NEW DEVELOPMENTS IN IRRIGATION SCHEDULING

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Background

Although scientific irrigation scheduling techniques have been available for over 30 years, most growers do not use them. Reasons include complexity, time required, and lack of confidence in the predictions. The three primary approaches are soil water monitoring, plant stress monitoring, and weather-based water use predictions. Soil water monitoring is either labor intensive or equipment intensive. Many automatic sensors have been developed and marketed in the last few years, but all have shortcomings. Reliable methods tend to be expensive or labor intensive. Soil water monitoring is tedious as a primary monitoring technique, but valuable as a periodic check on other methods. Plant stress based techniques are poorly developed for most crops, although they may become more useful as remote sensing methods and our understanding of plant stress improve.

Weather-based irrigation scheduling remains the most common and practical method. Direct estimation of water use by a crop using surface energy balance techniques (Bowen Ratio or Eddy Correlation) remain too complex for other than research use. Exciting new surface energy balance methods using remotely sensed information from satellites is being tested. These techniques include SEBAL, METRIC, and RESET, which are all based on the same basic concepts. However, all require thermal infrared data which is not readily available in the frequency or resolution required to schedule irrigations on fields.

The most common method to estimate crop water use and schedule irrigations is through use of reference evapotranspiration, ETo, calculated from local weather parameters, and a crop coefficient, based on crop and stage of growth (Allen et al. 1998). Many irrigated regions in the Central Plains have weather station networks to calculate regional ETo (eg: Colorado Agricultural Meteorological Network (CoAgMet) http://ccc.atmos.colostate.edu/~coagmet/ , High Plains Regional Climate Center network http://www.hprcc.unl.edu/ , and Texas High Plains Evapotranspiration Network http://txhighplainset.tamu.edu/). Several scheduling programs are available to assist users in estimating crop water use from ETo (eg. Wateright http://www.wateright.org/ , KanSched http://www.oznet.ksu.edu/mil/Resources/User%20Guides/KanSchedExcel.pdf Oregon Irrigation Scheduling OnLine http://oiso.bioe.orst.edu/RealtimeIrrigationSchedule/index.htm , and Basic Irrigation Scheduling http://biomet.ucdavis.edu/irrigation_scheduling/bis/BIS.htm).

The weakest link in this weather based approach to predict crop water use and irrigation requirements is the difficulty in reliably estimating the crop coefficient. Crop coefficients are commonly estimated based on days since planting or (occasionally) growing degree days (Allen et al. 1998). A wide variety of irrigated crops are grown under a wide range of conditions, and dependable crop coefficients are not available for many of the crops and growing conditions. This is especially true for horticultural and other specialty crops that are increasingly important in irrigated areas. These crops are often not well studied and include widely varying varieties grown under a wide range of planting densities and cultural practices.

Crop water use is related to the interception of incoming solar radiation and the amount of transpiring leaf surface. Sunlit leaves transpire at a higher rate than shaded leaves. Both leaf area index (LAI) and crop light interception have been related to crop transpiration. Light interception, as represented either by the portion of the ground surface that is shaded or the crop canopy cover, is much easier to measure than LAI. Although light interception varies with the crop canopy structure and the sun angle, several studies have found that mid-day shading, or equivalently, canopy cover measured vertically, provides a good relative representation of crop transpiration (Johnson et al. 2004, Williams and Ayars 2005, Trout and Gartung 2006, Grattan et al. 1998).

Previous studies have shown that various spectral vegetation indices, calculated from visible and near-infrared reflectance data, are linearly related to the amount of photosynthetically active radiation absorbed by plant canopies. Related efforts have tried to estimate crop coefficients in specific crop systems by ground-based and airborne spectral data (Bausch, 1995; Hunsaker et al. 2005; Johnson and Scholasch 2005). Moran et al. (1997) describe the potential and limitations of using satellite imagery for crop management.

Functional relationships between remotely sensed vegetation indices and crop light interception, and light interception and basal crop coefficient, Kcb, allow efficient estimation of crop water use where reference ETo is available. This could allow estimation of crop water use in near real time for individual fields on a regional scale. Such a process was proposed in the DEMETER project in southern Europe (Calera-Belmonte et al. 2003). In this paper, I present preliminary relationships between vegetation indices, light interception, and Kcb developed from data collected in the San Joaquin Valley on horticultural crops, and propose a possible structure for an irrigation scheduling system based on remotely-sensed vegetation indices and ETo.

