.87	5.75	4.28
			Std. Dev.	0.17	0.24	0.38	0.33	0.33	0.30	0.28
		K_{cs}	Mean	1.09	1.08	0.92	0.96	0.97	1.01	1.06
			Std. Dev.	0.03	0.04	0.06	0.05	0.05	0.05	0.07
0.3 - 0.4	43	ET_a (mm/d)	Mean	4.81	5.76	5.42	5.67	5.19	5.19	4.03
			Std. Dev.	0.36	0.44	0.56	0.76	0.61	0.57	0.37
		K_{cs}	Mean	0.97	0.96	0.79	0.86	0.86	0.90	0.98
			Std. Dev.	0.07	0.07	0.08	0.12	0.10	0.10	0.09

<u>Coachella Valley.</u> Average ET_a for 107 citrus fields in the Coachella Valley with estimated f_c greater than 0.3 are presented in Figure 5 along with CIMIS ET_o. Estimated K_{cs} values for f_c classes and from Snyder et al. are presented in Figure 6. Summary statistics of ET_a and K_{cs} for each fractional cover class are presented in Table 6.

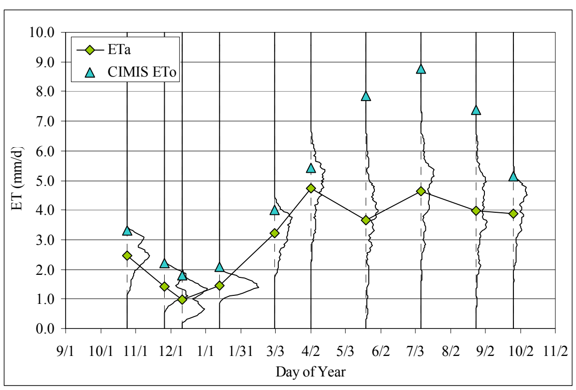

Figure 5. Coachella Valley Citrus ET_a and ET_o.

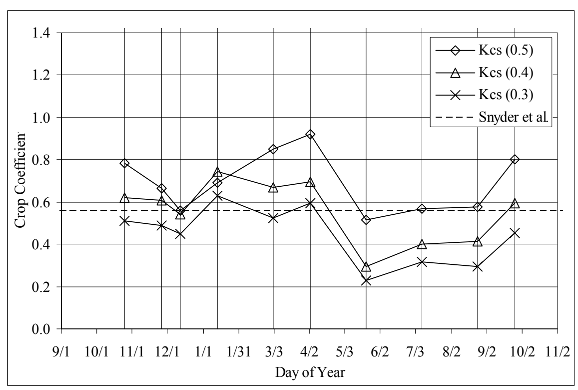

Figure 6. Coachella Valley Citrus Crop Coefficients from Remote Sensing and Snyder et al. (1989).

Estimated daily ET_a fell approximately 1 mm less than ET_o from late fall to March. Then, ET_o rose due to increasing evaporative demands. Despite the dramatic rise in ET_o from April through July, ET_a values appear to remain relatively constant. Steady ET_a values and decreases in K_{cs} for the summer months may be due to overprediction of ET_o or due to stresses related to weather conditions, salinity, and possibly moisture. Variation in K_{cs} among groups of fields classified based on NDVI is likely due to differences in fractional ground cover. Across the season, calculated K_{cs} values agree relatively closely to those reported by Snyder et al.

