Performance of METRIC Model in estimating evapotranspiration fluxes over an irrigated field in Saudi Arabia using Landsat-8 images

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Abstract. Accurate estimation of evapotranspiration (ET) is essential for hydrological modelling and efficient crop water management in hyper-arid climates, like the one in the Eastern Region of Saudi Arabia. Therefore, a study was designed to apply the METRIC algorithm on Landsat-8 images, acquired from June to October 2013, for the development of ET maps for a 50-ha center pivot irrigated alfalfa field. The METRIC estimated energy balance components and ET were evaluated against the data provided by an Eddy Covariance (EC) flux tower installed in the field. Results indicated that the METRIC algorithm provided accurate ET estimates over the study area, with RMSE values of 0.13 mm h^{-1} and 4.15 mm d^{-1}. The METRIC algorithm was observed to perform a relatively better in full canopy conditions compared to that in partial canopy conditions. On the average, the METRIC algorithm overestimated the hourly ET by 6.6% in comparison to the EC measurements; however, the daily ET was underestimated by 4.2%.

Keywords. Arid region, energy balance, eddy covariance, landsat-8

1 Introduction

In the Kingdom of Saudi Arabia (KSA), which suffers from severe water shortage problems, the agricultural sector was estimated to consume about 85% of the total freshwater used in 2008 (Al-Kahtani and Ismaiel, 2010), which increased to 90% by 2012 (Elnesr and Alazba, 2013). With the limited water resources and to fulfill the needs of the increasing population in the KSA, efficient use of water for crop production is essential (Hussain et al., 2010; Praveen et al., 2012). Various studies (Kassem and Al-Moshileh, 2008; Atta et al., 2011; Al-Ghobari et al., 2013; Mohammad et al., 2013) recommended advanced irrigation systems for improving agricultural water use efficiency in the Kingdom. As an example, a reduction in the irrigation water of 30-40% was attained through sprinkler irrigation compared to traditional methods, and an additional saving of 10-25% can be reached with drip irrigation systems (Rizaiza and Al-Osaimy, 1996). Furthermore, implementation of recent innovative precision irrigation technologies, in conjunction with the accurate estimation of crop water requirements through remotely sensed data, could significantly enhance the efficient use of irrigation water in the agricultural sector.

Evapotranspiration (ET) measurements are recognized as essential prerequisite for various water management applications such as irrigation scheduling, hydrologic modelling, nutrient cycles and drought monitoring (Bastiaanssen et al., 2000; Allen et al., 2005; Chavez et al., 2005; Senay et al., 2008; Santos et al., 2010; Anderson et al., 2012; Mkhwanazi and Chavez, 2012; Gowda et al.,2013; Lagos et al., 2013; Moorhead et al., 2013; Yee et al., 2014). In semiarid climates, ET is characterised as one of the most significant components influencing the hydrologic cycle. Hence, accurate determination of ET is considered as one of the crucial/essential factors influencing the optimal management of crop water use through different irrigation systems (Hoedjes et al., 2008). On the other hand, the accurate determination of energy balance (EB) elements such as sensible heat (H), soil heat (G) and latent heat (LE) fluxes are also of great importance for water management practices, especially in arid and semi-arid regions (Zeweldi et al., 2010).

Estimation of ET has been performed through different direct/indirect methods such as lysimeter, water balance, Bowen Ratio (BR), Eddy Covariance (EC) and scintillometer techniques (Allen et al., 2011a; Rana and Katerji, 2000). Of which, lysimeter and EC methods provide direct measurements of ET, while other methods use certain equations and assumptions to estimate heat fluxes using measurable parameters (FAO, 1977; Drexler et al., 2004; Chavez et al., 2009a). Moreover, FAO-56 (Allen et al., 2007) method also widely used in numerous studies. This method consists of estimating crop evapotranspiration (ETc) for a crop canopy using a reference evapotranspiration (ETr) and a crop coefficient (Kc). The ETr can be computed based on the Penman-Monteith (PM) method. Subsequently directed to the computation of Actual evapotranspiration corresponding to the real water consumption of a crop as per the weather parameters, crop factors, and surface characters. The FAO-56 computed actual ET can be utilised in the monitoring of spatialized ET developed with RS approaches (Courault et al., 2005).

Recently, EC systems have gained a lot of popularity in the determination of ET. Several studies have been conducted to investigate the effectiveness of the EC systems in estimating accurate values of H, LE and ET. Lack of surface energy budget closure is a common issue raised in conjunction with EC flux measurements. For example, Chavez et al. (2009b) reported that the EC measured energy balance components (H and LE) were underestimated by about 30% compared to those measured by the large weighing lysimeter on an irrigated cotton field in the USA. Similarly, Twine et al. (2002) reported that carbon dioxide fluxes measured over a sorghum crop with four EC systems (equipped with the same models of instruments), were underestimated by the same factor when energy balance closure was not achieved. However, the EB closure can be improved by adjusting the EC data through the Bowen ratio-BR (Ding et al., 2010; Teixeira and Bastiaanssen, 2012). Ding et al. (2010) reported that the EC measured ET (ET$_{EC}$) compared to the lysimetric data (ET$_L$) of maize crop showed an EB closure of up to 84% for the daytime fluxes. However, the forced energy balance closure with BR data improved the EB closure from 79.2% to 95.2%. Therefore, it is important to adjust ET values measured by the EC system, through BR method to improve their accuracy.

In-situ point measurements provide accurate ET values; however, these methods are limited to small areas only. Alternative method such as remote sensing (RS) models, have been successfully used in assessing the spatial distribution of ET on larger scales, which is hard to achieve by conventional methods over different landscapes (Bala et al., 2013; Farah et

al., 2004; Colaizzi et al., 2006) and agricultural fields (Kalma et al., 2008; Gowda et al., 2008). One of the most RS models, commonly used for the determination of ET, is the Surface Energy Balance Algorithm for Land (SEBAL) with an accuracy ranging from 67% to 97%. Recently, several SEBAL based models have been developed and successfully implemented in different water management practices (Paul et al., 2013). Examples of such models include the Mapping Evapotranspiration at high Resolution and with Internalized Calibration (METRIC), Modified SEBAL (M-SEBAL), Simplified Surface Energy Balance (SSEB), Remote Sensing of Evapotranspiration (ReSET), Surface Energy Balance System (SEBS) and Surface Energy Balance with Topography Algorithm (SEBTA). The METRIC model, which was developed to determine the quantity and spatial distribution of ET over large areas, is considered as one of the most appropriate models for the continuous estimation of ET over crops during the growing season (Allen et al., 2007; Patil et al., 2015).

Accurate estimation of ET is critical for crop water management, especially in hyper-arid climates with scarce freshwater resources, as in the KSA. Over the past decades, hydrology studies in the Kingdom have been directed to accurate ET estimates at various spatial and temporal scales. As an example, Mahmoud and Alazba (2016) processed a spatial ET dataset over Western and Southern regions of Saudi Arabia with SEBAL on MODIS. However, quantification of ET from satellite data in conjunction with EC data is still limited in the KSA. As the Eastern region experiences severe dry conditions than other regions, long-term EC data in conjunction with Landsat-8 data will enhance the accurate estimates and distribution of ET over various landscapes/agricultural fields. Therefore, the main goal of this study was to address the performance of the METRIC model in estimating ET using Landsat-8 images acquired over alfalfa fields in the hyper arid climate of the Eastern region of Saudi Arabia.

