Technical Completion Report for USGS 104b Project 2005ID 54B: Evaluation of Remote Sensing of Leaf Area Index for Estimating Evapotranspiration on Irrigated Lands

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INTRODUCTION

Evapotranspiration is a major component of basin water budgets and consequently knowledge of this feature is essential to studies and planning of water management. For example, in the eastern Snake River Plain, estimates of evapotranspiration (ET) were used to represent the consumptive portion of ground water irrigation pumping in calibration of an aquifer model, and in applications of that model to determine effects of pumping upon spring discharge (Cosgrove et al., 2006) . ET estimates are often used in water balance analyses to help determine lesser-known components such as aquifer recharge.

Remote sensing can be a valuable tool in estimating evapotranspiration on large scales due to the high areal variability of ET and the difficulty of obtaining crop-mix data for large areas. In previous work, algorithms such as METRIC (Allen et al., in press, a; Allen et al., in press, b) and SEBAL (Bastiaansen et al., 1998) have made use of the thermal band data of satellites such as LANDSAT in energy-balance calculations of ET. However, the continued use of these tools is in jeopardy due to the planned discontinuation of distribution of the thermal band of data from LANDSAT (Allen, 2005 a). Additionally, SEBAL and METRIC require significant expertise and processing time, and rely upon operator selection of "hot" and "cold" pixels.

The purpose of this project was to develop and evaluate alternative means of determining the magnitude and areal distribution of irrigated ET, using visible and near-infrared bands from LANDSAT. The goal of this effort was to identify methods that are:

1. not reliant on thermal-band data
2. low cost
3. easily applied
4. objective and repeatable

The project used the existing Normalized Difference Vegetative Index (NDVI) as a proxy for leaf area index, developed relationships between this index and crop coefficients (e.g. the ratio of ET for a specific crop and field to reference ET), and tested relationships developed by others. Other remote-sensing indices using LANDSAT visible and near-infrared data were also explored.

Some of the relationships developed in this project, as well as one externally-developed relationship, were calibrated to METRIC-estimated crop coefficients for specific locations and periods. All relationships were tested by application to another location and comparison with METRIC estimates of crop coefficient for that location. The cost and time requirement for application were also evaluated to help assess the potential for practical application of the method.

This research indicates that NDVI-based estimates of crop coefficient produce full-season, wide-area results that are within ten percent of the METRIC remote-sensing results, even when prediction equations were derived from different areas. In fact, two of the successful relationships were developed in a different state than the test location, and in a different decade. NDVI-based estimates may be prepared at significantly less cost that METRIC estimates, are independent of thermal-band data and require no operator judgment for selection of "hot" and "cold" pixels. Except for very early in the spring, the temporal distribution of NDVI-based estimates is similar to the METRIC estimates. However, the individual-pixel frequency distribution of NDVI-based estimates does differ from METRIC, and this can translate into spatial effects of practical concern at resolutions finer than a township (six mile by six mile) basis if crop distributions are not uniform.

Part of the findings of this research are reported in an article submitted to the journal <u>Remote Sensing of Environment</u> (Rafn et al., in review). A draft accompanies this report as file "Rafn et al_NDVI_Kc_2007.pdf".

METHODS

The study had three basic phases:

1. Review and calculate various remote-sensing vegetative indices.
2. Develop NDVI/K_c relationships and obtain relationships from the research of others.
3. Test relationships.

<u>Review and calculate indices</u>

Reviewed indices included the Normalized Difference Vegetative Index (NDVI, Payero et al., 2004), Soil Adjusted Vegetative Index (SAVI, Payero et al., 2004), MSAVI (Modified Soil Adjusted Vegetative Index, Payero et al., 2004), Second Derivative indices (Li et al., 1993), and the Band 5/Band 7 ratio (Musick and Pelietier, 1988). The procedures and equations for each of these were obtained from the literature, and applied to digital numbers ("raw" satellite data) and at-satellite reflectance values ("processed" data, obtained from M. Tasumi at U of Idaho Kimberly) for LANDSAT Row 30, Path 39 and Path 40, which cover most of the irrigated agriculture in south east and south central Idaho, respectively. Resulting scatter plots were assessed visually, with some statistical testing of promising candidates.

Develop and obtain NDVI/K_c relationships

Evapotranspiration may be estimated using equation (1) (Allen et al., 1998):

$$ET_{crop} = K_c * ET_{ref} \qquad (1)$$

where ET_{crop} = actual evapotranspiration for a given crop or parcel
K_c = crop coefficient (also known as ETrF)
ET_{ref} = reference ET; a measure of the evaporative power of the atmosphere, calculated from local weather data or derived from pan evaporation or lysimeter measurements.