VEGETATION INDEX vs. CANOPY COVER

On July 1, 2005, and June 19-20, 2006, canopy cover, CC, of 12 high value crops (watermelon, cantaloupe, pepper, bean, tomato, lettuce, onion, garlic, cotton, pistachio, almond, grape) in various stages of growth was measured on 33 fields on the west side of the San Joaquin Valley in California. Most fields were drip irrigated and essentially weed free with a dry soil surface. These fields were selected to represent a wide range of major SJV perennial and annual horticultural crops with widely varying canopy cover. Fields were selected that had uniform cropping patterns. Most fields were at least 200 m in the smallest dimension. Details of this study are given in Trout et al. (2008).

Canopy cover was measured with a TetraCam®[1] ADC multispectral camera suspended from a frame directly above the crop and aimed vertically downward. The camera was designed for capture of red, green and near-infrared wavelengths of reflected light. The photos were analyzed to determine the percentage of the photo area that contained live vegetation. Landsat 5 satellite images of the study area for July 1, 2005 and June 18, 2006 were acquired from the U.S. Geological Survey Landsat Project (http://landsat.usgs.gov/gallery/). On both days there were no clouds over the study area. The Landsat red and near infrared (NIR) data were converted to surface reflectance (SR) and used to calculate the normalized difference vegetation index, NDVI (Tucker, 1979) as:

$$NDVI = (SR_{NIR} - SR_{red}) / (SR_{NIR} + SR_{red}) \qquad (1)$$

for each Landsat image pixel (100 x 100 ft).

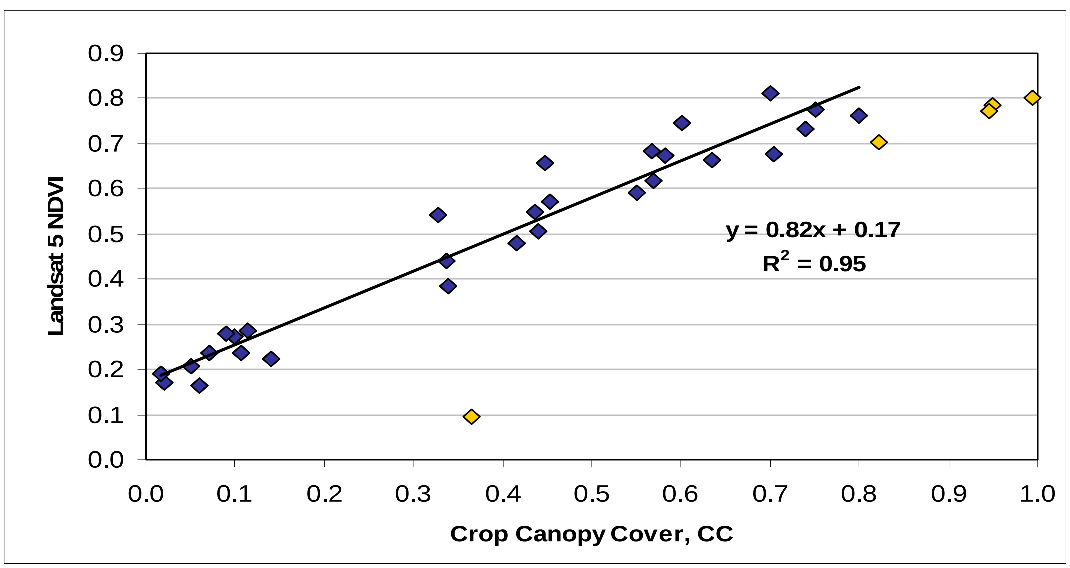

Figure 1. Relationship between Landsat NDVI and Camera Canopy Cover, CC, and the linear regression line for the data represented by blue diamonds.

[1] Reference to specific equipment and brand names are for the benefit of the reader and do not imply endorsement of the product by USDA

Figure 1 shows the relationship between NDVI and CC. NDVI increased linearly with CC to about 0.8, but did not increase further with increasing CC. This finding agrees with past work showing that NDVI levels off at high vegetation biomass. One field of dark red lettuce had a very low NVDI (= 0.1) in comparison to CC and was excluded as an outlier.