2 Materials and Methods

2.1 Study area

The study was carried out on a 50-ha alfalfa field, which was one of the 48 agricultural fields of Todhia Arable Farm (TAF) located about 250 km Southeast of Riyadh, the capital city of Saudi Arabia, at coordinates of 24° 11' 00" E and 48° 56' 14.6" N (**Figure 1**). The farm was under an arid climate with hot summers (40 ± 2 °C) and cold to moderate winters (15 ± 3 °C) and a mean air temperature of 35°C. The annual rainfall was about 90 mm, most of which occurred in the period from November to February. The study area, of mainly sandy loam soil with a mean value of soil pH of 7.58 and soil electrical conductivity (EC) of 2.36 dSm^{-1}, is characterized as a flat terrain with slight undulations in the desert environment with an elevation ranges from 329 m to 453 m. The major crops cultivated in the study area were alfalfa, Rhodes grass and corn. Due to the high crop water demand combined with the highly erratic rainfall, irrigation is a pre-requisite for crop growth. It is entirely provided using underground water delivered by center pivot irrigation systems. The experimental field was cultivated with an alfalfa crop (Green Master) sown on December 6th, 2012 at a seeding rate of 20 kg ha^{-1}, and was irrigated through a center pivot system using a groundwater of mean values of EC, pH and Sodium Absorption Ratio of 2.917 dS m^{-1}, 7.82 and 1.42, respectively. In the study region, alfalfa crop is usually cultivated for two years; with, on the average, each

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30-35 days cut during summer periods and each 45-60 days cut during winter periods. The mean alfalfa hay yield for each cut is estimated at 2.0-3.0 kg ha^{-1} during winter and 4.0-5.0 kg ha^{-1} during spring/summer periods (Kayad et al., 2016).

2.2 Eddy Covariance (EC) flux data

Eddy Covariance (EC) system was installed, on May 27th, 2013, over the selected alfalfa field. The EC flux tower was powered by solar pannels with rechargable batteries. The meteorological and gas exchange (flux) measurements wre made ata height of 3.67 m. The EC was equipped with response sensors, including an open-path infrared gas analyzer, IRGA (LI-7500), a 3-axis ultrasonic anemometer (3D Master Pro), Gill Instruments, Lymington, UK), a net radiometer (CNR-4, Kipp and Zonen), and a quantum sensor. Soil heat flux plates (HFP01, Hukseflux) were installed at various depths (5, 10, 15, 20, 25 and 30 cm). The sonic anemometer and IRGA were set to record flux data logged at 10 Hz (CR3000) and stored as 30 min files (*.ghg). On the other hand, data on crop condition, growth, and phenological parameters were also recorded on frequent visits.

The recorded EC data, for the period from June to October 2013, was used for this study. The collected 30-minute raw datasets (*.ghg files) were processed with the use of "advanced mode" of an automated software program Eddypro (ver. 5.0) developed by LI-COR Biosciences, USA. During the process, such as wind speed measurement offsets, axis rotation for tilt correction, de-trending turbulent fluctuations, time lag optimization settings, spectral corrections and footprint estimation following the procedures described in the Eddypro software instruction manual (LI-COR). As the sonic anemometer was tilted 243º towards the North, an angle-of-attack correction for wind components was also performed. During the filtering process, EC data was excluded whenever there was a condensation, a covariance with missing values (-9999) or periods with incorrect sonic temperatures (i.e. >50 °C). The missed data was filled with the standard methods (basic interpolation) as described in the manual (LI-COR). The gaps an hour order were linearly interpolated; whereas, gaps resulted because of malfunction of EC system for longer than 24 hours was not performed. Subsequently, the processed EC data was used for the computation of the ET (i.e. ET$_{EC}$).

2.3 Footprint analysis (FTP)

As described in Nappo et al. (1982), the footprint (FTP) or representativeness as of measurements from the EC tower is "the extent to which a set of measurements was taken in a given space-time domain". In this study, an effort was made to understand the spatial representation area or footprint (FTP) of flux measurements from the EC system. The FTP mainly depends on the function of surface roughness with respect to the wind speed, direction, and wind shear. Thus, the FTP for a single 30-minute data will be unique and may vary for the next segment as atmospheric conditions change. Moreover, the shape and length of the FTP may vary with upwind direction, as well as the relative weights (magnitude of flux contributions); in each area inside the FTP, i.e. the weighted FTP function is used to attribute the measured flux to a weighted areal estimate (Gockede et al., 2006). The areas very close to the EC tower may contribute less to the total flux

sensed by the instrument. Whereas, areas away (upwind) from the EC tower contribute significantly, up to a point where a peak is reached. Thereafter, the contribution may decrease rapidly (Verma, 1998).

Depending on the complexity, numerous FTP estimation models existed the literature. The widely used Flux Source Area Model (FSAM) described by Schmid (1994), was used in this study for the determination of FTP. The FSAM was computed based on contributes (up to 90%) of the sensed fluxes by the EC tower. Subsequently, the obtained FTP was used to compare the EC tower and Landsat-8 estimates of energy flues. As described by Schmid (1994), the EC contributions starting 1.5 hours after sunrise and ending 1.5 hours before sunset was considered and the FTP was computed for each 30 minutes corresponding to the averaging period used for the EC tower analysis. The FSAM variables such as observation point height, Obukhov length, the standard deviation of lateral wind speed fluctuations; and friction velocity were taken from the EC measurements. Surface roughness length was estimated by measuring the crop (alfalfa) height at regular site visits using linear interpolation between observations. Crop height was transformed into roughness length as described by Allen et al. (1998).

In the FTP analysis, the utilized wind parameters such as wind speed, wind direction, and yaw angle at the time of Landsat-8 overpass were provided in **Table 1**. The produced oval-shaped "fetch area" was oriented to the mean wind direction corresponding to that half hour time-period. A weighting matrix for the FTP surrounding the EC tower was developed for each day. Subsequently, a 30-meter grid matching to the Landsat-8 pixels was created for each 30-minute interval, with a binary coding. The grid cell which falls "in the fetch area" was coded as "1", and the pixels "outside the fetch area" were given the value of "0". The daily FTP fetch calculation was computed by scoring the grid cells coded with "1" divided by the total number of observations recorded during the day.

2.4 Energy balance (EB)

Eddy Covariance (EC) system facilitates the process of accurate measurements of energy balance (EB) components. Hence, using the measured EB components, the surface energy budget can be estimated (Equation 1) along with the EB closure. The four flux components (R_n, H, G and LE) measured by the EC system were assessed for the EB closure (Kustas et al., 2005). The EB closure rate for the EC system ranged between 71% and 99%, with a mean value of 87% **(Table 2 and Figure 2).** Energy balance closure was significantly influenced by the amount of the unaccounted energy lost (i.e. lack of closure in the energy balance equation due to advection and measurement errors in the field) in the partition of the net radiation into latent and sensible heat fluxes and soil heat flux. It may be due to the portion of energy that is missing in the budget was accounted for between 5 and 20% of the total R_n. This was attributed to the inherent errors in measuring the EB components by the ground systems, which was reported to be 15 - 20%, 5 – 10% and 20 – 30% according to Weaver (1990), Field et al. (1994) and Twine et al. (2000), respectively.

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2.3 Landsat-8 images and pre-processing

Eight cloud free Landsat-8 TIRS (Thermal Infrared Sensor) and OLI (Operational Land Imaginer) data of experimental field (Path 165, Row 43) were downloaded for the study period (June to October 2013) from the United States Geological Survey (USGS) Earth Explorer site (http://earthexplorer.usgs.gov), **Table 3**. The downloaded data were georeferenced to the Universal Transverse Mercator (UTM) Map projection using the World Geodetic System 84 (WGS84) datum. Subsequently, Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) algorithm in ENVI software was used to convert Landsat-8 digital numbers to Top-Of-Atmosphere (TOA) spectral reflectance. Also, land surface temperature (LST) layers were generated using split window algorithm (USGS). The obtained spectral reflectance and the land surface temperature values were utilized as inputs for the ET estimation employing the METRIC algorithm. Image analysis and the execution of the METRIC algorithm were performed using ENVI software program (ver. 5.1). Subsequently, spatially distributed ET fluxes were weighted and integrated using an FTP for comparison to ET measured with EC system against the METRIC model derived ET.

