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Evaluation of a hybrid remote sensing evapotranspiration model for variable rate irrigation management

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Abstract. *Accurate generation of spatial irrigation prescriptions is essential for implementation and evaluation of variable rate irrigation (VRI) technology. A hybrid remote sensing evapotranspiration (ET) model was evaluated for use in developing irrigation prescriptions for a VRI center pivot. The model is a combination of a two-source energy balance model and a reflectance based crop coefficient water balance model. Spatial ET and soil water depletion were modeled for a 10 km^2 area consisting of rainfed and irrigated maize fields in eastern Nebraska for 2013. Multispectral images from Landsat 8 Operational Land Imager and Thermal Infrared Sensor were used as model input. Modeled net radiation and soil heat fluxes compared well with measurements from eddy covariance systems located within three fields in the study area. Modeled sensible heat flux did not compare well. Latent heat flux compared well for the only mid-summer image, but poorly for the one spring and two fall images. The water balance ET compared well with the two-source energy balance ET for irrigated maize, but not for dryland maize. Image frequency is thought to be a contributing factor in the poor performance of the water balance. In 2015 the hybrid model will be used to generate irrigation prescription maps for a VRI system located in the study area based on modeled soil moisture depletion. Future research will focus on model parameterization and utilize aerial imagery and satellite imagery from other sensors for improved image frequency. Note: this is a revision of the original paper correcting erroneous data where one of the flux sites was mistakenly analyzed as soybeans, when it was actually maize. Mean biased error signs have also been corrected.*

Keywords. remote sensing, evapotranspiration, models, irrigation scheduling, center pivot irrigation

Introduction

Variable Rate Irrigation Management

Site-specific or variable rate irrigation (VRI) technology is a management tool that has been shown to have potential in optimizing the beneficial use of irrigation water (King et al. 1995). The assumption of VRI technologies is that irrigation requirements may vary spatially within a given field. The premise of the technology is that site-specific management of water for individual subareas (or zones) in a field would be beneficial. Several center pivot manufacturers now offer VRI options for site-specific water management within a field (Evans et al. 2013, Kranz et al. 2012). Evans et al. (2013) have shown that adoption of these technologies by producers has been slow. They linked the slow adoption rate, in part, with a need to quantify economic and other benefits of VRI technology. Evans and King (2012) and Evans et al. (2013) discussed the need to develop technologies to inform VRI water management schemes (commonly referred to as VRI prescriptions).

Prescription development is an active area of research relating to VRI technology (e.g. Evans and King 2012, Evans et al. 2013, McCarthy, Hancock, and Raine 2014b, Hedley and Yule 2009a). Much of the research to date has focused on tailoring irrigation based on soil spatial variability (e.g. Hedley et al. 2009). Hedley and Yule Hedley and Yule (2009a), Hedley and Yule (2009b), and Hedley et al. (2009) related apparent soil electrical conductivity (EC_a) to available water holding capacity (AWHC). They generated AWHC management zones based on EC_a maps. They were then able to run a simulated water balance separately for each zone, using uniform precipitation and evapotranspiration (ET). One advantage of this approach is an increased ability to obtain the maximum benefit from rainfall as compared with irrigating an entire field based on a soil with relatively low AWHC.

Hedley et al. (2013) improved on some of the earlier models by combining EC_a and terrain maps coupled with nine soil moisture sensor locations to show that they could make a model (using these inputs) to develop VRI prescriptions. They plan to validate the procedure in future years. McCarthy, Hancock, and Raine (2014b) used a more complicated model by coupling a crop development model with the soil water balance to provide optimized VRI management based on various objectives. These objectives included maximum yield, maximum water use efficiency, maximum net return, etc. They found that their irrigation management model when coupled with a predictive crop model performed better than when informed via soil and crop status sensors (McCarthy, Hancock, and Raine 2014a). In both cases the analysis was purely model based.

Hillyer and Higgins (2014) used a deficit irrigation optimization model to develop prescription maps for deficit irrigation with VRI. They generated management zones by grouping soils by field capacity (FC) and AWHC. Their assumption was that soils with similar FC and AWHC will have similar soil water depletion (assuming all else to be equal). They used a Monte Carlo approach to generate depletion for each zone. Their preliminary results suggested a net water and energy savings after applying four consecutive prescriptions on a study field near the end of the growing season in 2013.

