Evaluation of a Method for Estimating Irrigated Crop-Evapotranspiration Coefficients from Remotely Sensed Data in Idaho

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Abstract: Hydrologic modeling and agricultural water consumption analyses typically require some estimation of expected evapotranspiration (ET) from any given land cover or crop type. The main parameter used to make such estimations is the "crop coefficient" (K_c), also known as "reference ET fraction" (ETrF). An efficient remote-sensing methodology to obtain ETrF is mapping evapotranspiration at high resolution and with internalized calibration (METRIC), which requires thermal data, as obtained from the Landsat satellite. Unfortunately, the possibility of future Landsat satellites containing thermal sensors is uncertain, and other satellites' data have access or spatial resolution concerns. Even when thermal-band data are available, energy-balance approaches can be costly. In this paper we continue ongoing efforts by the University of Idaho and others to estimate the evapotranspiration parameter K_c (or K_{cb}) using the more readily available normalized difference vegetation index (NDVI) satellite-derived data product. Results from a case study in Idaho for irrigated agriculture indicate that the NDVI/K_c method has significant potential to estimate K_c because it is a fully objective and repeatable process, is comparably fast, easy, and less costly to apply, and does not require images from the thermal band. Preliminary work suggests that NDVI-based estimates produce results comparable to METRIC estimates over large spatial areas and full-season sample periods, even when the estimation equations were derived from different locations or crop type and management settings. While it is unclear whether empirical methods to derive the K_c product are more robust than either remote-sensing estimation method, this ongoing NDVI/K_c method is studied as an alternative, especially when empirical data are sparse or too costly to obtain, and when the METRIC approach cannot be taken. We find that NDVI-based estimation equations may be practically applied to areas other than the area of development.

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CE Database subject headings: Evapotranspiration; Evaporation; Crops; Coefficient; Remote Sensing; Idaho; Water consumption; Agriculture.

Introduction

This paper presents the research results testing the applicability of crop coefficient (K_c) estimation methods developed in Idaho and Colorado for irrigated agriculture to a study area in Eastern Idaho. Reference evapotranspiration (ET) (ET_{ref}) is primarily "an index of climatic demand" (Allen et al. 1998). K_c=fraction of climatic demand of the atmosphere that is actually used to evaporate and transpire water [Eq. (1)]. It is an "integration of four primary" crop and soil characteristics

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

An alternate approach parses K_c into a component representing crop effects (K_{cb}) and soil effects (K_e) (Allen et al. 1998). Typically, reference ET is estimated using evaporation pans (Stanhill 1965) or meteorologic-data based equations such as Penman-Monteith (Penman 1948; Monteith 1965). Coefficients (K_c, or K_{cb} and K_e) are estimated using lysimeter data (Makkink 1957) or calculated based on empirical or physical-process-based equations (Allen et al. 1998).

State-of-the-art remote-sensing techniques, such as surface energy balance algorithm for land (SEBAL) and mapping evapotranspiration at high resolution and with internalized calibration (METRIC) (Bastiaanssen et al. 1998; Allen et al. 2005) use surface energy balance algorithms and thermal remote-sensing data to estimate ET directly for a given image time and location. ET estimates from the time of the remote-sensing image may be interpolated to estimate ET for between-image time periods. Alternately, the energy-balance estimates may be used to estimate K_c values which are then applied to ET_{ref} estimates calculated from local meteorological data, to obtain intermediate-time ET estimates. The SEBAL and METRIC systems depend upon data acquired from thermal sensors on satellite platforms, but because of the future possibility that Landsat thermal sensor data on satellite platforms will be unavailable there exists motivation for studying alternative methods to estimate ET, such as methods that rely on vegetative indices. Further, energy-balance approaches are time consuming and require specialized software and knowledgeable personnel, making them potentially cost prohibitive for some applications.

Indeed, researchers in Colorado (Bausch and Neale 1989;

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Bausch 1993, 1995; Neale et al. 1989), Idaho (Tasumi et al. 2006), and elsewhere (Gonzalez-Piqueras et al. 2003; Cuesta et al. 2004) have demonstrated that ET for irrigated agriculture can be estimated by applying empirical data to develop a relationship between the normalized difference vegetation index (NDVI) and K_c. Then K_c can be used to parameterize Eq. (1) even if thermal band methods are not available. Choudhury et al. (1994), Montoro et al. (2007), Bausch and Neale (1989), Bausch (1993, 1995), and Neale et al. (1989) have similarly used remote sensing to estimate K_{cb} (note that K_{cb} methods can be transformed to K_c methods by adding an estimate for K_e to K_{cb}).

In this study, we tested previously developed NDVI relationships to estimate K_c for calculating ET in Idaho. NDVI is a commonly used remote-sensing product that provides an indication of the density and robustness of surface vegetation. It is widely used for applications such as land-cover characterization, change detection, or identification of dense, dark vegetation as an initial step to estimate leaf area indices (LAI) (Carlson and Ripley 1997). Other NDVI uses include determining the robustness of agricultural crops (Rouse et al. 1974) and, more recently, in understanding the correlation between the index and the parameter K_c used to estimate ET, as noted above. We were interested in the applicability of estimation equations to areas different from the area of development.