Table 6. ET_a and K_{cs} Summary Statistics for Coachella Valley Citrus.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date 10/26/97	11/27/97	12/13/97	1/14/98	3/3/98	4/4/98	5/22/98	7/9/98	8/26/98	9/27/98
> 0.5	85	ET_a (mm/d)	Mean	2.61	1.47	1.01	1.44	3.40	5.00	4.05	4.97	4.31	4.14
			Std. Dev.	0.38	0.37	0.40	0.20	0.45	0.65	0.96	0.74	0.87	0.64
		K_{cs}	Mean	0.79	0.67	0.56	0.69	0.85	0.92	0.52	0.57	0.58	0.80
			Std. Dev.	0.11	0.17	0.22	0.10	0.11	0.12	0.12	0.08	0.12	0.12
0.4 - 0.5	16	ET_a (mm/d)	Mean	2.07	1.34	0.97	1.55	2.68	3.79	2.31	3.53	2.98	3.05
			Std. Dev.	0.37	0.34	0.34	0.16	0.44	0.58	1.16	0.60	0.94	0.62
		K_{cs}	Mean	0.62	0.61	0.54	0.74	0.67	0.70	0.29	0.40	0.41	0.59
			Std. Dev.	0.11	0.16	0.19	0.08	0.11	0.11	0.15	0.07	0.13	0.12
0.3 - 0.4	6	ET_a (mm/d)	Mean	1.70	1.08	0.81	1.31	2.10	3.22	1.79	2.79	2.12	2.31
			Std. Dev.	0.29	0.17	0.12	0.20	0.44	0.61	1.09	0.56	0.87	0.67
		K_{cs}	Mean	0.51	0.49	0.45	0.63	0.52	0.59	0.23	0.32	0.29	0.45
			Std. Dev.	0.09	0.08	0.07	0.09	0.11	0.11	0.14	0.06	0.12	0.13

Comparison Among Regions. Crop coefficients for citrus trees with estimated f_c greater than 0.5 differed substantially between the San Joaquin and Coachella Valley regions. These differences may be due to differing environmental conditions (e.g., weather and soil conditions), production practices (e.g., irrigation methods and cover cropping), and differences between varieties grown. In general, the K_{cs} values for the Coachella Valley region appear substantially lesser and more variable with time than values from Kern County.

Almonds

Southern San Joaquin. Average ET_a values for 653 fields in Kern County with estimated f_c greater than 0.3 are presented in Figure 7 along with CIMIS ET_o. Estimated K_{cs} values for each f_c class are presented in Figure 8. Summary statistics of ET_a and K_{cs} are presented in Table 7.

Almond ET_a was similar to reported ET_o across the image dates, with differences in ET_a (and K_{cs}) among fields explained in part by differences in NDVI.

Interestingly, the 112 fields in the 0.3 – 0.4 estimated fractional cover class were found to have substantially lower K_c values than classes with higher NDVI. This may be due in part to the prevalence of drip rather than microsprinkler irrigation on recently planted orchards, which reduces the wetted soil surface area subject to evaporation. The majority of fields evaluated were found to have K_{cs} values at mid and late season (June – September) within the range of values suggested by Snyder et al. for orchards with and without a cover crop. Cover crops are likely present in some orchards, which would result in NDVI values representative of the combined tree and cover crop vegetation.

Similar to the results for citrus, relatively greater K_{cs} values were calculated for the first two image dates and for the final image date. Greater K_{cs} values early in the season may be due to a number of factors including presence of a cover crop early but not late in the season, presence of greater soil moisture early and late in the season leading to greater soil surface evaporation, greater transpiration early in the season prior to the onset of stress, inaccuracies in ET_o estimates early or late in the season, and inaccuracies in ET_a estimates for early and late season images.

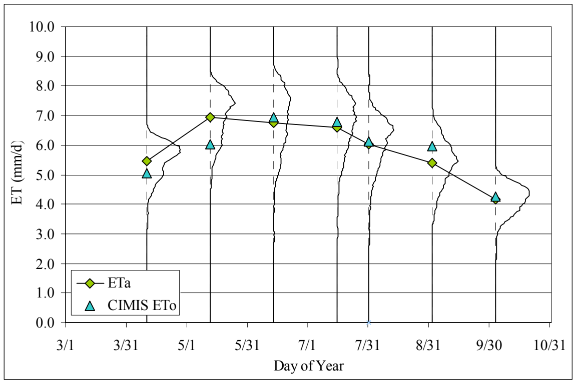

Figure 7. Kern County Almond ET_a and CIMIS ET_o.