2.4 Land Surface Temperature (LST) – Split window (SW) algorithm

Landsat-8 TIRS Bands (10 and 11) and OLI Bands (2 to 5) were utilized in the estimation of LST through Split Window algorithm executed ENVI (ver. 5.1). During the process of LST estimation, the algorithm used brightness temperatures of two TIRS bands, and mean and difference in land surface emissivity (LSE) of an area under observation. The SW algorithm for LST determination was given in Equation (1) as described by Skokovic et al., 2014).

$$LST = TB_{10} + C_1(TB_{10} - TB_{11}) + C_2(TB_{10} - TB_{11})^2 + C_0 + (C_3 + C_4\,W)\,(1 - \varepsilon) + (C_5 + C_6\,W)\,\Delta\,\varepsilon \qquad (1)$$

Where, LST – is the Land Surface Temperature (K), C_0 to C_6 – are the values of Split-Window coefficient (**Table 4**), TB_{10} and TB_{11} – are brightness temperatures of Landsat-8 band 10 and 11 (K), ε - is the mean LSE of TIR bands, W – is the atmospheric water vapour content and $\Delta\varepsilon$ - is the difference in LSE.

The brightness temperature (TB), a microwave radiation radiance travelling upward from the top of Earth's atmosphere, was calculated using Equation (2).

$$TB = \frac{K_2}{Ln\left(1 + \frac{K_1}{L\lambda}\right)} \qquad (2)$$

Where, K_1 and K_2 – are thermal conversion constants of TIRS bands (**Table 5**), $L\lambda$ - is the Top of Atmospheric spectral radiance; which was determined by multiplying multiplicative rescaling factors (**Table 5**) using Equation (3).

$$L\lambda = M_L \times Q_{cal} + A_L \qquad (3)$$

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Where, M_L – is the Band specific multiplicative rescaling factor (radiance_mult_band_10/11), Q_{cal} – is the band 10/11 image, A_L – is the band specific additive rescaling factors (radiance_add_band_10/11).

Subsequently, LSE was calculated using Equation (4). The ε_s and ε_v are soil and vegetation emissivity values of the corresponding bands (**Table 5**). The fractional vegetation cover (FVC) was estimated based on the Normalized Difference Vegetation Index (NDVI) obtained over the experimental area (Equation 5).

$$LSE = \varepsilon_s (1 - FVC) + \varepsilon_v * FVC \quad (4)$$

$$FVC = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \quad (5)$$

Where, $NDVI_S$ and $NDVI_V$ are the reclassified NDVI for soil and vegetation areas respectively. OLI bands 2, 3, 4 and 5 were layer stacked and NDVI was calculated using ENVI (ver. 5.1) software. The output value of NDVI ranged between -1 and 0.59. To get $NDVI_S$ and $NDVI_V$, the NDVI image was reclassified into soil and vegetation. After generating LSE for both the bands of TIR, the mean and difference LSE were obtained according to Equations (6 and 7).

$$\varepsilon = \frac{\varepsilon_{10} - \varepsilon_{11}}{2} \quad (6)$$

$$\Delta\varepsilon = \varepsilon_{10} - \varepsilon_{11} \quad (7)$$

2.4 METRIC algorithm and ET estimation

The METRIC algorithm has been developed exclusively for the estimation of ET from Landsat data (Allen et al., 2005). A total of eight Landsat-8 images were processed and used for the estimation of ET (ET_{METRIC}) over the experimental alfalfa field. During the ET_{METRIC} computation, surface characteristics such as surface albedo, vegetation indices, surface emissivity and surface temperature were estimated as intermediate products. Anchor pixels (hot and cold) were selected, and the energy components such as the net radiation (R_n), the soil heat flux (G) and the sensible heat flux (H) were estimated as well. Finally, the latent heat flux (LE) was predicted as a residual of the land surface balance (Allen et al., 2005, 2007), Equation (8). Consequently, the instantaneous ET (ET_{inst}) for each pixel was calculated. Moreover, Hence, the obtained leaf area index (LAI_G) and the reference ET (ETr) over the alfalfa field were used as inputs to the METRIC-based Landsat-8 ET prediction **(Table 6)**. The ground-based LAI (LAI_G) of alfalfa was recorded on the day of satellite overpass using plant canopy analyzer (LAI-2200).

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$$LE = R_n - G - H \qquad (8)$$

The first step in the METRIC model was to compute the net radiation (R_n) using the surface radiation balance, Equation (9). The R_n estimation was accomplished in a series of steps by summing up the net short-wave radiation and net long-wave radiation (Hipps, 1989; Brunsell and Gillies, 2002; Allen et al., 2007).

$$R_n = R_{s\downarrow} - \propto R_{s\downarrow} - R_{L\downarrow} - R_{L\uparrow} - (1 - \varepsilon_o) R_{L\downarrow} \qquad (9)$$

Where, $R_{s\downarrow}$ is the incoming shortwave radiation (W m^{-2}), α is the broadband surface albedo (dimensionless), $R_{L\downarrow}$ and $R_{L\uparrow}$ are the inbound and outgoing longwave radiation (W m^{-2}), respectively. ε_o is the broad-band surface thermal emissivity (dimensionless), The $(1-\varepsilon_o) R_{L\downarrow}$ term represents the fraction of incoming longwave radiation reflected from the surface. Spectral reflectance of bands 1-7 was used to calculate surface albedo (α) as described in Allen et al. (2007).

The surface emissivity correction was performed using an empirical Equation (10) by Tasumi (2003) based on soil and vegetative thermal emissivities. Leaf area index (LAI) is computed as per Equation (11) as proposed by Bastiaanssen (1998). During the correction, the typical bare soil and the fully vegetated surface values were set as 0.93 and 0.98, respectively. where, the soil adjusted vegetation index, SAVI was calculated based on TOA reflectance of bands 4 and 5 (Huete, 1988).

$$\varepsilon_o = 0.95 + 0.01 \, LAI \, for \, LAI \leq 3 \qquad (10)$$

$$LAI = \frac{-\ln[(0.69 - SAVI)/0.59]}{0.91} \qquad (11)$$

For the estimation of soil heat flux (G), various empirical equations can be found in the literature (Bastiaanssen, 1998; Singh et al., 2008; Gowda et al., 2011). However, this study adopted the empirical model described by Bastiaanssen (2000) representing values near midday for the prediction of Landsat-8 G (i.e. G_{METRIC}), as a ratio G/R_n based on the NDVI, Equation (12).

$$\frac{G}{R_n} = (T_s - 273.15)(0.0038 + 0.0074 \propto)(1 - 0.98 \, NDVI^4) \qquad (12)$$

Where T_s is the surface temperature (K), and α is the surface albedo. Subsequently, the G_{METRIC} was obtained by multiplying G/R_n with R_n.

The sensible heat (H_{METRIC}), however, was estimated from an aerodynamic function as expressed in Equation (13). In the calculation of r_{ah}, wind speed measurements were used.

$$H = \rho_{air}\, C_p\, \frac{\Delta T}{r_{ah}} \qquad (13)$$

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Where ρ is the air density (kg m^{-3}), C_p is the specific heat capacity of the air (J kg^{-1} °K^{-1}), ΔT is the near surface air temperature and r_{ah} is the aerodynamic resistance for heat transfer (s m^{-1}) between two near-surface heights (i.e. at alfalfa canopy height and the EC measurement height. For further detail steps of H_{METRIC} computation refer Allen et al. (2007).

10 **2.5 Calculation of ET**

Following the establishment of R_n, G and H from the Landsat-8 processing, LE was calculated as a residual of the energy balance equation. The obtained LE is equivalent to the ET_{inst} at the time of Landsat-8 overpass, Equation (14).

$$ET_{inst} = 3{,}600\, \frac{LE}{\lambda \rho_\omega} \qquad (14)$$

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Where ET_{inst} is the instantaneous ET (mm h^{-1}); 3,600 converts from seconds to hours, ρ_ω is the density of water ($\sim$1,000 kg m^{-3}) and λ is latent heat of vaporization (J kg^{-1}) representing the heat absorbed when a kilogram of water evaporates. The λ component was computed as per Equation (15).

20 $\quad \lambda = [2.501 - 0.00236\, (T_s - 273.15)] \times 10^6 \qquad (15)$

Finally, as presented in Equation (16), the reference ET fraction (ET_rF) was calculated as the ratio of the computed ET_{inst} from each pixel to the reference ET (ET_r), which was computed from the weather data.