The hypothesis of this paper is that equations used to estimate K_c (and hence ET), developed in South-Central Idaho (P40) and Colorado study areas will be applicable in Eastern Idaho (P39). P39 and P40 are specific Landsat-path swaths that contain Eastern and South-Central Idaho, respectively. To test the hypothesis, a K_c estimation equation was developed for the P39 study area, based upon METRIC estimates. The University of Idaho at Kimberly provided METRIC-derived K_c values for the P39 study area to compare against NDVI-derived K_c values.

The primary hypothesis is that estimation equations developed in adjacent Landsat paths have statistically equivalent slopes. Our secondary hypothesis is that equations used to estimate average total-seasonal ET estimated by applying the P40 and Colorado methods to the P39 study area will be practically useful; that is, they will reasonably approximate the average volume of total-seasonal ET estimated by applying the METRIC method.

Data and Methods

Reference fraction of evapotranspiration (ETrF) and ET maps for this study were made by Masahiro Tasumi from the University of Idaho using the METRIC surface energy balance algorithm (some of these data are presented in Tasumi et al. 2006). The two maps made using METRIC are based upon Landsat thermal band images that vary in resolution between 60 m by 60 m and 120 m by 120 m, Landsat 7, and Landsat 5, respectively. Other data used include visible and near-infrared Landsat images and derivative maps for the study area, including at-satellite reflectance, cloud cover, and NDVI. The maps made using visible and near-infrared images have a resolution of 30 m by 30 m (Tasumi et al. 2006; Allen et al. 2007a,b).

The study area is Eastern Idaho (P39) irrigated lands (see Fig. 1) where major crop types are alfalfa, small grains, potatoes, corn, sugar beets, dry beans, and peas. Typical irrigated fields are larger than the aforementioned resolutions, including the largest Landsat resolution of 120 m. In processing we ensured that each sample point was located near the center of the irrigated field—at least 200 m from the field edge—to avoid edge contamination.

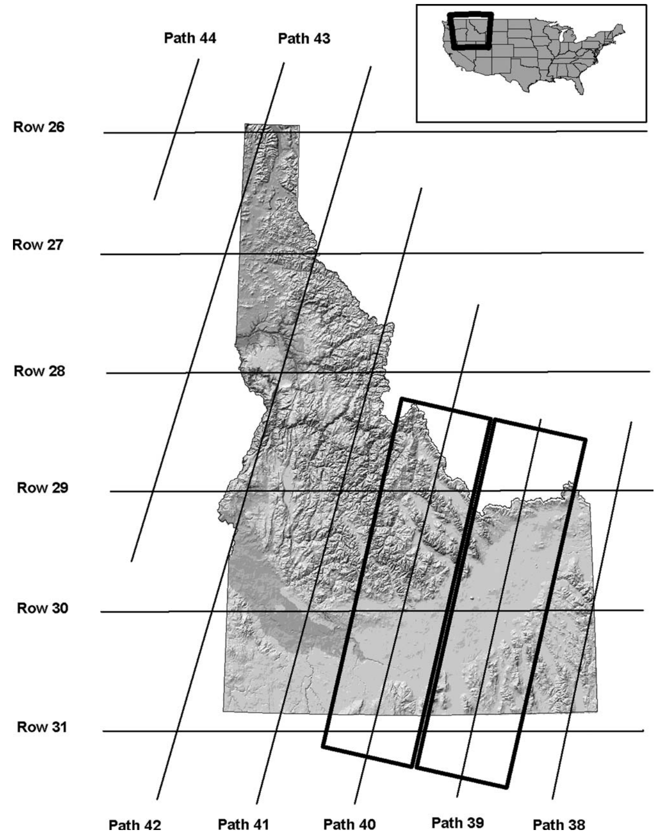

Fig. 1. Idaho Path 39 and Path 40 study areas (Idaho Geospatial Data Clearinghouse 2004) (1201, color shaded relief of Idaho with a horizontal grid spacing of 10 m: Idaho Geospatial Data Clearinghouse, Moscow, Idaho, United States, with permission)

Twelve Landsat images from March 16 to October 18, 2000 (March 16, April 1, May 3, June 4, June 20, July 6, July 22, August 7, August 23, September 8, September 16, and October 18) were used to develop NDVI maps by applying standard techniques (e.g., as presented in Rouse et al. 1974). The study used 9,385 sample points that overlaid irrigated agricultural fields within the P39 study area.