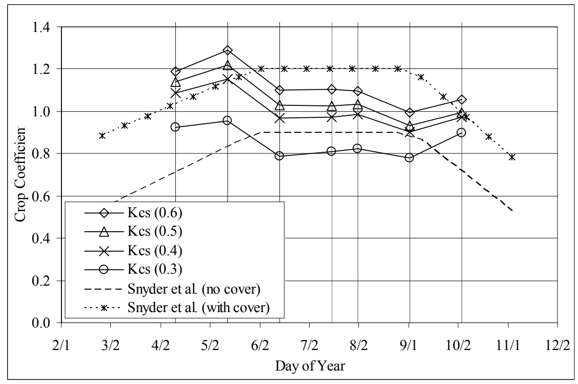

Figure 8. Kern County Almond Crop Coefficients from Remote Sensing and Snyder et al. (1989).

Table 7. ET_a and K_{cs} Summary Statistics for Kern County Almonds.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date						
				4/12/02	5/14/02	6/15/02	7/17/02	8/2/02	9/3/02	10/5/02
> 0.6	138	ET_a (mm/d)	Mean	5.96	7.77	7.63	7.43	6.68	5.86	4.42
			Std. Dev.	0.39	0.26	0.73	0.49	0.56	0.61	0.39
		K_{cs}	Mean	1.19	1.29	1.10	1.11	1.10	1.00	1.06
			Std. Dev.	0.08	0.04	0.11	0.07	0.09	0.10	0.09
0.5 - 0.6	219	ET_a (mm/d)	Mean	5.72	7.32	7.16	6.91	6.29	5.54	4.25
			Std. Dev.	0.32	0.33	0.62	0.57	0.50	0.57	0.39
		K_{cs}	Mean	1.14	1.22	1.03	1.03	1.03	0.93	0.99
			Std. Dev.	0.06	0.06	0.09	0.09	0.08	0.10	0.09
0.4 - 0.5	184	ET_a (mm/d)	Mean	5.25	6.56	6.33	6.21	5.74	5.18	4.01
			Std. Dev.	0.48	0.43	0.70	0.67	0.66	0.59	0.43
		K_{cs}	Mean	1.04	1.09	0.91	0.92	0.94	0.87	0.94
			Std. Dev.	0.09	0.07	0.10	0.10	0.11	0.10	0.10
0.3 - 0.4	112	ET_a (mm/d)	Mean	4.72	5.80	5.53	5.65	5.24	4.83	3.86
			Std. Dev.	0.48	0.47	0.84	0.89	0.83	0.71	0.43
		K_{cs}	Mean	0.92	0.96	0.79	0.81	0.82	0.78	0.90
			Std. Dev.	0.09	0.08	0.12	0.13	0.13	0.11	0.10

Sacramento Valley. Average ET_a values for 616 almond fields in the Sacramento Valley with estimated f_c greater than 0.4 are presented in Figure 9 along with CIMIS ET_o. Estimated K_{cs} values for each f_c class are presented in Figure 10. Summary statistics of ET_a and K_{cs} are presented in Table 8.

ET_a tracked closely with CIMIS ET_o for 4 of 8 image dates with ET_o exceeding ET_a in May, late July, late August, and September. Deviations for the May and late July images may be due to inaccuracies in reported ET_o, inaccuracies in ET_a, or possibly other factors. Decreases in ET_a relative to ET_o late in the season may be due to drying of the soil for harvest and the onset of dormancy and senescence.

Midseason K_{cs} values for fields with estimated f_c from 0.5 to 0.6 agree closely to the values provided by Snyder et al. for orchards without cover crops. K_{cs} values for fields with greater NDVI approach the values reported for fields with cover crops. Relatively greater K_{cs} values for the April image may be due to soil surface evaporation or the presence of a cover crop. Lesser K_{cs} values during September and October may be due to deficit irrigation practices prior to harvest or to an earlier end to the season for the Sacramento Valley than estimated based on the published values.