Many of the models for developing VRI prescriptions currently in the literature focus on variability in soil properties, in particular AWHC. However, other pertinent properties are also variable within some fields, including topography, nutrient concentrations, plant density, etc. These and other parameters can be difficult to quantify, but all may affect crop health and subsequently ET. While most existing prescription models rely on uniform estimates of ET, it is apparent that accurate spatial estimates of ET can help improve VRI management (Sadler et al. 2005).

Remote Sensing for Variable Rate Irrigation Management

Remote sensing is a tool to estimate ET spatially. King et al. (1995) identified remote sensing as a technology that could aid in VRI management. Multispectral remote sensing imagery has been successfully implemented to estimate ET at varying spatial scales (e.g. Bausch and Neale 1987, Bastiaanssen et al. 1998, Allen, Tasumi, and Trezza 2007, Hunsaker et al. 2005, Neale et al. 2012). Two common classes of remote sensing ET estimation methods are energy balance (EB) and reflectance based crop coefficient (K_{cbrf}) methods.

Energy balance techniques use multispectral imagery to estimate available energy and sensible heat flux. Latent heat flux is typically found as the residual balance between the two. Bastiaanssen et al. (1998) developed a method of estimating these energy fluxes. Allen, Tasumi, and Trezza (2007) suggested some modifications to the Bastiaanssen et al. (1998) approach. In both methods assumptions are made with regard to sensible and latent heat fluxes in image pixels of known ground cover. Such methods require certain skill by the user in properly selecting the necessary reference pixels. A benefit is that these methods do not require the rigorous atmospheric corrections of other methods (Allen, Tasumi, and Trezza 2007).

One alternative EB method is the two-source energy balance method (TSEB) such as that proposed by Norman,

Kustas, and Humes (1995). This method differs from those of Bastiaanssen et al. (1998) and Allen, Tasumi, and Trezza (2007) in that it considers the soil and plant surfaces separately rather than as a combined surface, hence two sources. The TSEB does require relatively rigorous atmospheric corrections to input imagery (Neale et al. 2012), as compared to the other two methods discussed above. The TSEB has been successfully adapted for sparse canopies by Kustas and Norman (2000). Colaizzi et al. (2012) found a version of the TSEB compared well with ET measured using a weighing lysimeter.

The K_{cbrf} approach couples spatially determined crop coefficients with reference ET (ET_0) from a nearby weather station. Bausch and Neale (1987) and Neale, Bausch, and Heermann (1989) demonstrated the use of the normalized difference vegetation index (NDVI) to generate basal crop coefficients (K_{cb}). Others (e.g.Campos et al. 2010, Hunsaker et al. 2005) have successfully coupled similar approaches with water balance (WB) models such as the method described by Allen et al. (1998).

Campos et al. (2010) found that a combined K_{cbrf} – WB model compared well with eddy covariance ET measurements for irrigated Grapes. Hunsaker et al. (2005) used an NDVI-based K_{cbrf} method and a traditional, time-based K_{cb} approach to schedule irrigations for cotton of varying stand densities and nitrogen treatments. They monitored soil moisture with a neutron probe. They found the traditional method outperformed the K_{cbrf} approach (in irrigation adequacy and yield) in the first year of their study. In the subsequent year both methods were site – adjusted and both performed similarly, on average. The K_{cbrf} did perform better when stand density was considered. Their results demonstrate the utility of the K_{cbrf} method, but also a potential need for local calibration.

The Spatial Evapotranspiration Modelling Interface (SETMI) model developed by Geli and Neale (2012) and Neale et al. (2012) is a hybrid of the TSEB model of Norman, Kustas, and Humes (1995) and a K_{cbrf} – WB model. The K_{cbrf} portion of the model allows for temporal interpolation of a spatial WB between input image dates. This WB has the potential to be used for real-time, site-specific irrigation scheduling. The inclusion of the TSEB model provides a self-adjusting capability to the model. The WB-based ET is dependent on the accuracy of the WB model in predicting water stress and soil water evaporation components of the estimated ET (Allen et al. 1998). Errors in inputs to the WB could, therefore provide undesired feedback into the model, particularly if irrigation is scheduled based on the modeled soil water depletion. The TSEB provides a spatial estimate of ET at the time an image is taken that is independent of the WB. In this way, the WB model can be adjusted when each new image is incorporated.