For the remaining 28 fields containing 12 different crops, NDVI correlated well with CC (R^2=0.95). The intercept value (0.17) represents the NDVI value for bare soil in the area. These results confirm that NDVI can be a good indicator of crop canopy cover for a wide range of crops with large differences in canopy structure and cover. The linear relationship is valid up to a CC of 0.8. For most crops, water use does not increase for canopy cover above 0.8, so this limitation does not impact estimates of crop water use.

We also estimated CC for each field using measurements of canopy widths or crown diameters and estimates of percent shade within the canopy. Our estimates were consistent (R^2 = 0.93) but tended to be about 10% lower than that measured with the camera. This indicates that visual measurements can provide useful estimates when NDVI measurements are not available.

CANOPY COVER vs. BASAL CROP COEFFICIENT

The USDA-ARS Water Management Research Unit in Fresno, CA uses weighing lysimeters to develop crop coefficients for horticultural crops. Past lysimeter research has shown that the basal crop coefficient for grape vines and fruit trees are closely related to mid-day light interception (Johnson et al., 2000, Williams and Ayars, 2005). Current research is determining the relationship between light interception and basal crop coefficient for annual vegetable crops. The objective is to develop relationships between light interception, represented by canopy cover, and basal crop coefficient. Results from lettuce, bell pepper, and garlic crops were presented by Trout and Gartung (2006) and are summarized here.

Canopy cover was measured several times throughout the growing season by the same camera technique described above. The crop coefficient was calculated as the ratio of the daily crop water use from the lysimeter to ETo (grass reference) measured by the CIMIS weather station #2 (CDWR 2006) located on an adjacent grass field. The crops were sub-surface drip irrigated and only data from days with a dry soil surface were used so that soil surface evaporation was very small and the calculated crop coefficient represented the basal crop coefficient, Kcb. Figure 2 shows the daily crop coefficient and measured canopy cover for the bell pepper crop. The early season Kc spikes result from sprinkler irrigations under low plant cover and illustrate the effects of soil surface evaporation. The late Kc decline results from termination of irrigation on day of year 226 and plant stress due to declining soil water content.