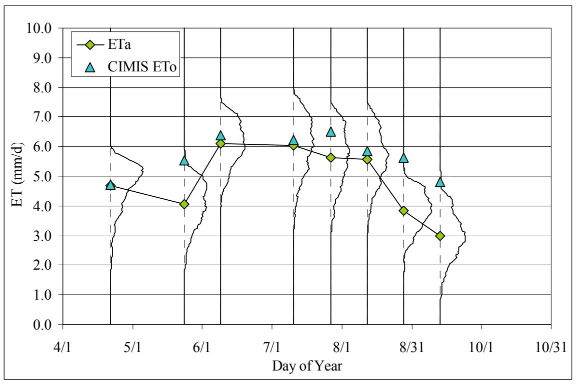

Figure 9. Sac Valley Almond ET_a and CIMIS ET_o.

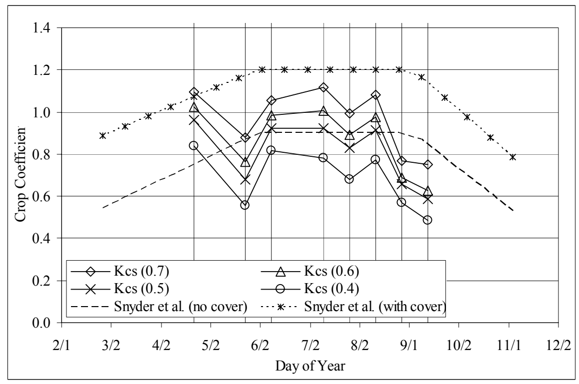

Figure 10. Sac Valley Almond Crop Coefficients from Remote Sensing and Snyder et al. (1989).

Table 8. ET_a and K_{cs} Summary Statistics for Sacramento Valley Almonds.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date							
				4/23/01	5/25/01	6/10/01	7/12/01	7/28/01	8/13/01	8/29/01	9/14/01
> 0.7	184	ET_a (mm/d)	Mean	5.19	4.77	6.78	6.99	6.58	6.40	4.33	3.62
			Std. Dev.	0.51	0.44	0.41	0.33	0.50	0.69	0.48	0.66
		K_{cs}	Mean	1.10	0.88	1.06	1.12	0.99	1.08	0.77	0.75
			Std. Dev.	0.11	0.08	0.06	0.05	0.08	0.12	0.08	0.14
0.6 - 0.7	138	ET_a (mm/d)	Mean	4.84	4.24	6.28	6.27	5.80	5.69	3.89	3.01
			Std. Dev.	0.53	0.40	0.39	0.35	0.48	0.59	0.49	0.59
		K_{cs}	Mean	1.02	0.76	0.98	1.01	0.89	0.97	0.69	0.63
			Std. Dev.	0.11	0.07	0.06	0.06	0.07	0.10	0.09	0.12
0.5 - 0.6	167	ET_a (mm/d)	Mean	4.56	3.84	5.88	5.71	5.33	5.30	3.71	2.83
			Std. Dev.	0.57	0.43	0.43	0.40	0.53	0.57	0.43	0.50
		K_{cs}	Mean	0.96	0.68	0.92	0.92	0.83	0.91	0.66	0.59
			Std. Dev.	0.12	0.08	0.07	0.06	0.08	0.10	0.08	0.10
0.4 - 0.5	127	ET_a (mm/d)	Mean	3.97	3.12	5.21	4.84	4.40	4.51	3.20	2.33
			Std. Dev.	0.68	0.53	0.46	0.59	0.67	0.66	0.48	0.57
		K_{cs}	Mean	0.84	0.56	0.82	0.78	0.68	0.77	0.57	0.48
			Std. Dev.	0.14	0.09	0.07	0.09	0.10	0.11	0.08	0.12

<u>Comparison Among Regions.</u> Comparison of calculated K_{cs} values for almonds in the Sacramento and San Joaquin Valleys show similarities and differences. In each case, April K_{cs} values appear to be greater than midseason values. Midseason, K_{cs} values for fields with

estimated cover from 0.5 to 0.6 are near 0.9 for the Sacramento Valley and near 1.0 for the San Joaquin. During September, calculated K_{cs} values for the Sacramento Valley declined to 0.6 while calculated San Joaquin K_{cs} values remain near 0.9.