25 $\quad ET_rF = \dfrac{ET_{inst}}{ET_r} \qquad (16)$

Where ET_{inst} is from Equation (7) and ET_r is for the standardized 0.5 m tall alfalfa at the time of the image. The EC system recorded weather parameters were used to calculate ET_r as described in ASCE-EWRI (2005). The obtained ET_rF was subsequently extrapolated to daily values. In the processes, ET_{24} was computed by assuming that the instantaneous ET_rF 30 computed at satellite overpass is the same as the average ET_rF over the 24 h average (Allen et al., 2007), Equation (17).

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$$ET_{24} = C_{rad}\,(EF)(ET_{r24}) \qquad (17)$$

2.6 Data analysis

The spatially estimated energy flux components, derived from the METRIC algorithm and the EC flux tower, were subjected to heat flux correction and energy balance and footprint (FTP) analysis, as described in Schmid (1994). On the other hand, different statistical performance indicators (RMSE, MBE, and Nash-Sutcliff coefficient). As the samples were limited, the Mann-Whitney U test and/or Kruskal-Wallis H test (Gisondi et al., 2004; McCune and Grace, 2002), which are often used in applications involving small size samples, were performed for the assessment of the METRIC performance in estimating ET against the EC system.

3 Results and discussion

3.1 Footprint analysis (FTP)

The simple arithmetic averages of weighted/integrated heat fluxes over the fetch areas are the FTPs (Chavez et al., 2005). FTPs are widely used in validating the spatially distributed fluxes obtained from remote sensing (RS) with EC measured fluxes. The fetch area of the FTP was classified into six classes, based on the cumulative contribution of the eddies, as provided in **Figure 3**. Based on the FTP analysis, about 90% of the EC system observed eddies originated from the 122 to 144 m in the upwind direction. However, the peak (vertical) fetch was within 42 to 51 m. It was also observed that 10% of the fluxes were registered between 6 and 17.5 m from the flux tower. Whereas, about 30%, 50% and 70% of the fluxes were recorded between 35 to 63 m, 52 to 97 m and 81 to 136 m, respectively. On the other hand, energy fluxes were analyzed as per Chavez et al. (2005) by integrating Landsat-8 image acquisition (i.e. overpass), which showed the 90% of the FTP overlap with METRIC model (Kustas et al., 2005).

3.2 Surface temperature (T)

As illustrated in **Figure 4**, linear regression analysis of Landsat-8 derived surface temperature (T_{LST}) against the EC flux tower measured temperature (T_{EC}), obtained from the upwind longwave component measured by the CNR4, showed a good correlation with an R^2 value of 0.71 (P = 0.0084). However, the T_{LST} was observed to be underestimated compared to the T_{EC} as evidenced by the RMSE and MBE performance indicators of 4.23°C (-12.82 %) and -3.40° C (-9.34%), respectively. The recorded errors (4.2 % to 19.6%) in the T_{LST} was slightly higher than the values reported in previous studies. For example, compared to ground level infrared thermometer, Chavez et al. (2009a) reported METRIC errors of 11.1% and 1.9% in estimating surface temperatures for corn and sorghum fields, respectively. LAI significantly affect the accuracy of T_{LST}, as

the vegetation with higher LAI records the low temperatures because the amount of heat stored is reduced through transpiration (Omran 2012). It was evident with the Landsat-8 derived T_{LST}, which was underestimated about 20% at full foliage cover of alfalfa crop (i.e. LAI~6) compared to T_{EC}. Thus, the temporal variation in LAI would result in oscillations of the land surface temperature. As an example, at a low LAI (<1.23) coverage of alfalfa on the Day of Year (DOY) 154, 234

5   and 266 obtained the high T_{LST} (> 34.3 °C). However, there is a discrepancy at higher temperatures when the crop density of alfalfa was low (i.e. bare soil was visible to the radiometer) as evidenced by the low LAI values over the footprint and the recorded T_{EC} and T_{LST} (Chavez et al., 2005). Hence, the cooling effect of vegetation on the T_{LST} accelerated the error by 1 to 20% during the low and high LAI cases, respectively.

3.3 Energy balance (EB) components

10   The mean values of energy balance (EB) components obtained from both the EC system and METRIC algorithm are provided in **Table 7**. While, the performance indicators (RMSE, MBE, Nash-Sutcliff coefficient, Mann-Whitney U-test and Kruskal-Wallis H-test) are given in **Table 8**. An illustration (**Figure 5**) on the comparison of EC and METRIC estimates of EB components were provided.

3.2.1 Net radiation (R_n)

15   The temporal trend of EC (CNR-4) measured R_n (R_{nEC}) was analyzed for discrepancies. About 9% to 16% of the collected data exhibited infrequent errors; and hence, the abnormal data has been discarded, and a gap-filling process was performed using the Eddy Pro software program (version 5.0). A scatter plot (Figure 5), representing the relationship between R_{nEC} and METRIC estimated R_n (R_{nRS}), was generated and analyzed for performance accuracy. Moderate linear correlation ($R^2 = 0.54$ and P>F = 0.0381), low RMSE (18.32 W m^{-2}; 3.8%) and very low MBE (8.66 W m^{-2}; 1.76%) indicated that the METRIC

20   model accurately (96%) estimated the R_n. The obtained RMSE and MBE values are in agreement with those reported by earlier studies of Mkhwanazi and Chavez (2012) where the RMSE value was 4.1% and MBE value was 3.3%, and Chavez et al. (2007) where the RMSE value was 9.8% for METRIC model estimated R_n using Landsat-8 TM image. In addition, the performance of METRIC was significant with Kruskal-Wallis H-tests (0.893) However, the null hypothesis was not rejected with the Mann-Whitney U-test (U and Z value are 23 and -0.892 respectively). These variations in R_n between METRIC and

25   CNR-4 estimates were likely due to variations in the computation of leaf area index along with LST and soil moisture conditions (Zhang et al., 2013).

3.2.2 Soil heat flux (G)

Figure 5 illustrates a scatter plot between the EC measured (G_{EC}) and the METRIC estimated (G_{RS}) soil heat flux values. The relationship was relatively fair with an R^2 value of 0.67 and a Nash-Sutcliffe coefficient of 0.59. The RMSE and MBE,

30   however, were determined at 28.46 W m^{-2} (37.33%) and 12.42 W m^{-2} (16.29%), respectively. These recorded errors were relatively higher than the values reported in similar previous studies. Mkhwanazi and Chavez (2012) reported an RMSE

value of 14.2 W m^{-2} (27.6%) and an MBE value of -3.0 W m^{-2} (-5.8%) in estimating G with the METRIC algorithm for irrigated alfalfa. The average observed values of G were similar to the majority of values recorded by Ham et al. (1991). The performance of METRIC model in estimating G was not significant with the Mann-Whitney U-test (U and Z value are 23 and -0.892 respectively) but it was significant with Kruskal-Wallis H-tests (0.397) and the null hypothesis was not rejected.

5   Furthermore, the ratio of R$_n$ to the G (G/R$_n$) derived from METRIC model against the LAI inferred from the Canopy analyser (PCA 2200, Li-COR, USA) is presented in **Figure 6**. The G/R$_n$ is one of the essential components in the analysis of the accuracy of Bowen ratio (Allen et al., 2011b). Correlating the LAI with the G/R$_n$ produced a moderate polynomial (3rd order) relationship for both the METRIC (R^2 = 0.288 and P>F = 0.23) and the EC (R^2 = 0.313 and P>F = 0.15) methods. However, the results suggested that beyond a certain value of LAI (up to 4.2), the relationship between the G/R$_n$ and LAI

10   was decreased. The scatter in the G/R$_n$ where the LAI increased to 4, was showed increased trend as the values of G/R$_n$ for full canopy cover are ranging between 0.05 and 0.15 as showed in Waters et al. (2002).