An alternative is to separate the evaporation and transpiration components in a "dual coefficient" approach (Allen et al., 1998) as shown in equation (2), or as alternately expressed in equation (3):

$$ET_{crop} = (K_{cb} + K_e) * ET_{ref} \qquad (2)$$
$$K_c = K_{cb} + K_e \qquad (3)$$

where K_{cb} = basal crop coefficient
K_e = soil-evaporation coefficient

The goal of this research was to develop methods to predict K_c for use in equation (1). Following the selection of NDVI as the index for further work, three equations for predicting K_c were obtained from other researchers, and additional equations were developed within the project.

One method to construct such equations is to use statistical regression with a set of "known" data. Equation (4) is a prediction equation for K_c developed by M. Tasumi of University of Idaho in Kimberly (Tasumi et al., 2006; Tasumi, 2006) using Ordinary Least Squares (OLS) regression. In developing the equation, Tasumi used the K_c or ETrF values from METRIC ET estimates (developed by Tasumi and others) from Path 40, year 2000 as the "known" values for K_c.

$$K_c = 0.05 + 1.1875 * NDVI \qquad (4)$$

Working in Colorado, Bausch, Neale and others (Bausch and Neale, 1989; Neale et al., 1989) developed equations (5) and (6) for predicting K_{cb} using a physically-based deterministic approach founded on knowledge of the transpiration processes represented by K_{cb}. Using hand-held devices to read reflected radiation, they identified the NDVI for a bare soil and set this value equal to K_{cb} of zero. Then, the NDVI for full-canopy corn was set to an upper-limit K_{cb} value. Intermediate values of NDVI were linearly interpolated between these limits. The equations were developed at different sites, and the difference between them is primarily due to the difference in bare-soil characteristics.

$$K_{cb} = -0.026 + 1.181 * NDVI \quad (5)$$
$$K_{cb} = -0.053 + 1.092 * NDVI \quad (6)$$

In this project, we applied OLS regression to various data sets, using Tasumi's METRIC K_c or ETrF as the "known" value. We also applied non-parametric regressions (Kendall-Theil Robust Line, Line of Organic Concentration) (Helsel and Hirsch, 2002) to some of these same data sets. In addition, following the lead of Neale and others, we used a physically-based approach. However, rather than measure NDVI in the field, we assumed that cutoff values could be extracted from the data; we set the 2nd percentile NDVI equal to K_{cb} = zero and the 98th percentile equal to K_{cb} = 1.10. We acknowledge that this process could be improved by calibrating the cutoff values to METRIC or other "known" data, though we did not do that. We applied this method to several different full- and partial-area, as well as full-season and single-date, data sets. Equation (7) is an example of one such percentile-based equation, obtained by applying the algorithm to full-season data from the entire Path 40 image:

$$K_{cb} = -0.132 + 1.47 * NDVI \quad (7)$$

Testing of relationships

We tested the applicability of equations to geographic regions other than the area of development by using a formal statistical test to compare the slopes of two Kendall-Theil Robust Line equations developed in different areas. This test failed; the slopes, though similar, were statistically different. Because the assumptions of OLS were not met, this type of test could not be applied to OLS equations.

We tested the practical applicability of various equations by comparing full-season, wide-area ET estimates of mean ET depth to the Tasumi METRIC estimates, using a "two one-sided test" procedure (Manly, 2001) to address the statistical difficulties associated with testing whether two methods are equivalent (traditional statistical testing, and the error protections inherent, are designed for testing whether methods or data sets *differ*). The various equations were deemed acceptable if their mean seasonal depth was within 10% of the METRIC depth at the alpha = 0.05 confidence level. In testing the K_{cb} prediction equations, we applied a very simplistic representation of K_e to equation (3) in order to obtain K_c.

Further testing was done by visually comparing histograms and seasonal patterns of K_c predicted by various methods, and by comparing mean depths across various-sized regions using GIS analysis. These spatial and temporal comparisons were made by normalizing all estimates to equal global mean seasonal K_c so that the comparisons only illustrated spatial and temporal characteristics. This implicitly assumes that any of the methods could be refined by calibration to produce an adequate mean result for a given study area.