Grapes

Southern San Joaquin. Average ET_a values for 352 grape fields in Kern County with estimated f_c greater than 0.3 are presented in Figure 11 along with CIMIS ET_o. Estimated K_{cs} values for each f_c class are presented in Figure 12. Summary statistics of ET_a and K_{cs} are presented in Table 9.

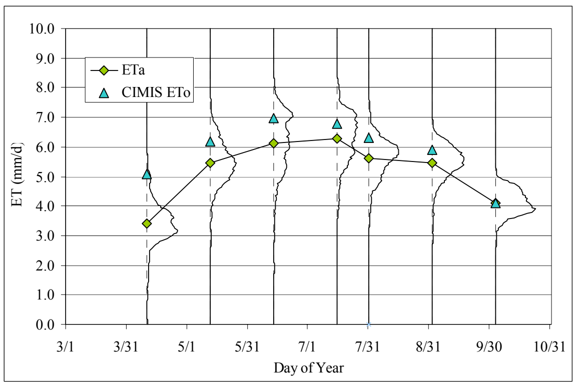

Figure 11. Kern County Grape ET_a and CIMIS ET_o.

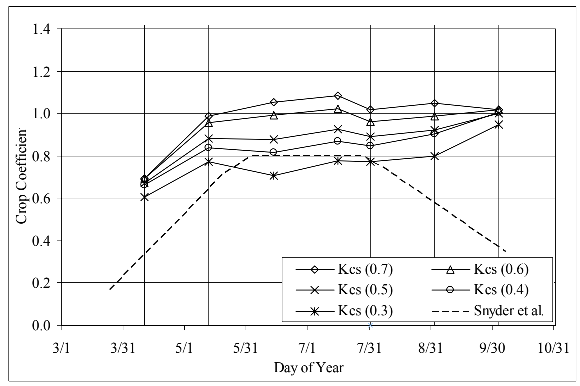

Figure 12. Kern County Grape Crop Coefficients. from Remote Sensing and Estimated from Snyder et al. (1989).

Calculated K_{cs} values for Kern County grapes were approximately 0.6 to 0.7 in early March and increased to 0.7 to 1.1 by midseason. Variation in K_{cs} among fields may be due to differences in f_c or other factors that influence NDVI. Late season K_{cs} values were not found to decrease as predicted based on reported values, possibly due to a longer crop season than estimated or due to soil evaporation late in the season.

Table 9. ET_a and K_{cs} Summary Statistics for Kern County Grapes.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date 4/12/02	5/14/02	6/15/02	7/17/02	8/2/02	9/3/02	10/5/02
> 0.7	43	ET_a (mm/d)	Mean	3.44	5.92	7.23	7.09	6.04	5.95	4.20
			Std. Dev.	0.53	0.42	0.31	0.31	0.31	0.34	0.35
		K_{cs}	Mean	0.69	0.99	1.05	1.08	1.02	1.05	1.02
			Std. Dev.	0.11	0.07	0.04	0.05	0.05	0.06	0.09
0.6 - 0.7	69	ET_a (mm/d)	Mean	3.48	5.86	6.89	6.86	5.96	5.76	4.21
			Std. Dev.	0.66	0.62	0.41	0.48	0.45	0.42	0.40
		K_{cs}	Mean	0.69	0.95	0.99	1.02	0.96	0.99	1.02
			Std. Dev.	0.13	0.10	0.06	0.07	0.07	0.07	0.10
0.5 - 0.6	77	ET_a (mm/d)	Mean	3.60	5.61	6.37	6.48	5.78	5.52	4.08
			Std. Dev.	0.57	0.58	0.50	0.56	0.45	0.40	0.36
		K_{cs}	Mean	0.72	0.91	0.92	0.97	0.92	0.95	1.01
			Std. Dev.	0.11	0.09	0.07	0.08	0.07	0.07	0.09
0.4 - 0.5	88	ET_a (mm/d)	Mean	3.38	5.23	5.71	5.91	5.43	5.37	4.12
			Std. Dev.	0.55	0.45	0.57	0.52	0.56	0.39	0.40
		K_{cs}	Mean	0.66	0.84	0.82	0.87	0.85	0.91	1.01
			Std. Dev.	0.11	0.07	0.08	0.08	0.09	0.07	0.10
0.3 - 0.4	75	ET_a (mm/d)	Mean	3.13	4.87	4.98	5.44	5.09	4.94	3.96
			Std. Dev.	0.93	0.73	0.86	0.78	0.68	0.63	0.40
		K_{cs}	Mean	0.60	0.77	0.71	0.78	0.77	0.80	0.95
			Std. Dev.	0.18	0.12	0.12	0.11	0.10	0.10	0.10