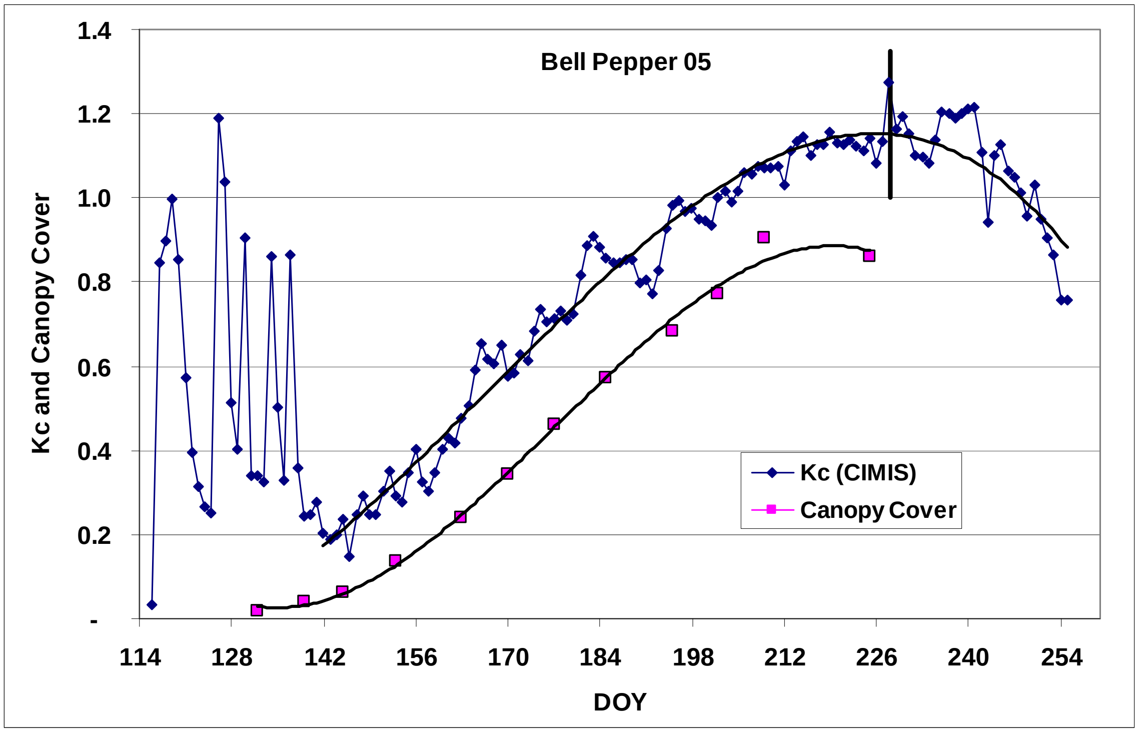

Figure 2. Daily crop coefficient, Kc, and canopy cover for a bell pepper crop grown on a weighing lysimeter on the west side of the San Joaquin Valley, CA in 2005. Peppers were transplanted on day of year (DOY) 115, five sprinkler irrigations were applied before DOY 140, and irrigation was terminated on DOY 226.

Figure 3 shows the relationship between Kcb and CC for the three crops. The lettuce and bell pepper crops, although structurally very different, followed the same linear relationship with an intercept of 0.14 and slope of 1.13 and a very high correlation coefficient. The garlic crop exhibited a higher intercept but smaller slope than the other two crops. The positive intercept is expected because with a sparse canopy during early growth, actual sunlight interception by the crop substantially exceeds vertical light interception and air movement within the canopy is high, resulting in a higher Kcb to CC ratio. As canopy cover increases, most light is intercepted by the top of the canopy and air movement within the canopy is reduced. Once the canopy approaches maximum cover (about 0.9 for these crops), the ratio should approach 1.0 to 1.2 (based on a grass reference), depending on crop height and roughness (Allen et al., 1998). The garlic crop exhibited unexpectedly high Kcb values, possibly due to its upright but fairly dispersed canopy structure.

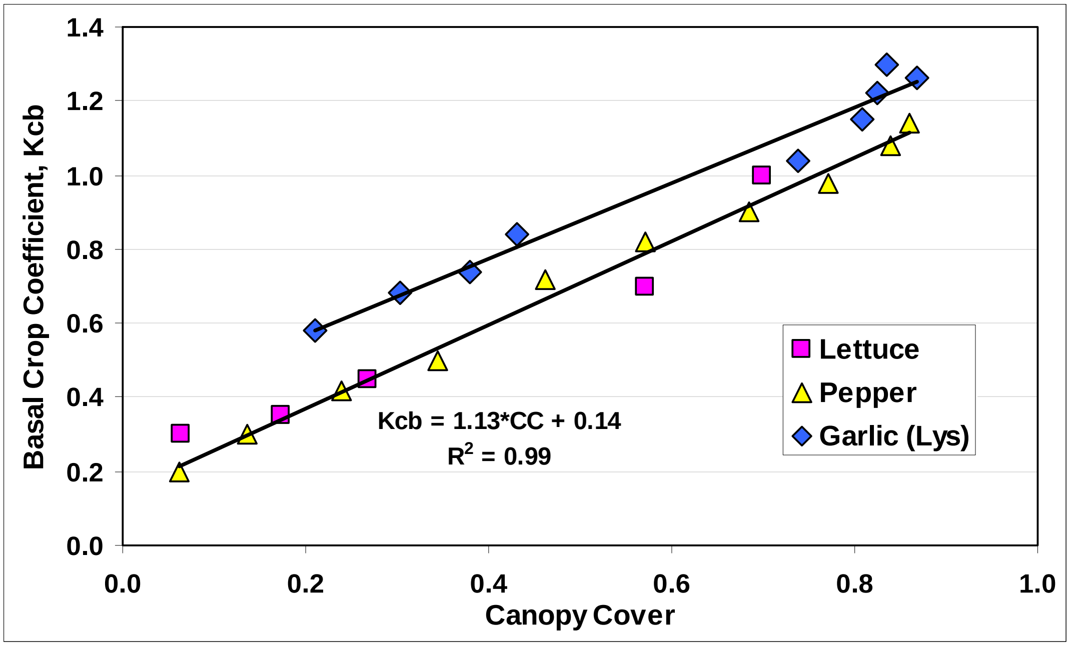

Figure 3. Relationships between basal crop coefficient, Kcb, and canopy cover for three crops grown on a weighing lysimeter on the west side of the San Joaquin Valley, CA. Regression equation is for lettuce and pepper data.