To test our hypothesis, we examined the statistical and practical significance of P40 and Colorado K_c estimation equations by applying them to the P39 Idaho study area. A K_c estimation equation developed for P40 Idaho by Tasumi et al. (2006) [Eq. (2)] was evaluated for its applicability in our study area (P39)

$$K_c = 1.1875 * \text{NDVI} + 0.05 \quad (2)$$

The Tasumi et al. (2006) equation, Eq. (2), was developed by applying ordinary least-squares (OLS) regression to observed (METRIC) K_c and computed NDVI data. However, this equation cannot be tested statistically for equivalence to an OLS equation developed in our study area, because it violates the constant-variance assumption (Helsel and Hirsch 2002). The nonconstant variance causes the unusual appearance in Fig. 2, where the distribution of outliers falsely gives the residual (predicted minus known) chart an appearance of nonzero slope. The actual slope of residuals is masked because one cannot see the high density of points near the horizontal axis, where large masses of points cluster about a line of zero slope. (Note that NDVI, which is a normalized index based on ratios of spectral-band intensities, does occasionally take on negative values. This can produce calculated

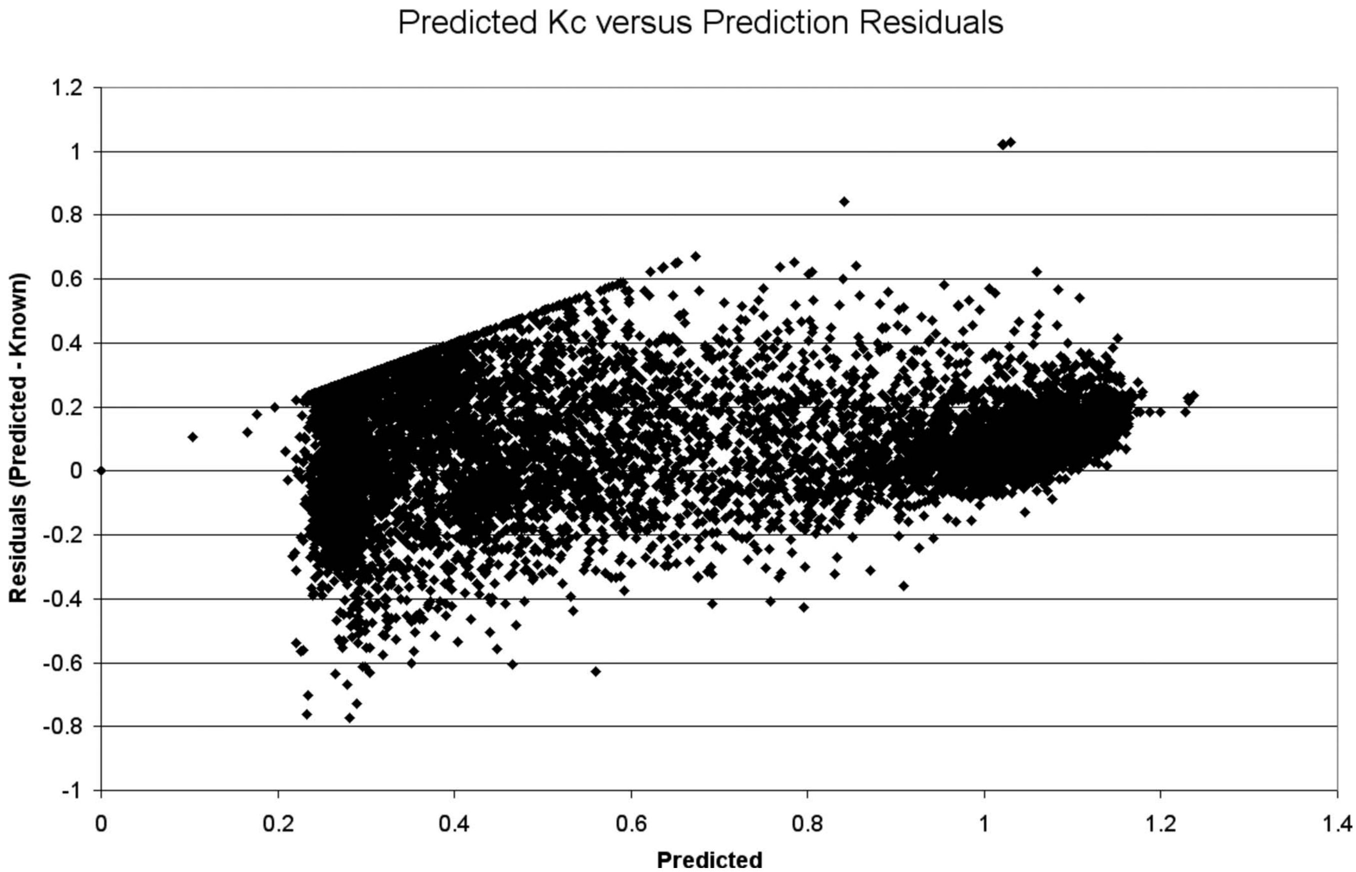

Fig. 2. Residuals (predicted—ETrF) versus predicted for Path 40 equation applied to Path 39 data

negative K_c values, which of course have no physical meaning.) The key content of Fig. 2 is that since the residuals do not show constant variance, we cannot statistically compare Eq. (2) to another least-squares regression equation. However, some nonparametric methods may be formally tested even when residuals do not show constant variance. The Kendall–Theil robust line regression used here is a nonparametric method used in water-resource studies when the sample data do not meet this assumption of the OLS regression (Helsel and Hirsch 2002).