Coachella Valley. Average ET_a for 208 grape fields in the Coachella Valley with estimated f_c greater than 0.5 are presented in Figure 13 along with CIMIS ET_o. Estimated K_{cs} for each f_c are presented in Figure 14. Summary statistics of ET_a and K_{cs} are presented in Table 10.

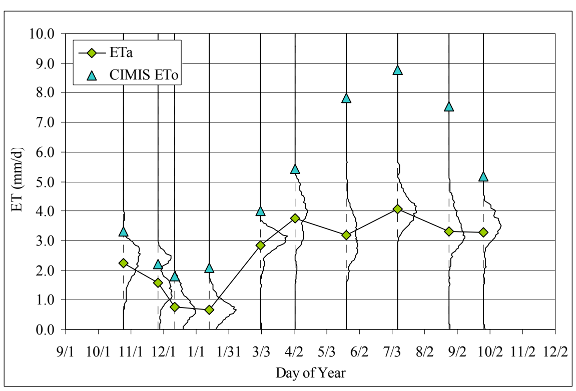

Figure 13. Coachella Valley Grape ET_a and CIMIS ET_o.

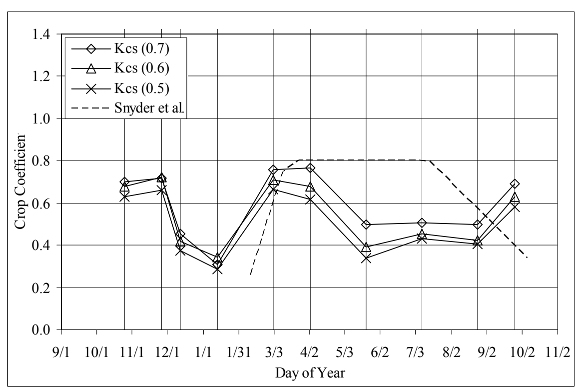

Figure 14. Coachella Valley Grape Crop Coefficients from Remote Sensing and Estimated from Snyder et al. (1989).

Table 10. ET_a and K_{cs} Summary Statistics for Coachella Valley Grapes.

Fractional Cover Class	Number of Fields	Parameter	Statistic	Image Date									
				10/26/97	11/27/97	12/13/97	1/14/98	3/3/98	4/4/98	5/22/98	7/9/98	8/26/98	9/27/98
> 0.7	54	ET_a (mm/d)	Mean	2.33	1.59	0.81	0.64	3.03	4.16	3.89	4.45	3.74	3.59
			Std. Dev.	0.43	0.65	0.44	0.30	0.47	0.68	0.71	0.50	0.74	0.60
		K_{cs}	Mean	0.70	0.72	0.45	0.31	0.76	0.76	0.50	0.51	0.50	0.69
			Std. Dev.	0.13	0.30	0.25	0.15	0.12	0.12	0.09	0.06	0.10	0.12
0.6 - 0.7	111	ET_a (mm/d)	Mean	2.25	1.60	0.75	0.72	2.84	3.70	3.07	3.98	3.19	3.26
			Std. Dev.	0.57	0.67	0.44	0.38	0.60	0.72	0.57	0.43	0.70	0.87
		K_{cs}	Mean	0.68	0.72	0.42	0.34	0.71	0.68	0.39	0.45	0.42	0.63
			Std. Dev.	0.17	0.30	0.24	0.18	0.15	0.13	0.07	0.05	0.09	0.17
0.5 - 0.6	43	ET_a (mm/d)	Mean	2.09	1.46	0.67	0.59	2.67	3.35	2.64	3.77	3.05	3.01
			Std. Dev.	0.56	0.67	0.43	0.28	0.49	0.83	0.55	0.37	0.59	0.74
		K_{cs}	Mean	0.63	0.66	0.37	0.28	0.67	0.62	0.34	0.43	0.40	0.58
			Std. Dev.	0.17	0.30	0.24	0.13	0.12	0.15	0.07	0.04	0.08	0.14