ESTIMATION OF FIELD AND REGIONAL CROP WATER USE

The two above relationships can be used to estimate Kcb from remotely sensed reflectance information.

$$CC = 1.22 * NDVI – 0.21 \qquad (2)\ \text{(from Fig 1)}$$

$$Kcb = 1.13 * CC + 0.14 \qquad (3)\ \text{(from Fig 3)}$$

This process should be carried out in two steps rather than attempting to directly link Kcb to NDVI. The intermediate step allows interpolation and extrapolation of CC between and beyond NDVI measurements, ground truthing of CC estimates, and crop specific Kcb:CC relationships.

Imagery to calculate NDVI will only be available at intermittent times, depending on the source, cost, and weather. For example, Landsat photos are available on 16 day intervals. Curve fitting of CC values or simple crop simulation models can be used to fill in between and extend beyond measured values. For a crop that has been studied previously, a generic CC vs. growing degree day (or days since planting) relationship can be developed and then adjusted using NDVI measurements for the current crop. Many crop simulation models output information on plant growth and phenology that can be converted to CC. Measured NDVI estimates of CC can be used to calibrate the models for the current crop and improve model CC projections into the future. When NDVI measurement intervals are long, visual estimates of CC can be used in place of NDVI-based estimates.

The measurements (Fig. 3) indicate that the Kcb:CC relationships are highly linear, and may be similar for broad crop types. Current data are inadequate to confidently project Kcb:CC relationships for a wide range of crops. Collecting these basic data should be a priority. Lysimetry is the most accurate way to develop this relationship. Surface energy balance measurements can also be used to estimate crop ET (bowen ratio, eddy correlation, SEBAL) and Kcb. Crop simulation models coupled with atmospheric energy balance relationships may be able to generate Kcb:CC relationships if the models have been adequately calibrated with field data.

Daily values of Kcb calculated from measured or interpolated CC values can be converted to Kc values by adding the soil evaporation coefficient, Ke. Soil evaporation can be estimated from irrigation schedule and method, canopy cover, soil type, and ETo (Allen et al 1998, chap. 8). Kc is then used with values for ETo from local weather stations, or interpolated ETo maps (Lehner et al. 2006) to estimate total water use for a field.

Information required to estimate crop water use/requirements includes:

1. Daily canopy cover from NDVI measurements and interpolation models
2. Daily ETo from weather stations
3. Soil type
4. Crop
5. Irrigation method and previous irrigation schedule

The first three items can be generated regionally from satellite or aerial images and ETo and soils databases. The last two can be provided by the farmer or from government or water district surveys. The first, second, and fourth items are required to estimate crop transpiration. The first, second, third, and fifth items are required to estimate soil evaporation, which becomes relatively less important as canopy cover increases. Farmer inputs of crop type, planting date, soil type, and irrigation method are common for irrigation scheduling programs.

When this method is used to generate regional estimates of crop water use, field-specific crop and irrigation method/schedule information will generally not be available. In this case, regional crop surveys may be used to assign the most appropriate Kcb:CC relationships, and regional irrigation methods/patterns used to estimate soil evaporation losses. Where crop information is altogether lacking, a generic Kcb:CC relationship can be assumed.

Figure 4 shows an example of maps of a 200 square kilometer region of San Joaquin Valley fields depicting NDVI, CC, Kcb and crop transpiration values for about 350 fields for July 1, 2005 based on a Landsat 5 image, Eqs. 2 and 3, and a daily ETo for the region on that day of 6 mm. Farmers could use such maps in a GIS framework to identify fields, verify crop canopy cover, and input and store crop and irrigation information for individual fields. The system could then estimate daily crop water use for the field up to the current day, project crop water demand based on historical ETo averages or weather forecasts, and produce maps and tables of cumulative crop water use for a chosen time period. This system would be more accurate than current methods for most crops. Aggregated information such as is shown on the maps, can be used by water suppliers to estimate water demand for individual canals or the whole district. By virtue of large-scale measurements offered by remote sensing and efficient data processing capabilities, such a system could be very efficient and require fewer ground-based measurements, than most current scheduling programs. Instead or providing users with information they would then use to calculate crop water use for their fields, it would provide growers with direct estimates of water use tailored to their crop and field.