The Kendall–Theil robust regression test uses the median of the pairwise slopes to estimate the regression slope. This nonparametric method was applied to data from both P40 and P39. The estimated slopes were formally tested to see if they were statistically different. Essentially, the test consisted of calculating 95% confidence intervals about the slopes of the robust line estimates. If the 95% confidence intervals do not overlap, the slopes are shown to differ; if the intervals overlap, they are not shown to differ. Eq. (3) was derived from the same data used to derive the OLS equation for P40 Idaho [Eq. (2)], using the Kendall–Theil nonparametric technique

$$K_c = 1.1507 * \mathrm{NDVI} + 0.1167 \qquad (3)$$

A second regression was developed for the P39 Idaho study area, also using the Kendall–Theil technique [Eq. (4)]. In both cases, METRIC K_c estimates were used as the known values to derive the regression equations

$$K_c = 1.063 * \mathrm{NDVI} + 0.29 \qquad (4)$$

Eqs. (3) and (4) were then statistically compared, to test the hypothesis that equations from different spatial regions are statistically equivalent. This was done by comparing 95% confidence intervals for the slopes of Eqs. (3) and (4), as described above.

To evaluate the second hypothesis, we tested whether equations developed in P40 and two additional study areas in Colorado are applicable from a practical point of view in our study area (P39). This was done by comparing total evaporation predictions using each of the test equations applied to our study area. The comparisons were based on NDVI maps (and hence ET calculations) from March through October 2000. A two one sided test was applied to the practical test, following an approach similar to that described by Manly (2001). This approach was adopted because standard statistical tests protect against a Type I error, which would declare a difference when none existed. In this case, where the assertion being tested is that two methods or treatments are equivalent, the relevant error to protect against is the Type II error, which would be to fail to find a difference when one exists (Ott 1993; Helsel and Hirsch 2002). The two one sided test is specifically designed to protect against Type II errors. To apply the test, one sets practical limits about a target value (in our case, the METRIC estimates). If the tested value is simultaneously shown to be less than the upper limit and greater than the lower limit, it can be declared to lie within the established limits, at the confidence level of the statistical tests.

Results and Discussion

Statistical Analysis Results

We formally conclude that the equations are statistically not equivalent. As shown in Fig. 3, the slopes of the Kendall–Theil