Calculated K_{cs} values at the end of the rapid development period (approximately March – April) were found to be similar to estimates from reported values, with differences due in part to variability in NDVI. Calculated K_{cs} values declined by late May and remained relatively constant through August, possibly due to overprediction of ET_o, deficit irrigation to control shoot growth following harvest (Coachella Valley grape harvest typically occurs from late May to early July), and due to environmental stresses. K_{cs} values were found to increase by late September and remained relatively constant through November, possibly due to overhead sprinkling of grapes to induce dormancy (a common practice in the Valley) and due to the presence of cover crops.

<u>Comparison Among Regions.</u> Calculated K_{cs} values for Kern County remained relatively constant through the summer months, while Coachella Valley K_{cs} decreased by late May. The decline in K_{cs} for the Coachella Valley region relative to Kern County may be due to differences in environmental factors such as weather conditions, soil characteristics, soil and water salinity, or due to differences in production practices such as deficit irrigation following harvest to control shoot growth.

Another factor that may explain differences in grape crop coefficients between the Coachella Valley and Kern County regions may be differences in production practices related to the end-product produced. In the Coachella Valley, grapes are produced exclusively for the fresh market, while in Kern County approximately 38% of grapes were grown for the fresh market, 35% were grown for wine, and 27% were grown for raisins during the study period (2002 Kern County Crop Report). Differences may include different trellis systems and resulting fractional cover differences as suggested by the relatively large number of Kern County fields with estimated f_c less than 0.5 (may be wine grapes, which often are grown on smaller trellises) when compared to the Coachella Valley, where the vast majority of the fields had cover greater than 0.5. Additionally, irrigation practices may differ (such as deficit irrigation to control wine grape quality), which may not affect fractional cover but does affect the ET flux.

CONCLUSIONS

Crop coefficients under actual field conditions vary substantially for individual crops within a region and across regions. Remote sensing of actual ET using high resolution satellite imagery allows for assessment of this variation. Impacts of field and region specific factors such as fractional cover, soils, weather conditions, irrigation and cultural practices, and salinity may explain these variations. Additional studies that incorporate spatial knowledge of these variables are needed to quantify their effect on crop water use under actual field conditions. Increased frequency of remotely sensed ET_a estimates as well as evaluation of K_{cs} values across more than a single growing season are needed to better define the variation in crop coefficients with time.

Crop coefficients estimated for this study were calculated based on reported ET_o values used for irrigation management. Future studies aimed at establishing standard K_{cs} values for general use must incorporate greater quality control to reduce uncertainties in ET_o for the remote sensing image dates. Additionally, ground based ET estimates using surface renewal or other techniques are needed to reduce inaccuracies in remotely sensed ET_a for individual image dates for K_c studies. The combination of remotely sensed ET_a with ground based estimates of ET_a and ET_o has the potential to increase the accuracy with which crop water use can be predicted at varying scales using the K_c x ET_o approach, enabling improved water management.

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REFERENCES

Allen, R.G., Morse, A., and Tasumi, M. (2003). Application of SEBAL for Western US Water Rights Regulation and Planning. Proceedings of the ICID International Workshop on remote Sensing. Montpellier, France.

Allen, R.G., Morse, A., Tasumi, M., Trezza, R., Bastiaanssen, W.G.M., Wright, J.L., and Kramber, W. (2002). Evaptranspiration from a Satellite-Based Surface Energy Balance for the Snake River Plain Aquifer in Idaho. Proceedings of the USCID/EWRI Conference on Energy, Climate, Environment, and Water. San Luis Obispo, California.

