Estimating Biomass and Yield Using METRIC Evapotranspiration and Simple Growth Algorithms

Azeem Khan, Claudio O. Stöckle,* Roger L. Nelson, Troy Peters, Jennifer C. Adam, Brian Lamb, Jinshu Chi, and Sarah Waldo

ABSTRACT
Crop models are used to assess crop yield under prescribed scenarios and at scales varying from point to field to region and beyond. The use of models to evaluate the performance of agricultural systems, as they exist in the real world, can be challenging and plagued with constraints. This is due to the difficulty in characterizing the spatial variability across the landscape of crops, soils, weather, management, miscellaneous stress factors, and the initial state of the system. We propose the use of actual evapotranspiration (ETa) estimated from remote sensing images and simple crop growth-transpiration algorithms as an alternative to the use of standalone crop models for real-world yield assessment. In this study, we combined ETa estimates from METRIC (Mapping Evapotranspiration at High Resolution with Internalized Calibration) with simple crop growth algorithms extracted from the CropSyst model to estimate biomass production and yield at high resolution (30 by 30 m). We tested this approach in four dryland agriculture sites in eastern Washington State with contrasting annual precipitation. All sites were equipped with an eddy covariance flux tower for ground ETa estimation. The proposed approach was able to provide good estimates of ETa, seasonal change of aboveground biomass and yields at all sites when compared with observations for a 3-year period, collectively including five different annual crops. Because estimations are made at high resolution, they can be scaled up to field or regional scales. Advantages and limitations of the proposed approach are discussed.

Core Ideas
• Crop models have significant limitations in estimating “real-world” yields across the landscape.
• Joining satellite-based evapotranspiration and leaf area index with growth algorithms provide good yield estimation.
• Proposed method evapotranspiration and yields compared well with observations at four dryland sites.

Crop yield estimation is of interest for managing agricultural lands, determining food pricing and trading policies (Hutchinson, 1991; MacDonald and Hall, 1980). Crop models can simulate yields for a wide range of environments if the input information is sufficient and accurate (Asseng et al., 2013). Evaluating crop performance under prescribed scenarios of climate, soil, and management constitutes the most typical application of crop models. However, their application for assessing crop yield under actual field growing conditions is often restricted by input data availability (de Wit and van Diepen, 2007; Dente et al., 2008; Ma et al., 2012; Mignolet et al., 2007; Zhao et al., 2013). The large spatial variation across the landscape of crop species and cultivars, management, water and nutrient inputs, miscellaneous limitations to growth, and initial soil conditions (water, nutrients, etc.) is difficult to characterize. Yet, this characterization is needed as input to crop models, typically requiring substantial parameterization and initialization of state variables. The need for model calibration is an additional limitation, particularly as the scale of analysis increases.

The integration of satellite observations into crop models, usually referred to as data assimilation, has been proposed for several decades as a means for improving yield estimations (de Wit et al., 2012; Dente et al., 2008; Fang et al., 2011; Liang and Qin, 2008; Ma et al., 2013; Xu et al., 2011). By reducing uncertainties, this approach has been shown to improve the performance of crop models (de Wit and van Diepen, 2007; Hansen et al., 2006; Vazifeidoust et al., 2009). For example, Maas (1988) tested a sorghum [Sorghum bicolor (L.) Moench] model using data sets from 37 fields in South Texas and found that the average yield was underestimated by approximately 30%, but when using

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Abbreviations: AGB, aboveground biomass; CFCT, Cook Farm conventional tillage; CFNT, Cook Farm no-till; EC, eddy covariance; ETa, actual evapotranspiration; ETc, short-grass reference crop evapotranspiration; HI, harvest index; LAI, leaf area index; LIND, Lind; METRIC, mapping evapotranspiration at high resolution with internalized calibration; MSMN, Moscow Mountain; SC, spring canola; SEE, standard error of the estimate; SG, spring garbanzo; WW, winter wheat.
satellite-derived leaf area index (LAI) data the same simulations resulted in a 2% overestimate of average yield. Dente et al. (2008) used LAI from remote sensing in the CERES-Wheat model to improve the accuracy of yield maps. Performance of the DSSAT-CSM-Maize model was improved after assimilating remote sensing data for LAI and soil moisture (Ines et al., 2013). Ma et al. (2013) estimated LAI from remote sensing and used it in the WOFOST crop growth model to conduct a regional winter wheat yield assessment. Their water-limited yield estimates were improved, and the root mean square error (RMSE) decreased from 983 to 474 kg ha\(^{-1}\) and 667 kg ha\(^{-1}\), respectively, in two different optimization schemes. Despite some success, the assimilation of remotely sensed data (mainly LAI) into crop models only partially compensates for the need of characterizing soil, plant, management, and other conditions affecting crop growth, and may reduce some of the uncertainty of model parameterization but not the need for calibration and determination of initial conditions for model simulations.