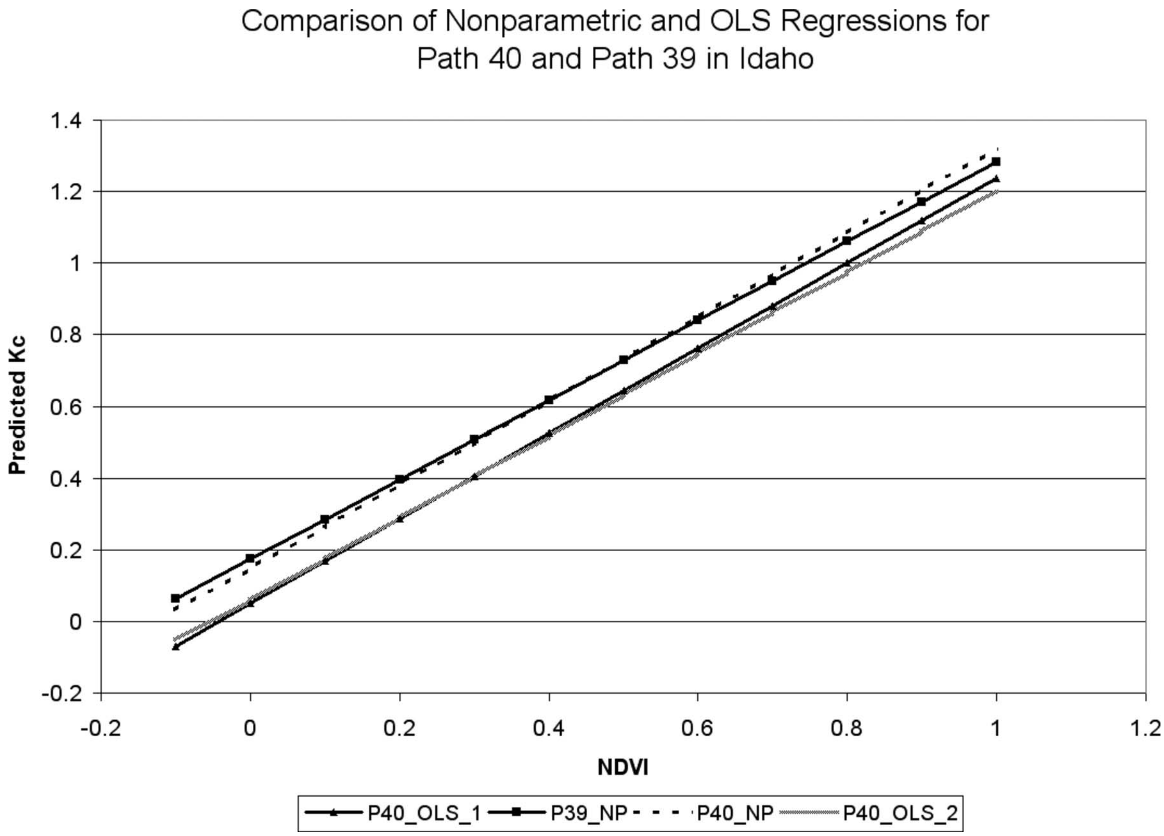

Fig. 3. Comparison of nonparametric and ordinary least-square regressions that use NDVI to predict crop coefficient (K_c)

robust line regressions developed for P39 and P40 are similar. However, the nonparametric confidence intervals for the slopes did not overlap at $\alpha=0.05$ (95% confidence interval), indicating that the slopes are significantly different. Because the equations are not statistically equivalent, one cannot assert unequivocally that NDVI/K_c equations for any particular study area may be applied in other areas. The P40 and P39 study areas are both located in steppe vegetation, arid environments in the Snake River Plain (SRP), but in regions of different elevation and seasonal temperature regime. Our statistical analysis results likely reflect differences in crop mix and slight variations in climatic conditions across the SRP. Soil and other geologic conditions also vary across the SRP, potentially adding to the discrepancies between the NDVI/K_c equations generated in P40 and P39.

Practical Analysis Results

The purpose of the practical analysis was to determine if the P40 equation, as well as NDVI/K_c equations derived in two Colorado study areas, are useful from a practical point of view in the P39 region of Idaho. While the nonparametric equations allowed formal statistical testing and the OLS equations did not, Fig. 3 shows that the slopes of the OLS and nonparametric equations are visually similar. Though the violation of assumptions affected the testability of OLS equations, they still may be used for prediction (Helsel and Hirsch 2002). Further, OLS regressions have the characteristic that the derivation of the intercept causes the regression line to pass through the mean of the data, while the Kendal–Theil robust line passes through the median. Fig. 3 shows that this causes an offset (because the data do not have a symmetrical distribution), and for prediction of total depth of ET the OLS assumption is preferable. OLS is also desirable because its regressions are more easily made and more broadly understood, and one of the goals of the project is to confirm simply applied methods for future practical application. Therefore, while we resorted to a nonparametric method for formal testing of the first hypothesis, we returned to the OLS equations for the second (practical) test.

In considering the practical impact of differences in equations, one must consider that many uses of ET estimates focus primarily on total seasonal volume of consumptive use of water, or maximum daily consumptive use during a season. For these purposes, midseason estimates, when ET is highest, are most important. Consequently, we examined the pattern of differences between two OLS equations (one developed in P39 and one developed in P40) across the expected range of NDVI values, as shown in Fig. 3. The smallest differences between the two equations occur at higher values of NDVI. Fig. 4 illustrates that these higher NDVI values, where differences between the two OLS equations are smallest, are associated with the midsummer period when the majority of annual ET occurs. This mitigates the larger differences that appear at low NDVI values. If one considers the use of K_c in Eq. (1), the ET value for a given date will depend both on K_c and on ET_{ref}. Early and late in the season, ET_{ref} is low and the contribution of ET from those dates to full season ET is proportionally smaller than ET from midseason dates. During the more important midseason, high-ET periods, differences between the two NDVI equations are smallest. Fig. 5 illustrates that the majority of the NDVI values for the important midseason dates are in Bins 0.3 and greater, where percentage differences between the two equations are smallest.

Figs. 4 and 5 and the previous discussion outline a qualitative basis for considering the two equations to be practically equivalent. To more objectively test the second hypothesis, we estab-