3.2.3 Sensible heat flux (H)

After the adjustments of EB closure, the error in recorded H$_{EC}$ flux was ranged from 10.89 W m^{-2} (low LAI conditions) to

15   38.91 W m^{-2} (full canopy condition). It may be due to advection, which vary very strong in the hyper arid environment. The H$_{METRIC}$ estimated with an MBE value of 15.72 W m^{-2} (13.87%) compared to H$_{EC}$. The high RMSE value of 72.01 W m^{-2} (63.54%) for the H$_{METRIC}$ might be due to the selection of anchor pixels especially during 22nd August, where the landsat-8 image was viewed at the time of irrigation. Hence, the advection and variability in the wetness across the fetch /FTP area and canopy reflectance affected the calculations in RS estimated of H$_{METRIC}$ (Brutsaert and Stricker, 1987; Yang et al., 2013).

20   During the earlier (June) and late summer (August) periods, the observed sharp humidity variations are linked to changes in wind direction. However, during the alfalfa post-harvest practices, the fields are under fallow condition. Hence, the LE flux was always less as most of the available energy partitioned as H rather than LE flux. This was evident in the linear regression analysis (**Figure 5**), where a good correlation between the H$_{RS}$ and H$_{EC}$ (R^2 = 0.61) was observed; however, it was not significant (P>F = 0.021), and it was also confirmed with the MBE of 13.87%. The obtained results are resembling with

25   the reported values on H$_{METRIC}$ performance (MBE of 10%) by Carrasco-Benavides et al. (2013).

3.2.4 Latent heat flux (LE)

A scatter plot was established between the METRIC estimated (LE$_{RS}$) and the EC determined LE (LE$_{EC}$) values as illustrated in **Figure 5**. The correlation was relatively good (R^2 = 0.66); however, it was not statistically significant (P>F = 0.14). This was attributed to the fact that the LE$_{RS}$ was a residual component of the energy balance equation that mainly depends on the

30   calibration accuracy of the H$_{RS}$, which was purely based on the quality of the selected anchor pixels (Weaver, 1990; Field et al., 1994).

Although the regression analysis showed a non-significant correlation, the performance indicators such as the MBE (2.45 W m^{-2}; 0.73%) and the RMSE (115.04 W m^{-2}; 34.33%) are in accordance with the earlier reported values indicating that the METRIC algorithm was useful in the accurate determination of LE over large areas. However, Carrasco-Benavides et al. (2013) stated that the METRIC algorithm overestimated the LE by 14% (RMSE). The obtained average absolute error of the LE$_{RS}$ for the eight images was 35%. It may be due to the accurate energy partition during the METRIC execution at peak growth stages, where the LE accounted for 80-85% of the net radiation. In addition, the H component accounted only 5 to 8% of the Rn during the growing season on the daily scale. For the fallow periods, the recorded partitions of LE and H were in the range of 6.9 to 8.2 % and 77 to 84 %, respectively. On the monthly time scale, H and LE fluxes varied throughout the cropping periods. METRIC algorithm was observed to perform a relatively better in full canopy conditions compared to that in partial canopy conditions. Due to the cooling effect of vegetation, the selection of anchor pixels for H calculation are challenging in continuous irrigation regimes.

The LE was high during the full coverage of LAI and irrespective of alfalfa growth stages. Three environmental factors including atmospheric water demand, humidity and wind speed during the growing season have a high impact on the LE measurements, which in-turn triggered the computation of anchor pixels especially at the time of irrigation. Moreover, in the fallow period, H can be accurately determined with METRIC by selecting the targeted pixels after the harvest of both alfalfa. Advection in dry months are common in hyper arid regions, which affect the H computation, which in-turn affect the LE and ET estimates on a regional and long-term basis.

3.2.5 Evapotranspiration (ET)

The correlation between the ET values obtained from both the METRIC algorithm and the EC system was found to be highly significant (R^2 = 0.93 and P>F = 0.0001) as illustrated in **Figure 7**. Further assessment of the accuracy of the METRIC algorithm in estimating the ET was performed using the RMSE and MBE indicators. The performance of METRIC model in estimating ET on hourly and daily interval was significant with the Mann-Whitney U-test (U and Z value are 32 and 0.052 respectively), similarly the null hypothesis was not rejected with Kruskal-Wallis H-test (0.916). Comparing the hourly ET calculated using the METRIC algorithm to that using the EC system resulted in a RMSE value of 0.13 mm h^{-1} (25.91%) and an MBE value of 0.04 mm h^{-1} (6.6%). For the daily mean ET, the RMSE and MBE values were 4.15 mm d^{-1} (34.33%) and 0.38 mm d^{-1} (4.2%), respectively. These results are in agreement with the results reported by Mkhwanazi and Chavez (2012), where the performance errors in estimating the ET using the METRIC model were determined at 0.14 mm h^{-1} (17.6%) and -0.08 mm h^{-1} (-10.3%) for RMSE and MBE, respectively. Similarly, Chavez et al. (2007) reported a METRIC error of 0.7 mm d^{-1} (7.4 %) in predicting the ET compared to lysimeter data. On the average, present study found that the METRIC algorithm overestimated the hourly ET by 6.6% in comparison to the EC measurements; however, the daily ET was underestimated by 4.2% (Figure 8). There is a fluctuation in EC and Landsat estimated Sensible Heat flux, it might be due to the advection in case of hourly ET and variability in the canopy density with respect to studied footprint". Advection may vary strongly in hyper-arid environments.

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4 Conclusions

The METRIC algorithm was applied on Landsat-8 images for the ET mapping, and its performance was evaluated against the EC flux tower measured EB components and ET at hourly and daily intervals over irrigated alfalfa field in the Eastern Region of Saudi Arabia. The following are the specific conclusions of this study:

- The METRIC algorithm was successfully utilized to estimate the ET with an average error of 6.6% (hourly ET) and 4.2% (daily ET). The performance of the METRIC algorithm was found to be more accurate in estimating the hourly ET ($R^2 = 0.81$) than the daily ET ($R^2 = 0.66$) compared to the ET_{EC}.

- Compared with the EC data, the RS estimated R_n component was found to be highly accurate (an accuracy of more than 95%). In addition, the H obtained from satellite data was associated with errors ranging between 10.89 W m^{-2} and 38.91 W m^{-2} at low (< 1.2) and high (>5.0) LAI values, respectively. However, the corresponding LE estimates are indicated by the low mean value of MBE of 2.45 W m^{-2} (0.74%).

- METRIC algorithm was observed to perform a relatively better in full canopy conditions compared to that in partial canopy conditions. Due to the cooling effect of vegetation, the selection of anchor pixels for H calculation are challenging in continuous irrigation regimes.

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Tables

Table 1. Details of wind parameters at the time of satellite overpass

Date	Wind Speed (m/s)		Wind Direction (° from North)	Yaw angle (°)
	Min.	Max.		
03 June, 2013	6.02	12.45	13.54	56.46
19 June, 2013	5.61	9.69	6.49	63.51
05 July, 2013	2.43	5.28	23.98	46.02
21 July, 2013	5.25	10.71	35.13	34.87
22 August, 2013	1.61	4.91	27.80	42.20
07 September, 2013	1.11	8.17	59.82	10.18
23 September, 2013	5.12	8.93	38.13	31.87
09 October, 2013	4.60	8.67	25.40	44.60

5

Table 2. Energy Balance analysis of EC measured heat fluxes.

Date	Day of the year 2013	Stability parameter (ξ)	Condition	Bowen Ratio	Energy Balance Closure %
3-June	154	0.02	Stable	-0.17	90.84
19-June	170	-0.15	Unstable	0.7	95.81
5-July	186	0.07	Neutral	-0.24	99.14
21-July	195	-0.24	Unstable	0.63	96.80
22-August	234	-0.28	Unstable	-0.42	80.82
7-September	250	0.04	Stable	-0.42	84.09
23-September	266	-0.03	Unstable	0.14	75.14
9-October	282	0.04	Stable	-0.13	71.74
Average		-0.06		0.01	86.79

10   **Table 3.** Details of Landsat-8 data used in the study.