Developing VRI prescriptions with the SETMI model has potential to account for spatially variable water requirements with the added benefit of incorporating multispectral imagery as an indirect measurement of actual crop water status.

Objectives

The present research is an attempt to assess the utility of the SETMI model for VRI management by:
- Comparing the SETMI model results run using Landsat 8 imagery for 2013 near Mead, NE with eddy-covariance energy flux data.
- Evaluating the magnitude of the adjustments made to the WB model at each self-calibration step (image date) for the SETMI model as a metric of the model's ability to provide real-time VRI prescriptions.

Methods

Research Site

The research site is located at the University of Nebraska Agricultural Research and Development Center (ARDC) located near Mead, NE. The research for this study was focused on a 10 km^2 area of the ARDC facility planted primarily in maize and soybean (see Figure 1). The study area included both irrigated and rainfed crops. The soils are predominantly silt loam and silty clay loam soils in the fields of interest.

The area has been the site of the University of Nebraska Carbon Sequestration Program (CSP) research, an extensive study of carbon and water flux for over a decade (e.g. Suyker et al. 2004). Three eddy covariance systems, from which fluxes were made available for the current study, have been maintained as part of the CSP project. Energy fluxes from the three systems were used to evaluate the hybrid model. A summary of the crops and cropping dates for the three CSP fields is presented in Table 1. The study area also includes a 50 ha field in which a zone control VRI equipped center pivot was installed in 2014. This VRI system will be used to test the SETMI model for irrigation scheduling in 2015.

Table 1. Summary of Study Fields and Cropping Dates.

Field	Crop	Planting Date	Harvest Date
CSP1	Continuous Maize - Irrigated	4/29/2013	10/23/2013
CSP2	Maize on Soybeans - Irrigated	4/30/2013	10/23/2013
CSP3	Maize on Soybeans - Dryland	5/13/2013	11/22/2013
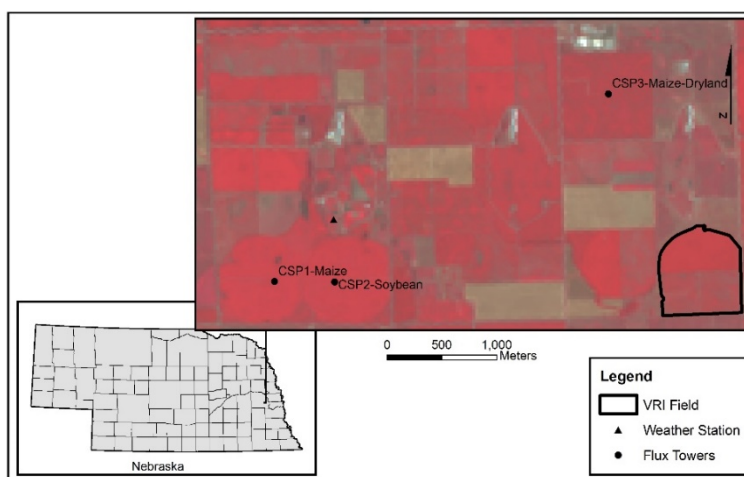
**Figure 1. Study area map with July 21, 2013 Landsat 8 false color image background.
Nebraska county map source: USDA-NRCS (2009).**

Model Inputs

Satellite Imagery

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) multispectral imagery was obtained for four cloud free overpasses in 2013. Imagery dates are listed in Table 2.The Landsat 8 OLI has a ground spatial resolution of 30 m and the TIRS is resampled from 60 m to 30 m for the commonly available data products. This resolution is likely too coarse for some precision agriculture activities. However, Hillyer, Higgins, and Kelly (2013) evaluated the spatial resolution of management for a VRI equipped pivot in Oregon. They found that the minimum management zone size for which the center of the management zone could remain independent of adjacent zones, was essentially two times the sprinkler wetted diameter in any direction. For a sprinkler with a reasonable wetted diameter of 15 m, two diameters would be 30m. This suggests that the Landsat imagery is of adequate spatial resolution to test the SETMI model for future VRI prescription development.

Landsat 8 surface reflectance products were provided courtesy of the U.S. Geological Survey. Landsat 8 thermal infrared imagery was corrected for atmospheric interference using parameters calculated with the application developed by Barsi, Barker, and Schott (2003). Surface emissivity for the corrections was calculated following Brunsell and Gillies (2002).