Another approach involving remote sensing and crop simulation models consists of using model estimations of yield to train regression equations that relate simulated yields to vegetation indices derived from satellite images (e.g., Sibley et al., 2014). Lobell et al. (2015) developed a more elaborate approach that uses crop models to generate a large number of simulations for a range of soil, climate, and management combinations in a region. Daily model outputs are converted to quantities that can be observed remotely (e.g., vegetation indices), and these synthetic remote sensing “observations” and crop model simulated yields are used to train regression equations that can be used with actual satellite observations to estimate yields. However, these methods do not eliminate the need for model calibration (Jin et al., 2017; Sibley et al., 2014) and retain some of limitations in using crop models.

Because crop ET\(_a\) is a good integrator of weather, soil hydrology, and stress factors influencing crop growth (Allen et al., 2011), coupling ET\(_a\) and LAI derived from remote sensing data with simple transpiration-based crop growth algorithms is a novel approach for field yield estimation that overcomes many of the limitations associated with the use of standalone crop models. Large uncertainty in the estimation of ET\(_a\) by crop models has been reported (Cammarano et al., 2016; van Bussel et al., 2016). On the other hand, high-resolution ET\(_a\) estimation using satellite data combined with surface energy balance approaches is rapidly improving (Allen et al., 2007b, 2011; Bastiaanssen et al., 2005, 2012; Ma et al., 2012; Senay et al., 2011). These ET\(_a\) estimates can be readily extended from the pixel scale (currently 30 by 30 m for Landsat satellite) to field and regional scales without the need to quantifying complex hydrological processes (Byun et al., 2014; Hwang and Choi, 2013; Jia et al., 2009).

Methods for the estimation of ET\(_a\) using remote sensing data varies in mechanism and degree of complexity (Chirouze et al., 2014; Choi et al., 2009). Mapping Evapotranspiration at High Resolution with Internalized Calibration (Allen et al., 2007a, 2007b), a widely utilized method, estimates ET\(_a\) as the residual of the energy balance using an inverse calibration technique to compensate for biases in other components of the energy balance. Liaqat and Choi (2015) evaluated METRIC ET\(_a\) over rice (Oryza sativa L.) paddy croplands in Northeast Asia for a period of 12 yr via comparison with EC flux ET\(_a\) estimates, reporting a RMSE from all sites of 0.06 mm d\(^{-1}\). Singh and Irmak (2011) reported RMSE of 1.1 mm d\(^{-1}\) at three irrigated sites with maize (Zea mays L.) and soybean (Glycine max (L.) Merr.) crops from 2005 to 2007 in Nebraska. Allen et al. (2007a) compared seasonal estimates of METRIC ET\(_a\) with lysimeter measurements for two agro-ecosystems in Idaho and found 4% error in METRIC ET\(_a\) estimates for meadow in the Bear River Basin, Idaho, and 1% for irrigated sugar beet in Kimberly, ID, respectively. The METRIC has been extensively evaluated in irrigated croplands (Chávez et al., 2012; Mkhwanazi et al., 2012; Morton et al., 2013; Trezza et al., 2013), but less so in water-stress prone dryland agriculture (Chávez et al., 2007).

The objectives of this study were to (a) evaluate METRIC ET\(_a\) estimates in dryland agriculture sites of eastern Washington State, and (b) evaluate the estimation of biomass production and yield in these sites using simple crop growth algorithms extracted from the CropSyst model combined with METRIC ET\(_a\) estimates.

**METHODOLOGY**

**Study Sites**

We conducted these evaluations at four sites with annual precipitation ranging from 240 to 680 mm, including three growing seasons and five annual crop species winter wheat (Triticum aestivum L.), spring garbanzo (Cicer arietinum L.), spring canola (Brassica napus L.), spring barley (Hordeum vulgare L.), and spring pea (Pisum sativum L.). The sites were: Lind (LIND), Pullman (Cook Farm conventional tillage, CFCT), Pullman (Cook Farm no-till, CFNT), and Moscow Mountain (MSMN). The sites were positioned within a single scene setting of the Landsat 8 path 43 row 27, and 26 images were available for the study period. Details of site characteristics and crops are presented in Table 1.