FINDINGS

Findings include:

1. Literature suggest that the NDVI index is less robust than some other indices to differences in soil color and condition at low vegetation densities (Li et al., 1993); this would affect accuracy of NDVI-based estimates for early and late growth stages.
2. Despite finding (1), the NDVI index was selected over other vegetation indices for this application, due to its resistance to atmospheric effects (Allen, 2006), its more linear relationship to crop coefficient, its ease of applicability and the fact that it is generally recognized and understood.
3. An index based on LANDSAT band 5 and band 7 data, which is designed to be responsive to soil moisture, was added to the NDVI regression equation in an attempt to overcome obstacle (1). However, the improvement in predictive ability (as indicated by the adjusted R^2 statistic) was too small to justify the addition of an additional predictor in the equation.
4. "Digital numbers" (raw satellite data) do not provide consistent results; satellite data must be processed to "reflectance" values prior to calculating vegetation index.
5. NDVI/crop coefficient relationships are of practical use for estimating wide-area, full-season ET depth on irrigated lands.
6. Relationships developed in other areas may be applied to irrigated lands in eastern Idaho.
7. Relationships developed in a given year may be applied to subsequent years.
8. Except for early-spring differences (when NDVI-based estimates do not capture ET from wet, bare soil), the temporal pattern of NDVI-based crop coefficients matches the temporal pattern of METRIC-based crop coefficients.
9. OLS equations (even when applied to a different path than where developed) are practically useful, though the residuals characteristics resulting from applying OLS regression to these data preclude formal testing of hypotheses (Helsel and Hirsch, 2002).
10. The tested physically-based methods, though developed in Colorado on different soils and with corn, during a different decade, are practically useful in eastern Idaho even using simplistic estimates of K_e.
11. Even though the cutoff percentiles were not calibrated, percentile-based equations produced practically useful results. Though not formally tested against METRIC seasonal totals, equations based on summer-time-only data had very similar slope and intercept to equations based on full-season data, as long as a full range of NDVI values were represented in the data.
12. The Kendall-Theil Robust Line equation uses an intercept based on the median rather than the mean (as does OLS). Whenever data have a skewed distribution, the mean and median will differ. With these data, the Robust Line produced estimates of ET depth consistently higher than other methods.
13. The Line of Organic Concentration equation produced overall estimates similar to other methods (except the Kendall-Theil Robust Line).

14. Regressions (OLS or non-parametric) require a full set of "known" data for calibration. The physically-based method requires measurements of the bare soil and full-canopy NDVI. The percentile-based method requires no outside data but relies upon the assumptions used in selecting the cutoff percentiles (or in the data used to calibrate them).
15. Across multiple pixels, the histogram distributions of the various NDVI-based coefficients are visually quite different from one another, as well as from the distribution of METRIC-based coefficients. This raises concerns with spatial distribution of estimated ET, if crop distribution is not uniform throughout a study area or if localized measures of ET are important to the purpose of the estimates. (Note, however, that crop distribution data for non-remote-sensing methods are often only available at a spatial resolution of county- or state-wide averages.)
16. Testing suggests that on irrigated lands in south-central Idaho for water-year 2000, averaging at a county scale appears to generally overcome differences in spatial distribution between methods, but on a township (six miles by six miles) or smaller basis, differences in methods may approach a level of practical concern.
17. It appears that NDVI-based ET estimates can be prepared in approximately 20 person-days for an area represented by two LANDSAT paths, one row, using 16 images per irrigation season. This contrasts with an estimate of 56 person-days to prepare corresponding METRIC ET estimates (Allen, 2005 b). Further, the METRIC estimates require technicians of greater skill and knowledge than do the NDVI-based estimates.

In addition to the article by Rafn and others, which has been submitted to document findings (5) and (6), it is anticipated that other findings will be the subjects of future journal article(s) by Contor and Rafn.

STUDENT INVOLVEMENT

The project provided a summer internship for one undergraduate geology student, and provided a one summer of work experience for a different student in a master's degree program in GIS systems. The first journal article prepared under this project is part of that student's degree requirements and comprises part of the thesis.

FURTHER RESEARCH

The concept of ET encompasses separate physical processes of evaporation and transpiration. Theoretically, the dual-coefficient approach taken by Bausch, Neale and others (Bausch and Neale, 1989; Neale et al., 1989) is more sound than using NDVI to predict combined K_c, because vegetative indices are designed to respond primarily to vegetation. With further research to provide more robust wide-area estimates of K_e, a dual-coefficient approach could improve upon the results presented here.

The percentile-based approach is attractive because it can be performed without a calibration data set, once appropriate cutoff percentiles are determined. Its good performance in this test, despite the fact that the cutoff percentiles were not calibrated, suggests that this method can be made even more useful with further research to refine understanding of the selection of cutoff percentiles.

Another potentially profitable study area would be to continue to explore indices other than NDVI, in order to better reject the soil signal and more consistently represent leaf cover at low densities (Gardner and Blad 1986).

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