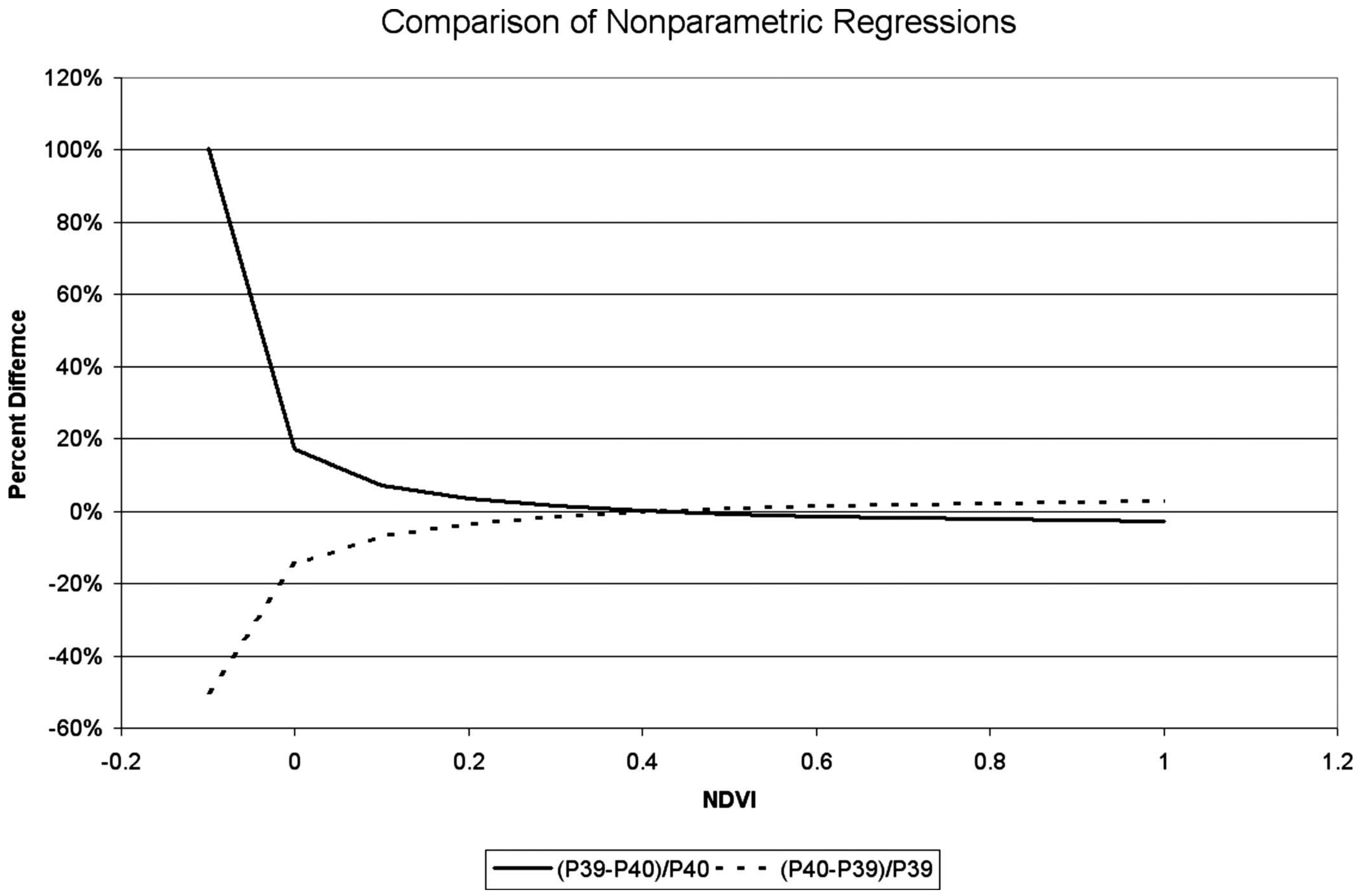

Fig. 4. Percent difference between equations developed for South-Central Idaho (P40) and Eastern Idaho (P39) plotted against NDVI

lished test limits about the METRIC-estimated seasonal ET totals for the two one sided test. For practical purposes, given the level of uncertainty of other data typically in use (e.g., land-cover data derived by remote sensing, reports of water diversion or extraction volumes, and flows in surface-water channels), we determined that equations would be deemed "useful" if the equation produced an annual mean depth of ET for the study area within 10% of the METRIC-estimated ET depth. That is, if ET discrepancies were no greater than 10%, the range of error for calculated ET values would be similar to uncertainties for other components of typical project water budgets. Fig. 6 represents a comparison of a satellite derived K_c equation (P40 of Idaho) and physically based K_c equations (two sites in Colorado). The Colorado equations were developed using in situ field observation with a field spectrometer (multispectral imaging unit) to set the range of NDVI values that corresponds to full cover and bare soil (Neale et al. 1989). The prediction Eqs. (5) and (6) linearly interpolate K_c between the K_c values associated with these two extremes of canopy cover

$$K_{cb} = 1.181^{*}\text{NDVI} - 0.026 \quad (5)$$

$$K_{cb} = 1.092^{*}\text{NDVI} - 0.053 \quad (6)$$

Using the two one sided test procedure described in the "Methods" section, the Tasumi OLS equation from P40 in Idaho [Eq. (2)] and the two equations developed in Colorado [Eqs. (5) and (6); Neale et al. (1989)] were tested [K_c values for comparison were obtained by adding estimates of K_e to the K_{cb} values derived from Eqs. (5) and (6)]. All the tested equations were deemed practically useful for the irrigated lands in P39. Using the two one sided test, the predicted values were formally found to be within 10% of the METRIC energy-balance estimates at the 95% confidence level.