Path	Row	Date of overpass
165	43	June 3, June 19, July 5, July 21, August 22, September 7, September 23 and October 9, 2013

20

Table 4. Split-window (SW) coefficient values (Skokovic et al., 2014)

SW Constant	Value
C_0	-0.268
C_1	1.378
C_2	0.183
C_3	54.300
C_4	-2.238
C_5	-129.200
C_6	16.400

Table 5. Thermal conversion constants and rescaling factors of Landsat-8 TIRS bands ([a]USGS, 2016; [b]Skokovic et al., 2014)

Landsat-8 TIRS	Thermal constants[a]		Rescaling factor[a]		Emissivity values[b]	
	K_1	K_2	M_L	A_L	ε_s	ε_v
Band 10	1321.08	777.89	0.000342	0.1	0.971	0.987
Band 11	1201.14	480.89	0.000342	0.1	0.977	0.989

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Table 6. Input parameters used for METRIC model for alfalfa crop.

DOY	T_{EC} (°C)	T_{LST} (°C)	LAI_G	ET_r	u (m s^{-1})	h_c (m)	Z_m (m)
154	36.42	34.67	1.22	1.21	0.55	0.39	3.2
170	39.59	33.01	3.28	0.61	0.43	0.48	3.2
186	34.7	32.32	4.29	0.83	0.46	0.59	2.2
195	40.96	32.6	5.92	0.96	0.68	0.51	3.0
234	42.98	40.99	1.11	0.31	0.62	0.24	3.0
250	35.48	32.09	3.19	0.52	0.65	0.52	3.0
266	34.52	34.18	1.13	0.27	0.39	0.29	2.3
282	26.78	24.36	2.28	0.41	0.40	0.52	3.2

DOY – Day of the year; T_{EC} – Temperature from flux tower; T_{LST} – estimated temperature from Landsat-8 images; LAI_G – Ground measured Leaf Area Index; ET_r – Reference ET; u – Average horizontal wind velocity; h_c – alfalfa canopy height; Z_m - Height of wind speed measurement.

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Table 7. EC measured and METRIC estimated Energy Balance (EB) components over an alfalfa field.

EB Component	Method	June 03 (154)	June 19 (170)	July 05 (186)	July 21 (195)	Aug. 22 (234)	Sept. 07 (250)	Sept. 23 (266)	Oct. 09 (282)
		Date of Landsat-8 overpass (Day of the year 2013)							
Soil Heat Flux (G), W m^{-2}	RS	28.6	92.5	143.73	80.65	97.92	48.16	19.98	98.31
	ECB	21.6	44.1	155.18	70.33	37.54	54.98	16.50	110.30
Net Radiation (R$_n$), W m^{-2}	RS	488.7	491.5	491.07	490.64	502.95	489.37	491.76	477.75
	ECB	468.0	500.6	506.22	463.27	513.17	476.86	469.6	456.49
G/R$_n$	RS	0.06	0.19	0.29	0.16	0.19	0.10	0.04	0.21
	ECB	0.05	0.09	0.31	0.15	0.07	0.12	0.04	0.24
Sensible Heat Flux (H), W m^{-2}	RS	-57.2	184.2	286.10	160.45	1.77	95.75	39.98	195.62
	EC	-65.8	112.3	274.59	127.34	14.26	230.79	19.03	68.39
Latent Heat Flux (LE), W m^{-2}	RS	574.5	214.8	61.25	249.55	500.20	345.46	551.72	183.82
	EC	335.7	160.2	72.12	260.79	637.84	505.40	560.80	148.80
Evapotranspiration (ET), mm hr^{-1}	RS	0.86	0.32	0.09	0.42	0.76	0.52	0.83	0.27
	EC	0.64	0.24	0.11	0.38	0.96	0.71	0.89	0.22

RS - Remote Sensing (METRIC algorithm), EC - Eddy Covariance, and ECB - Biomet sensors of Eddy Covariance system.

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Table 8. Performance indicators results for the METRIC algorithm estimated EB components.

Error		Rn W m^{-2}	G W m^{-2}	H W m^{-2}	LE W m^{-2}	ET mm hr^{-1}	ET mm d^{-1}
RMSE	Amount	18.32	28.46	72.01	115.04	0.13	4.15
	%	3.74	37.33	63.54	34.33	25.91	34.33
MBE	Amount	8.66	12.42	15.72	2.45	0.04	0.38
	%	1.76	16.29	13.87	0.73	6.6	4.2
Nash-Sutcliffe Coefficient		1	0.59	0.59	0.88	0.99	0.99
R^2		0.54	0.67	0.61	0.66	0.81	0.66
P>F		0.038	0.0131	0.0216	0.0137	0.002	0.013
Mann-Whitney U-test#		23 (-0.89)*	26 (-0.58)*	29 (-0.26)*	31 (-0.05)**	32 (0.05)**	31 (0.05)**
Kruskal-Wallis H-test		0.893*	0.397*	0.099*	0.011**	0.021**	0.001**

#Z-values are reported in the parenthesis; *Not-significant; **Significant
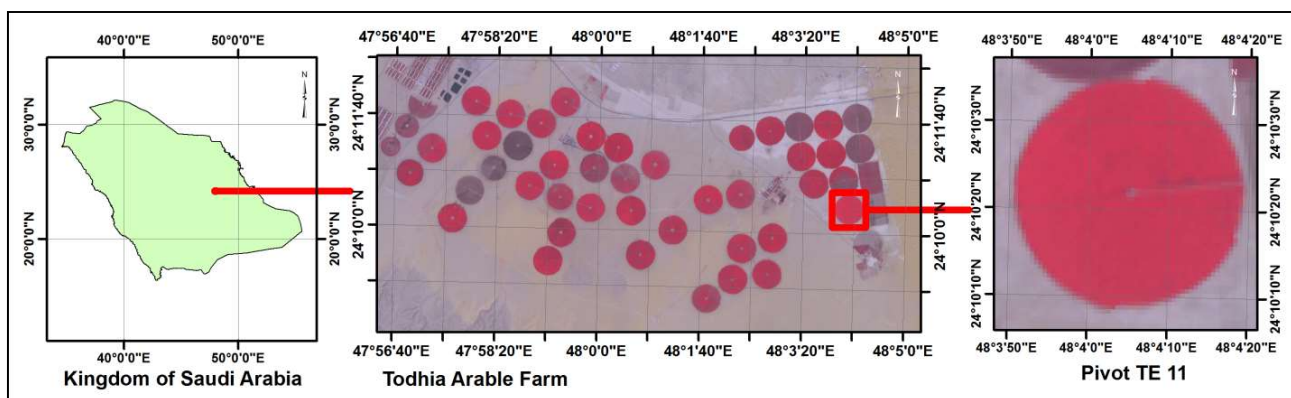
Figures
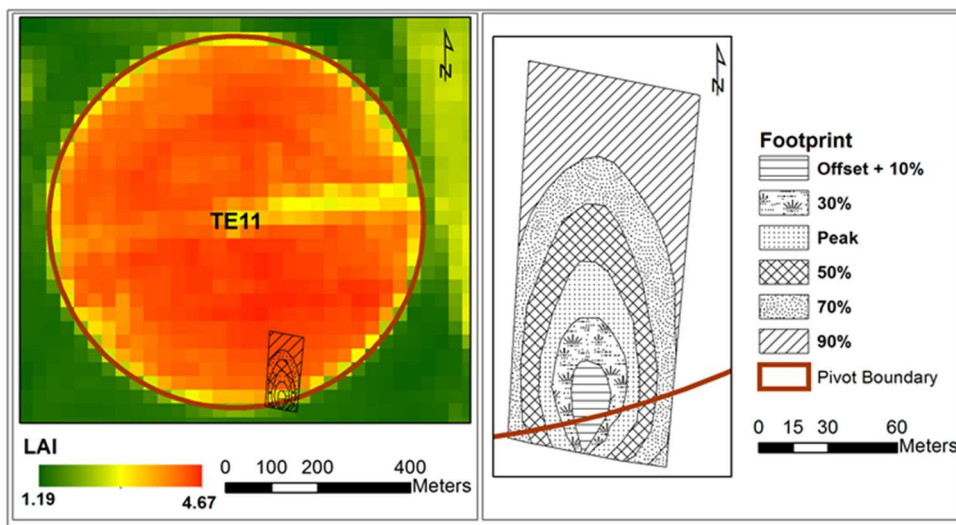