**Field Data**

**Eddy Covariance Evapotranspiration Estimation**

To obtain independent ET\(_a\) estimates, all sites were instrumented with EC flux towers. The EC system consisted of an open-path infrared CO\(_2\)/H\(_2\)O analyzer (EC150, Campbell Scientific, Logan, UT) and a three-dimensional sonic anemometer (CSAT3A, Campbell Scientific, Logan, UT), which was mounted at a height of 2.0 m. Data were collected at 10 Hz by a data logger (CR3000, Campbell Scientific, Logan, UT) and processed in EddyPro (LI-COR Biosciences, Lincoln, NE) to compute ET\(_a\) at 30-min intervals. Details regarding the instrumentation, data processing, and QA/QC at the study sites were previously reported in Chi et al. (2016) and Waldo et al. (2016).

**Weather Data**

Hourly and daily weather data were acquired from Washington State University’s AgWeatherNet stations (AgWeatherNet, 2014) including maximum and minimum air temperature (T\(_{max}\) and T\(_{min}\)), dewpoint, wind speed, solar radiation, and precipitation.

**Biological Measurements**

To track the accumulation of aboveground biomass (AGB), bi-weekly measurements were made through each growing season. Sample plots were set up following the protocol developed by Law et al. (2008). Four circular subplots (radius of 5 m) were established within a 1-ha circular plot. One subplot was in the center and the other subplots radiated out evenly spaced (120°)
Table 1. Key characteristics of four dryland study sites in the Pacific Northwest.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>CFCT†</th>
<th>CFNT</th>
<th>LIND</th>
<th>MSMN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average annual precipitation, mm</td>
<td>550</td>
<td>550</td>
<td>247</td>
<td>680</td>
</tr>
<tr>
<td>Crop year; 2013 precipitation (mm)</td>
<td>458</td>
<td>458</td>
<td>277</td>
<td>450</td>
</tr>
<tr>
<td>Crop year 2014 precipitation (mm)</td>
<td>330</td>
<td>330</td>
<td>168</td>
<td>455</td>
</tr>
<tr>
<td>Crop year 2015 precipitation (mm)</td>
<td>414</td>
<td>414</td>
<td>196</td>
<td>793</td>
</tr>
<tr>
<td>Location</td>
<td>46.78° N, 117.08° W</td>
<td>46.78° N, 117.09° W</td>
<td>46.99° N, 118.60° W</td>
<td>46.75° N, 116.95° W</td>
</tr>
<tr>
<td>Elevation (masl)</td>
<td>800</td>
<td>800</td>
<td>475</td>
<td>815</td>
</tr>
<tr>
<td>Soil type and order</td>
<td>Silt loam, Mollisol</td>
<td>Silt loam, Mollisol</td>
<td>Silt loam, Mollisol</td>
<td>Silt loam, Mollisol</td>
</tr>
<tr>
<td>Percentage of soil organic matter in top 5 cm</td>
<td>2–5</td>
<td>2–5</td>
<td>1–2</td>
<td>2–5</td>
</tr>
<tr>
<td>Avg annual temperature, °C</td>
<td>9</td>
<td>9</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Tillage type</td>
<td>Continuous cropping</td>
<td>Continuous cropping</td>
<td>Crop-fallow</td>
<td>Continuous cropping</td>
</tr>
<tr>
<td>Crop rotation</td>
<td>Continuous cropping</td>
<td>Continuous cropping</td>
<td>Spring barley</td>
<td>Continuous cropping</td>
</tr>
<tr>
<td>Crops in 2013</td>
<td>Spring garbanzo</td>
<td>Spring garbanzo</td>
<td>Winter wheat</td>
<td>Spring pea</td>
</tr>
<tr>
<td>Crops in 2014</td>
<td>Winter wheat</td>
<td>Spring canola</td>
<td>Winter wheat</td>
<td>Winter wheat</td>
</tr>
<tr>
<td>Crops in 2015</td>
<td>Spring pea</td>
<td>Spring canola</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

† CFCT, Cook Farm conventional tillage near Pullman, WA; CFNT, Cook Farm no till near Pullman, WA; LIND, near Lind, WA; MSMN, Moscow Mountain near Moscow, ID.
‡ Crop year: 1 Oct. to 30 Sept.

at a distance of 35 m. Biomass was manually harvested from the sampling plots. Before harvesting, a square metal frame with 1 m side length was placed around the sample area. Four samples from each site were weighed, and the samples collected shortly before harvest were threshed to determine yields (Waldo et al., 2016).

**METRIC Estimation of Actual Evapotranspiration**

METRIC estimates ETa as the residual of the surface energy balance (Allen et al., 2007b),

\[
LE = R_n - H - G
\]

where \(LE\) is latent heat flux, \(R_n\) is net radiation, \(H\) is sensible heat flux, and \(G\) is soil heat flux. The ETa is calculated by dividing the latent heat flux by the latent heat of vaporization of water. Details for the estimation of each component of the surface energy balance and internal calibration of biases can be found in Allen et al. (2007b, 2011).