Discussion

Equations developed in the P40 area of Idaho and in the Colorado study areas estimating average total seasonal ET using NDVI are useful in the P39 area of Idaho, even though these study areas are inherently different. This success in applying an equation developed in an adjacent area in Idaho, as well as equations developed in two different areas of Colorado, indicates that NDVI-based algorithms can have broad spatial applicability. Work by Tasumi et al. (2006) indicates that NDVI equations based on 1989 data gave good results in the same location in Idaho when applied to Year 2000 data, suggesting that NDVI-based algorithms can also have broad temporal applicability. Because the P40 Idaho equation was found to be practically useful in the P39 region, despite differences in the areas themselves, this suggests that the K_c estimation equation for P40 Idaho should be robust to other varying conditions. Because the P40 Idaho K_c and Colorado estimation equations are useful for the P39 study area, we find that a single equation can have broad geographical application. Though Cuesta et al. (2004) found differences in behavior of NDVI-predicted K_c depending on the full-development cover characteristics of indi-

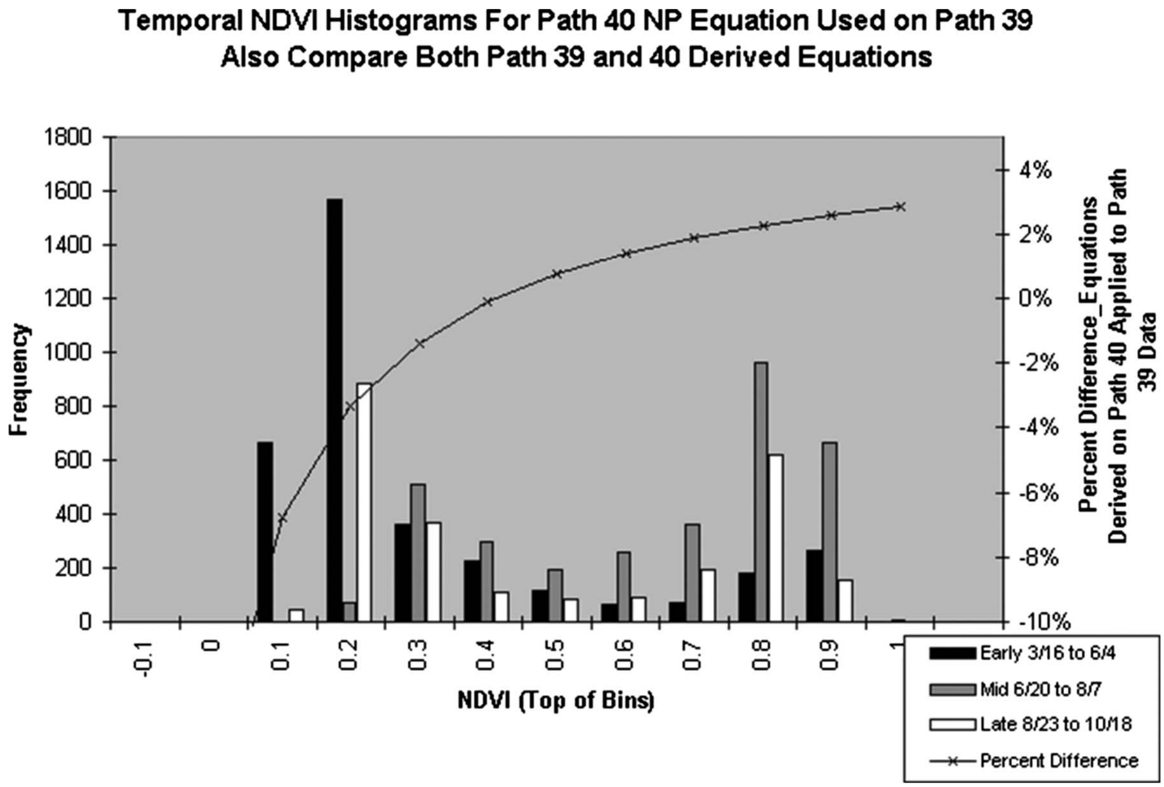

Fig. 5. Histogram of early, mid-, and late season NDVI values. This plot also shows percent difference between models derived on Path 40 and Path 39.