Figure 1. Location map of the study area

Figure 2. Flux Source Area Model (FSAM) Footprint, as % of the fetch area, of the Eddy Covariance system overlaid on LAI map of the alfalfa crop (date of landsat-8 overpass – 21 July, 2013).
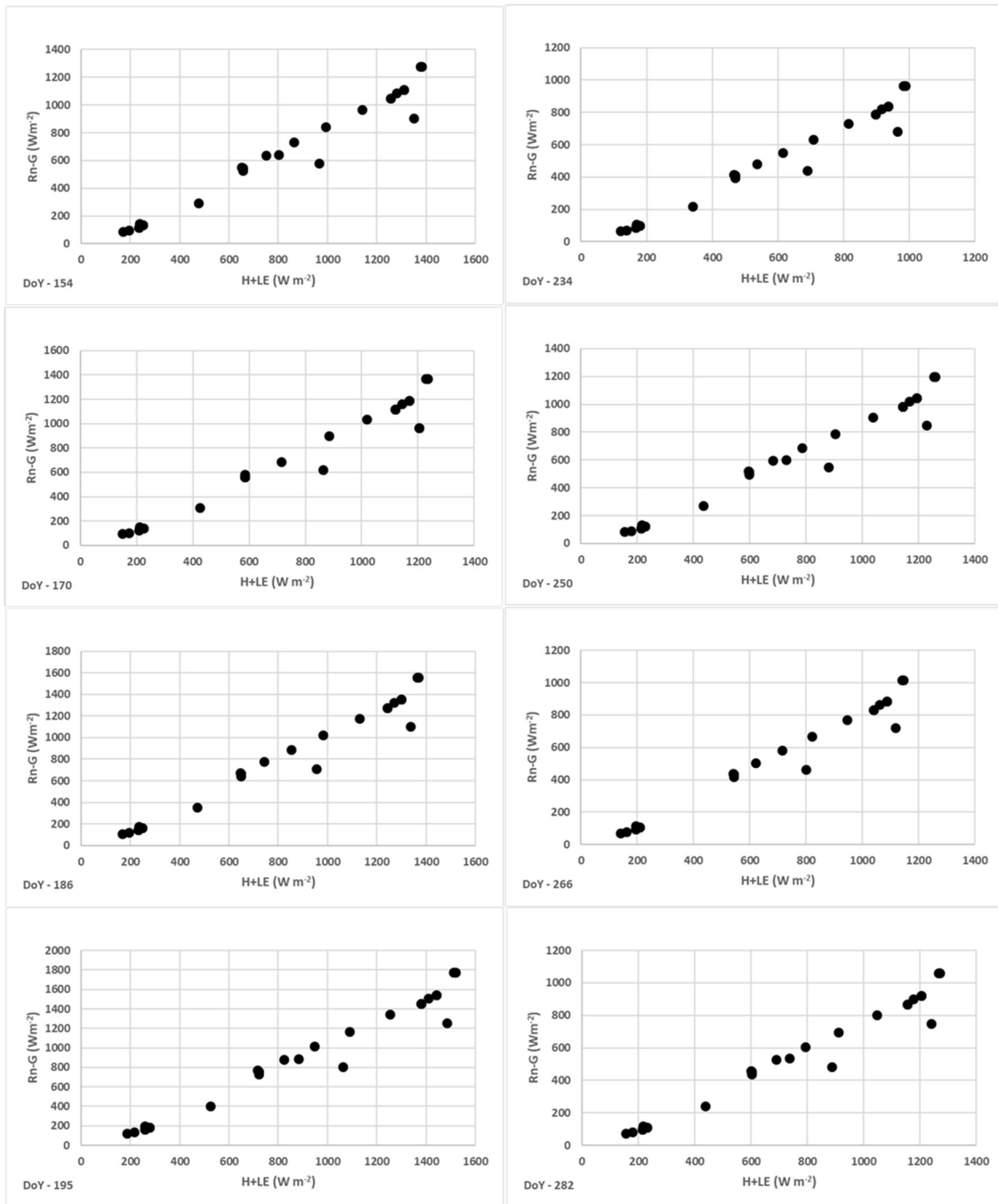
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Figure 3. Energy balance clousure of corrected Eddy covariance data for the studied landsat-8 date of overpass.
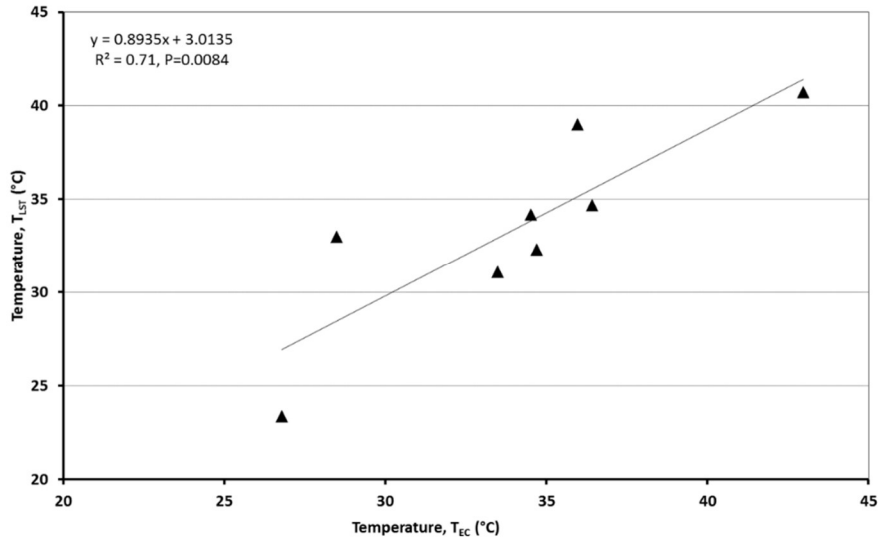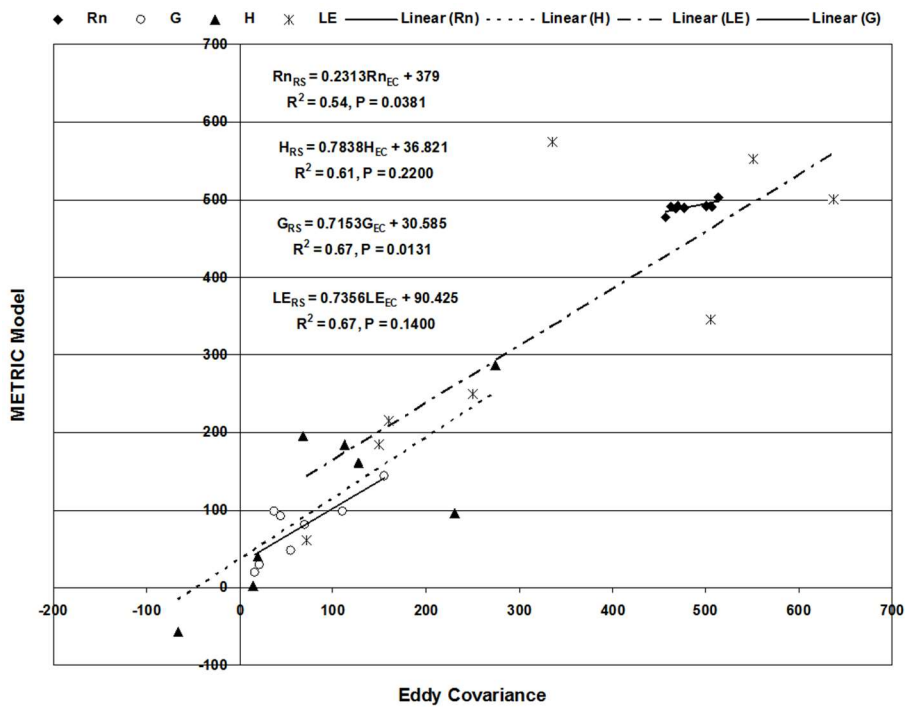
Figure 4. Comparison of EC measured (T_{EC}) and remote sensing derived (T_{LST}) surface temperature.