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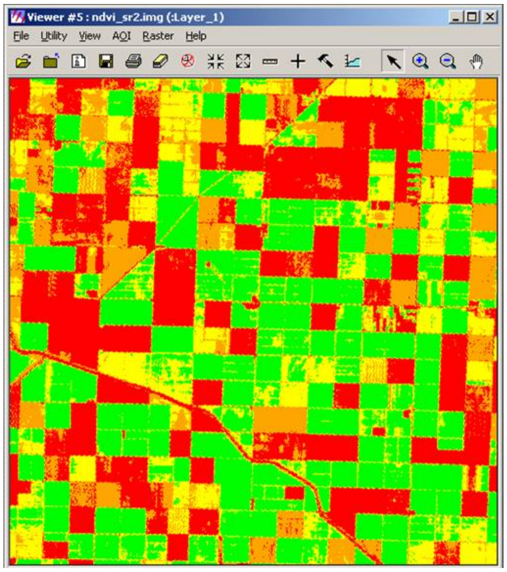
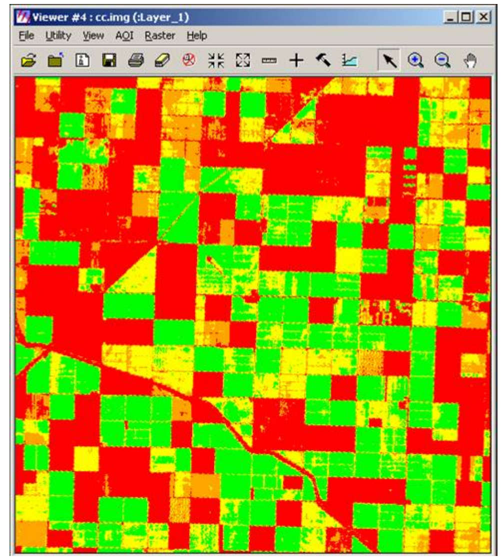
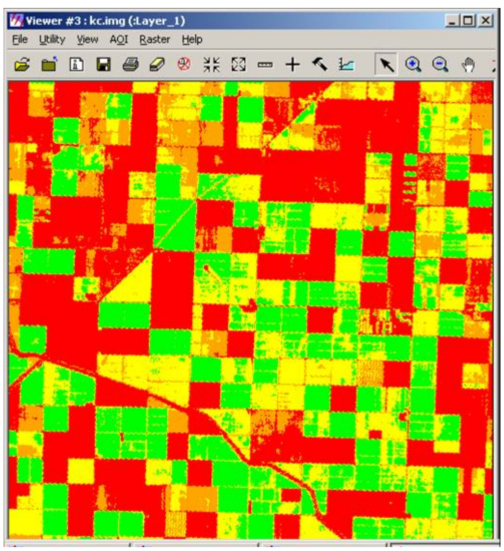


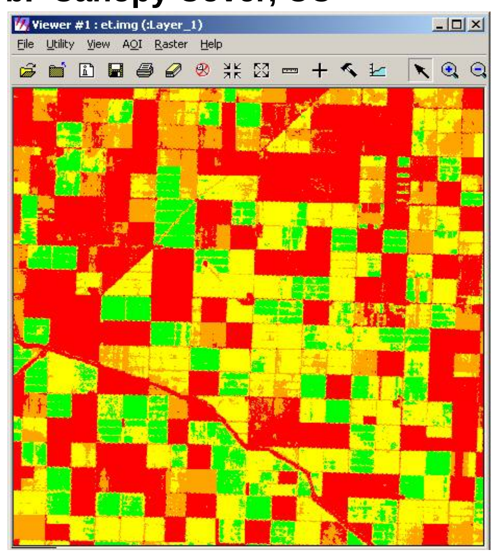
a. NDVI



b. Canopy Cover, CC



c. Kcb



d. Tc

Figure 4. Maps of (a) NDVI from a July 1, 2005 Landsat 5 image, (b) Canopy Cover converted from (a) with Eq. 2, (c) Kcb from Eq 3, and (d) Crop Transpiration for the day based on ETo = 6 mm from the regional CIMIS weather station.

	NDVI, CC	**Kcb**	**Tc *(mm/day)***
	<0.2	<0.3	<2
	0.2-0.4	0.3-0.6	2-4
	0.4-0.6	0.6-0.9	4-6
	>0.6	>0.9	>6

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