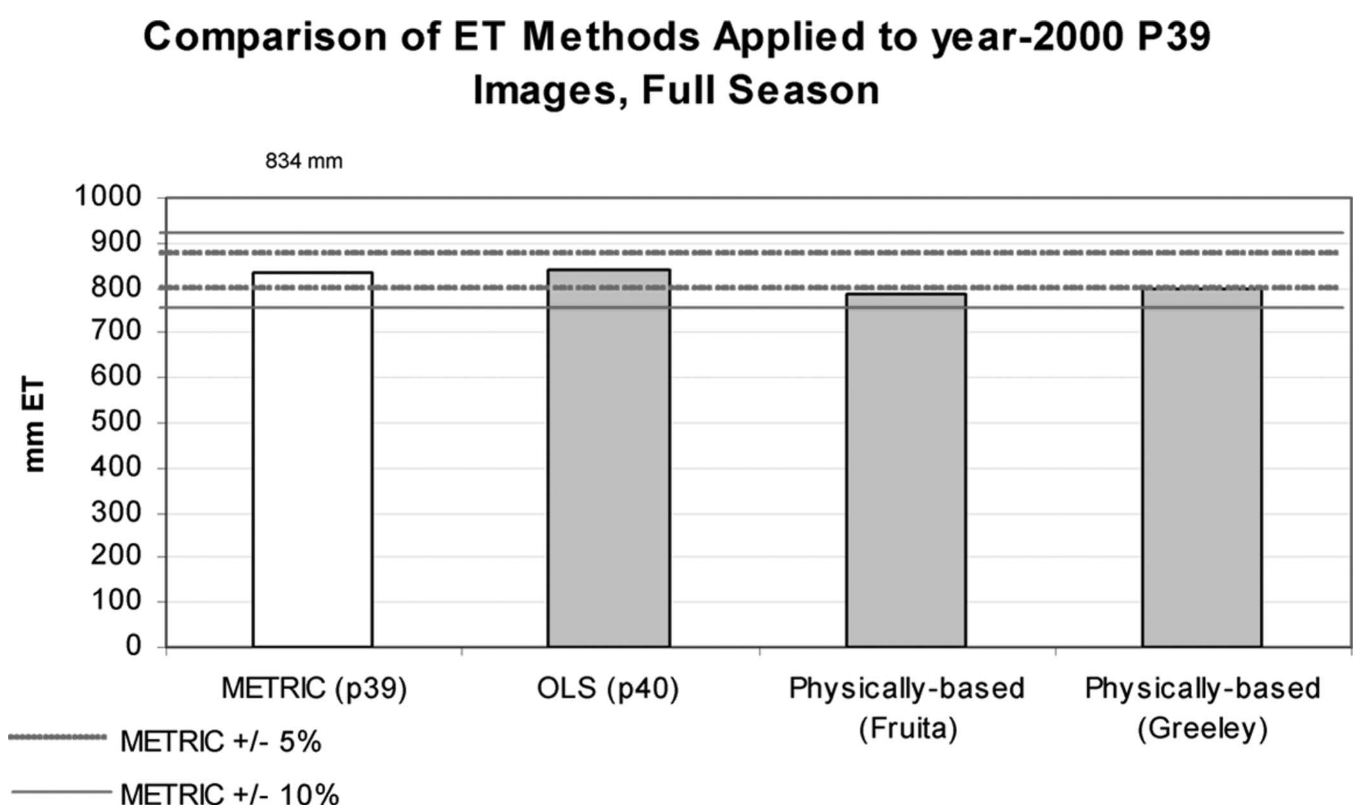

Fig. 6. Comparison of METRIC full-season ET estimation for study area with three ET estimation equations (NDVI derived K_c) derived in Path 40 (P40) and Fruita and Greeley, CO

vidual crops, our work indicates that a single equation can produce practically useful results over a wide area with mixed crops.

Conclusions and Future Work

We find that NDVI/K_c relationships developed in P40 of Idaho and in Colorado are shown to be practically useful for irrigated lands in the P39 region of Idaho; they give annual mean ET depths within 10% of the remote-sensing METRIC depths at the 95% confidence level ($\alpha = 0.05$). This indicates that such equations may be broadly applied without requiring costly recalibration of the method for each region of application. Other work (Tasumi et al. 2006) similarly suggests that these types of equations are applicable over time periods of at least a few years. However, we do conclude that NDVI-derived K_c equations developed in the P40 and P39 areas of Idaho are formally statistically different. Contributions to this result may include differences in crop mix, irrigation management, topography, soil, and climate.

We further conclude that NDVI/K_c approaches will be useful for irrigators, water model users, and water managers who need a K_c estimate when Landsat thermal sensors are unavailable or when costs preclude the use of energy-balance methods. This approach is relatively fast, easy, and requires little knowledge of evaporation physics and aerodynamics.

Suggested further work includes additional testing to verify these conclusions by applying the equations to other geographic regions, or testing other equations in the P39 area of Idaho. Additionally, one could apply the P40 equation to different spatial locations with similar climate and agriculture types, such as Wyoming, Utah, Eastern Oregon and Washington, New Mexico, and California to estimate total seasonal ET.

The NDVI index was selected for this work because of its mathematical robustness to atmospheric effects upon remotely sensed reflectances (R. G. Allen, personal communication 2005), but other indices may be more robust to the influence of variations in reflectance from soil surfaces (Bausch 1993 and Gonzalez-Piqueras et al. 2003); therefore, further work could include evaluation of other remote-sensing indices. Finally, one could test equations which use remotely sensed vegetative indices to predict basal K_c (K_{cb}), such as those developed by Choudhury et al. (1994), Montoro et al. (2007), or the Colorado equations tested here, for wide-area and multiseason applicability. Then, with knowledge of soils, application methods, and agricultural practices one could independently estimate evaporation from the soil (K_e) and use the vegetative index to estimate only evapotranspiration (K_{cb}, or in Choudhury's notion, T_c). Knowledge of crop type would be required to obtain the target K_{cb} data for method calibration, but the goal would be to develop methodology that could be applied without knowledge of crop type.

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