Other Spatial Datasets

SETMI requires the spatial input of field capacity (FC) and permanent wilting point (WP). These soil properties were obtained from the USDA NRCS Soil Survey Geographic (SSURGO) database (Soil Survey Staff 2014)

The SSURGO data were collected at a scale of 1:12,000 to 1:63,360 (Soil Survey Staff 2014), which is admittedly coarse for precision agriculture or VRI management. However, the dataset was used for this study because of the impracticality of obtaining higher resolution soil property information for the entire 10 km^2 area. In VRI prescription development in future research, SETMI will be run for a single field with soil maps based on EC$_a$ measurements at a spatial scale less than 10 m.

SETMI also requires the input of land use classifications, cover height and leaf area index (LAI). The land use was classified manually for 2013 based on satellite and aerial imagery. Crop height and LAI were calculated based on the optimized soil adjusted vegetation index (OSAVI) (Rondeaux, Steven, and Baret 1996) following the relationships reported by Anderson et al. (2004).

Table 2. Landsat 8 Images Used in the SETMI Model Verification Near Mead, Neb. for 2013.

Image Date	Image Time[1]	Path	Row
6/3/2013	11:08	28	31
7/21/2013	11:07	28	31
9/23/2013	11:07	28	31
10/9/2013	11:07	28	31

[1]Local standard time.

The SETMI model requires ground-based weather data with a temporal resolution of at least 60 minutes. Weather data was obtained from the High Plains Regional Climate Center (HPRCC) for the Mead Turf Farm weather station, located within the study area. Reference ET was calculated with an hourly time step using the ASCE Standardized Reference ET method for a short reference crop (ASCE 2005).

Model Verification

Model Implementation

The SETMI model (Neale et al. 2012) was implemented in the ArcGIS environment (ESRI, Redlands, Calif.). The model was run for each of the four image dates listed in Table 1. Crop ET was modeled between images using the K_{cbrf} – WB functionality of SETMI by linear interpolation of pixel K_{cbrf} between image dates. Reflectance based crop coefficients were calculated based on the soil adjusted vegetation index (SAVI) (Huete 1988) using a relationship for maize developed by Bausch (1993). The WB model was updated to reconcile the WB-based ET with the TSEB-ET, by a statistical method described by Neale et al. (2012).

Flux Data

Energy fluxes were obtained for three eddy covariance systems within the study area for the 2013 growing season. These EC systems were part of the University of Nebraska Carbon Sequestration Program and were provided as a courtesy for use in this study. Common corrections were applied to the data. Eddy covariance flux footprints were determined using a model developed by Hsieh, Katul, and Chi (2000). The resulting footprints represent 90% of the area from which the measured flux may be attributed. The flux footprints were overlaid on the SETMI energy flux output raster grids for flux comparisons.

Results

Two-Source Energy Balance Model

A comparison of TSEB modeled energy fluxes and eddy covariance fluxes is presented in Figure 2. The model appears to estimate Rn well for all image dates, but appears to generally underestimate H, and overestimate G and LE. Neale et al. (2012) found better agreement for all fluxes with an underestimate of H being of much smaller magnitude in their study over cotton than in the current study. They found good agreement with LE. It appears that the discrepancies in Figure 2 are less pronounced for the one mid-season image, July 21. However, it is acknowledged that there were not enough images to make conclusions regarding differences in model performance for different crop growth stages.