5   **Figure 5.** The relationship between EB components (W m^{-2}) measured by the METRIC algorithm and the EC system.
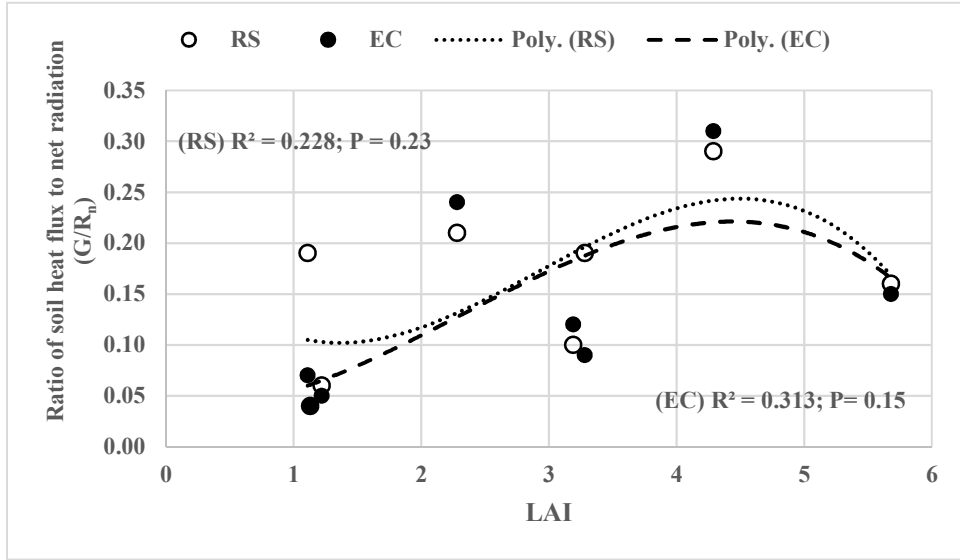
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Figure 6. LAI and G/Rn relationship of the study crop for remote sensing and Eddy Covariance.
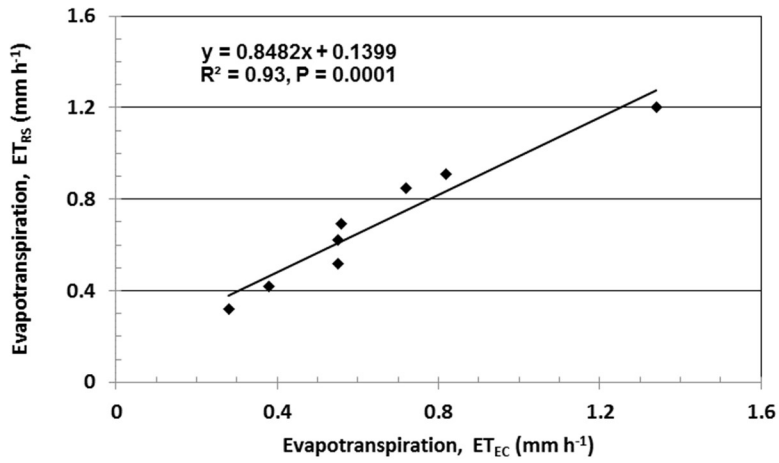
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Figure 7. METRIC-derived hourly evapotranspiration (ET$_{RS}$) versus Eddy Covariance measurements (ET$_{EC}$).
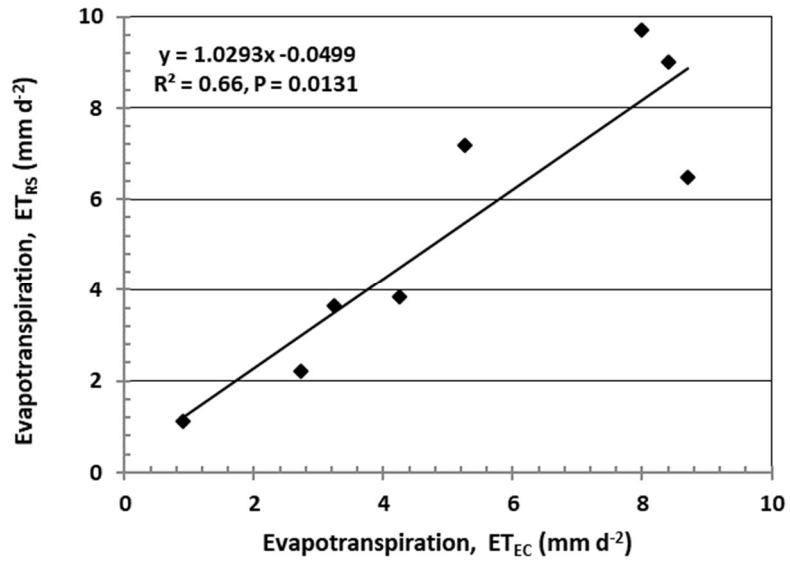
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The figure shows a scatter plot with the following text labels:

- Y-axis: Evapotranspiration, ET_{RS} (mm d^{-2})
- X-axis: Evapotranspiration, ET_{EC} (mm d^{-2})
- $y = 1.0293x - 0.0499$
- $R^2 = 0.66, P = 0.0131$

Figure 8. The relationship between daily estimates of ET_{RS} and ET_{EC}.
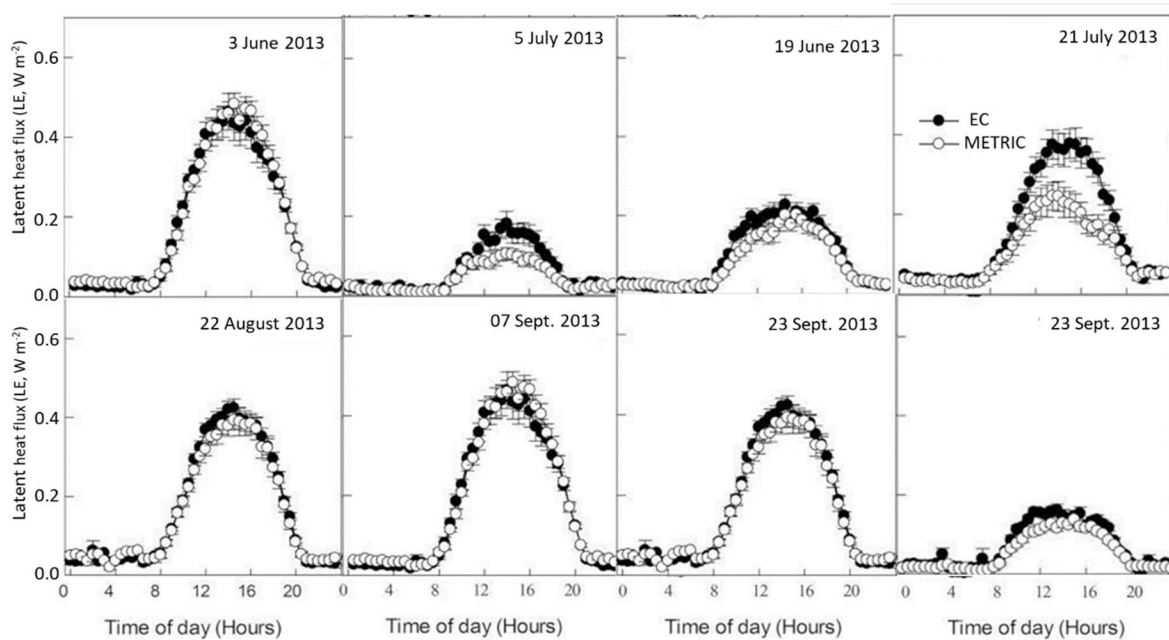
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Figure 9. Comparative assessment of Eddycovariance fluxtower measured against the METRC estimated Latent Heat flux
(LE, W m^{-2})over the study period. (The values are on x-axis are *x1000) data for the studied landsat-8 date of overpass.