Allen, R.G., Pereira, L.S., Raes, D., and Smith, M. (1998). Crop Evapotranspiration. Irrigation and Drainage Paper No. 56. Food and Agriculture Organization of the United Nations. Rome, Italy.

Bastiaanssen, W.G.M., Menenti, M., Feddes, R.A., and Holtslag, A.A.M. (1998). A Remote Sensing Surface Energy Balance Algorithm for Land (SEBAL): 1. Formulation. Journal of Hydrology, 212-213: 198-212.

Bastiaanssen, W.G.M., Noordman, E.J.M., Pelgrum, H., Davids, G., and Allen, R.G. (2005). SEBAL Model with Remotely Sensed Data to Improve Water Resources Management Under Actual Field Conditions. Journal of Irrigation and Drainage Engineering. 131(1), 85-93.

California Department of Water Resources (DWR). (2005a). California Water Plan Update. Volume 3: Regional Reports. Sacramento, California

California Department of Water Resources (DWR). (2005b). Description of CIMIS PM Equation. wwwcimis.water.ca.gov/cimis/infoEToCimisEquation.jsp.

Cassel S., Florence. (2006). Final Report: Remote Sensing of Evapotranspiration for Verification of Regulated Deficit Irrigation. Project #04FG203069. United States Bureau of Reclamation.

Choudhury, B.J., Ahmed, N.U., Idso, S.B., Reginato, R.J., and Daughtry, C.S.T. (1994). Relations Between Evaporation Coefficients and Vegetation Indices Studied by Model Simulations. Remote Sensing of Environment. 50, 1-17.

Consoli, S., O'Connell, N., and Snyder, R. (2006). Estimation of Evapotranspiration of Different-Sized Navel-Orange Tree Orchards Using Energy Balance. Journal of Irrigation and Drainage Engineering. 132(1), 2-20.

Doorenbos, J. and Pruitt, W.O. (1977). Crop Water Requirements. Irrigation and Drainage Paper No. 24, Food and Agriculture Organization of the United Nations. Rome, Italy.

Jensen, M.E., Burman, R.D., and Allen, R.G. (ed.). (1990). Evapotranspiration and Irrigation Water Requirements. ASCE Manual and Report No. 70, American Society of Civil Engineers, New York, New York.

Natural Resources Conservation Service (NRCS). (2006). A Review of Agricultural Water Use in the Coachella Valley. Watershed Planning Services, Natural Resources Conservation Service, US Department of Agriculture. Davis, California.

Pruitt, W.O. and Doorenbos, J. (1977). Proceedings of the International Round Table Conference on Evapotranspiration. Budapest, Hungary.

Snyder, R.L., Lanini, B.J., Shaw, D.A., and Pruitt, W.O. (1989). Using Reference Evapotranspiration (ET_o) and Crop Coefficients to Estimate Crop Evapotranspiration (ET_c) for Trees and Vines. Leaflet No. 21428, Cooperative Extension, University of California. Berkeley, California.

Soppe, R.W., Bastiaanssen, W., Keller, A., Clark, B., Thoreson, B., Eckhardt, J., and Davids, G. (2006). Use of High Resolution Thermal Landsat Data to Estimate Evapotranspiration within the Imperial Irrigation District of Southern California. Oral Presentation. American Geophysical Union 2006 Fall Meeting. San Francisco, California.

Tasumi, M. (2003). Progress in Operational Estimation of Regional Evapotranspiration Using Satellite Imagery. PhD Dissertation, University of Idaho, Moscow, Idaho.

Tasumi, M., Allen, R.G., and Bastiaanssen, W.G.M. (2000). The Theoretical Basis of SEBAL. Idaho Department of Water Resources, Idaho. 46-69.

Tasumi, M., Allen, R.G., Trezza, R., and Wright, J.L. (2005). Satellite-Based Energy Balance to Assess Within-Population Variance of Crop Coefficient Curves. Journal of Irrigation and Drainage Engineering. 131(1), 94-108.