A summary of the model statistics for the four image dates is presented in Table 3. The root mean squared error (RMSE) for R_n is 40 W m^{-2}, comparable to the 22 W m^{-2} reported by Neale et al. (2012). The mean bias error (MBE) for R_n was 19 W m^{-2}, which is larger in magnitude than Neale et al. (2012) and other studies. The RMSE and MBE for the other fluxes were, with the exception of G, greater magnitude than those reported by Neale et al. (2012). This could be a result of the atmospheric correction process. Overcorrection for atmospheric effects on the thermal radiation emission could cause erroneously high calculated surface temperatures. Neale et al. (2012) ran the model as part of a much more detailed experiment using high resolution multispectral and thermal infrared imagery from the Utah State University airborne system with more frequent data inputs. Their modeling period included the first half of the growing season with multiple remote sensing inputs during the vegetative stage of growth and full cover periods, so a comparison of late season performance could not be made.
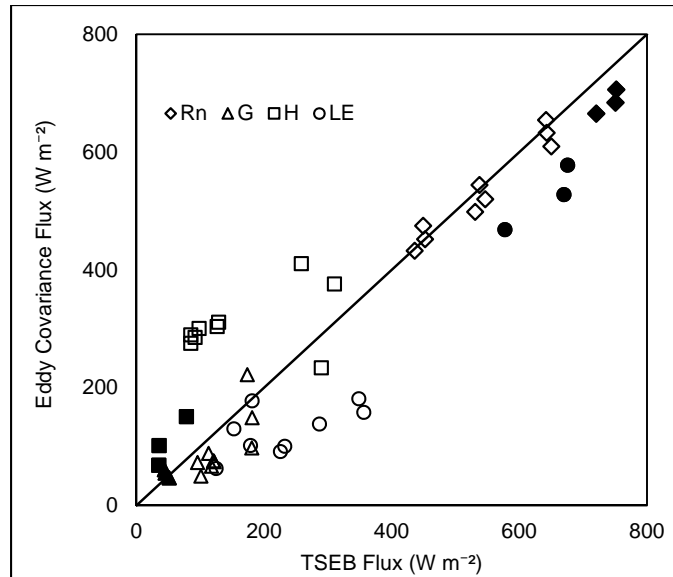
Figure 2. Comparison of TSEB modeled energy fluxes with eddy covariance fluxes for all four image dates; solid symbols are for 7/21/2013; the solid line is unity.

Table 2. Two-Source Model Performance Statistics (W m⁻²).

	Rn	G	H	LE
RMSE	33.9	42.1	147.5	121.6
MBE	19.3	23.8	-123.2	108.1

Reflectance based Crop Coefficient Model

Reflectance based crop coefficients (K_{cbrf}) calculated for the flux tower sites for the four image dates are plotted with time-based crop coefficients following Allen and Wright (2002) in Figure 3. The K_{cb} curves have been adjusted to minimize the sum of squares with the K_{cbrf}s for the study site cropping dates (see Table 2). The K_{cbrf} values generally fall near the time-based curves, with deviations in the dryland maize (CSP3).

A comparison of TSEB modeled ET and WB modeled ET just prior to adjustment for a single pixel in each CSP field for the last three image dates is presented in Figure 4. The values were obtained by running the SETMI model completely, including adjustments, for all previous image dates. (Hence no data is presented for the June 3 image as that date was used for model spin-up.) It is visually apparent that model performed better for irrigated crops than for the dryland maize. Neale et al. (2012) found the water balance model performed well for both irrigated and dryland conditions. It is possible that the water balance required large corrections, particularly for the July 21 image date because of the low frequency of images used in this study as compared with Neale et al. (2012), who had images every eight to 16 days.

The possible errors in the model caused by the low availability of satellite imagery used in this study due to cloud cover, highlight the importance of frequent image inputs for running this model. In future work, the model will be implemented using aerial imagery so that image inputs can be more frequent. In Eastern Nebraska there are relatively few cloud free dates in a summer. Only four for Landsat 8 were identified for 2013 for our study area. No cloud free Landsat 8 images were identified for the same area in the growing season of 2014. Another possibility is to use MODIS imagery at a lower spatial resolution but much higher frequency.
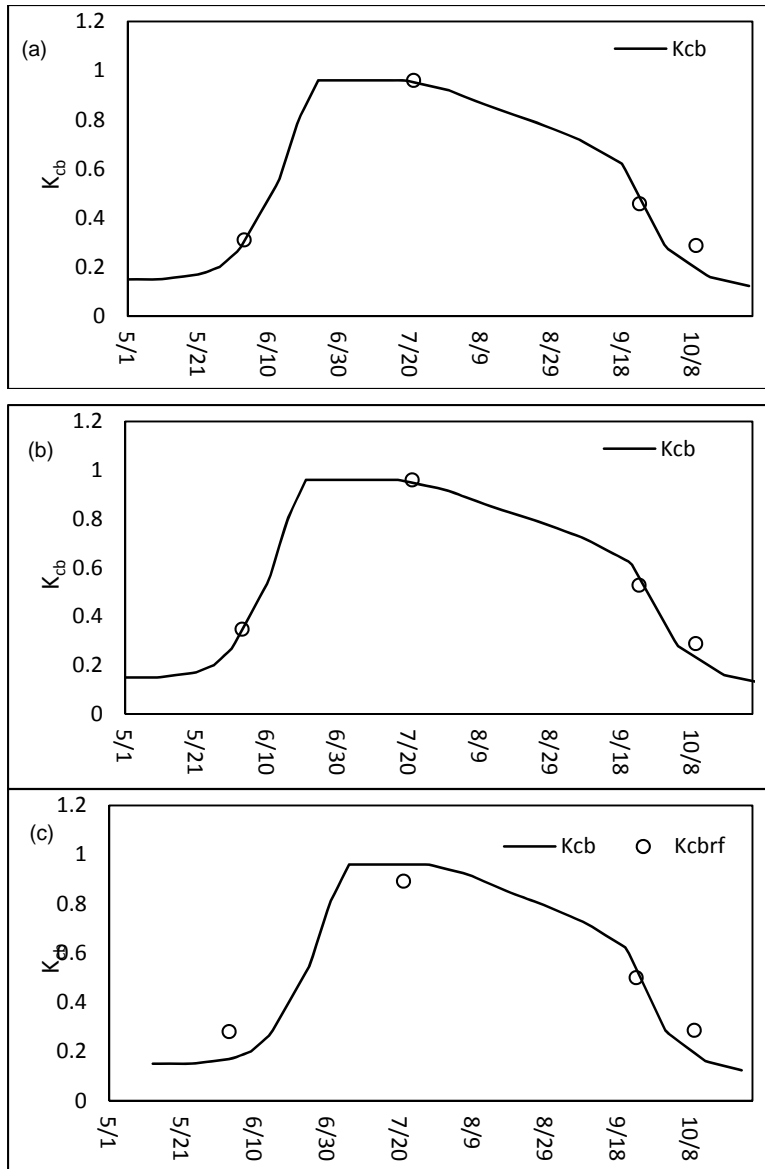
Figure 3. Plots of SETMI modeled K_{cbrf} with a typical K_{cb} curve following Allen and Wright (2002) for flux tower locations in (a): CSP1, (b): CSP2, and (c): CSP3.
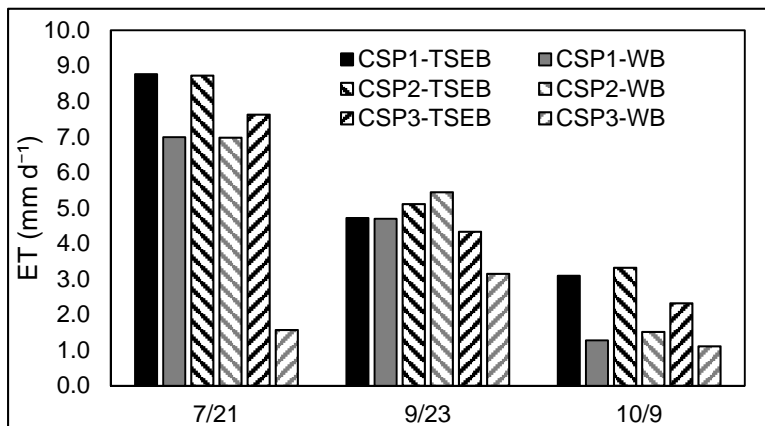

Figure 4. Comparison of TSEB and water balance modeled ET for the CSP flux tower locations. Water balance ET is presented for each date prior to adjustment (for each date the model adjustments had been made for all previous image dates).

Summary and Conclusion

A hybrid remote sensing ET and water balance model was evaluated for use in developing VRI prescriptions. The modeled energy fluxes were compared with eddy covariance fluxes for three sites within the study area. The model did not perform as well for maize in the current study as was presented for cotton by Neale et al. (2012). One possible source of error may be the present parameterization of the TSEB model as used herein to deal with late season and senescence periods of these crops. Water balance modeled ET compared well with the TSEB for irrigated crops but not for dryland maize and the reflectance-based crop coefficient indicated a more rapid senescence decline in greenness. Poor satellite image temporal frequency due to clouds was a contributing factor. Although the model did not perform as well in the current study as previously reported, the results for the July 21 image date are encouraging. The small number of images makes it difficult to evaluate model performance for different crop growth stags. Future work will focus on model testing and further parameterization of the model and the use of aerial imagery and coarser satellite imagery to improve the frequency of remote sensing inputs. The model will be used to generate VRI prescriptions for a field within the current study area in the 2015 season.

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