At the time of satellite-overpass, high ET ("cold pixel"), and negligible ET ("hot pixel") pixels were selected for internal calibration (Allen et al., 2007b). This procedure is based on information provided in the satellite images, and should not be equated to the calibration of crop models using observed field data. We used short-grass standardized Penman–Monteith reference crop evapotranspiration (ETo) (ASCE-EWRI, 2005), adopting the approach by Chávez et al. (2008, 2012), a crop coefficient \(K\), and the METRIC cold pixel ET (ETcold) to determine EToF, the ratio of ETcold to a calculated crop ET based on weather data [EToF = ETcold/(K ETo)]. Although \(K\) values are suggested in the METRIC literature, \(K\) was calibrated for this study using EC ETa measurements from the CFNT site in 2013. A \(K\) value of 0.85 was obtained, which is adequate for dryland conditions (Conrad et al., 2007; Liaqat and Choi, 2015). This is a one-time calibration used for all sites and years, and the resulting \(K\) value can be used for future studies in the region. Values of EToF for satellite pass days were calculated for all pixels in the image by scaling EToF of the cold pixel by ETpixel/ETcold.

Based on values for satellite pass days, daily EToF values for all pixels were determined using cubic spline interpolation and daily ETa determined from weather data, thus allowing the calculation of daily ETa (= EToF of each cell for the day multiplied by daily ETo). The cubic spline interpolation was performed primarily on cloud free images. However, some of the partial cloud covered images were also used after masking out the cloudy portion of the images. For comparison with EC, METRIC ETa estimates were obtained by selecting pixels in the upwind footprint source area of each EC flux tower.

**Satellite Data and Preprocessing**

Key input data for METRIC are satellite images at a resolution of 30 by 30 m, hourly and daily weather data for water balance, land use image, and digital elevation model. Landsat satellite path 43, row 27 covers our study region. Landsat 8 OLI satellite images, available every 16 d, were acquired from the USGS EarthExplorer website using the Glovis preview tool. The downloaded images were preprocessed by USGS EROS using the LPGS preprocessing system to obtain the georectified images corrected for radiometric and terrain effects.

**Aboveground Biomass and Yield Estimation**

The AGB production and yield were estimated based on algorithms from the CropSyst model (Stöckle et al., 1994, 2003). Crop LAI and ETa were derived from satellite data processing by METRIC. The resulting approach will be referred to as METRIC-CropSyst.

The partitioning of ETa into actual transpiration (\(T_a\)) and actual soil water evaporation (\(E_s\)) depends on the fraction of total solar radiation intercepted by the canopy, which is a function of crop LAI estimated from remote sensing data as done in METRIC (Allen et al., 2007b; Bastiaanssen et al., 1998). Leaf area index was determined on days of satellite overpass, and daily LAI values throughout the growing season were obtained by spline interpolation. The fraction of total solar radiation reaching the soil is equal to one minus the fraction of canopy interception, which multiplied by ETo yields the potential soil water evaporation, used in a soil water balance to determine actual soil water evaporation (Stöckle et al., 1994). The latter is subtracted from METRIC ETa to estimate crop transpiration (\(T_a\)).

Aboveground biomass was estimated based on \(T_a\) and transpiration use efficiency (Stöckle et al., 2003), defined as the
biomass produced per unit mass of water transpired, and determined as a function of vapor pressure deficit (Kemanian et al., 2005; Kremer et al., 2008).

The crop yield was calculated using a harvest index (HI), which is the fraction of the aboveground biomass at maturity that constitutes yield. The HI was adjusted for grain crops by the ratio of biomass production during yield formation to cumulative seasonal biomass and a translocation factor (Kemanian et al., 2007).

Table 2 shows the values of the crop parameters used for the five different crops included in this study.

RESULTS AND DISCUSSION

Figure 1 presents the comparison of METRIC and EC ETa for satellite overpass days with cloud-free satellite images. Overall, METRIC ETa compared well with EC ETa for satellite overpass days in the entire study period with a SEE of 0.34 mm d\(^{-1}\) (slope: 0.94, \(r^2\): 0.94), comparable to SEE values up to ~0.5 mm d\(^{-1}\) reported in irrigated areas (e.g., Carrasco-Benavides et al., 2014; Morton et al., 2013). Evaluated by site, CFNT had a SEE of 0.27 mm d\(^{-1}\) (slope: 0.91, \(r^2\): 0.96), CFCT had a SEE of 0.33 mm d\(^{-1}\) (slope: 0.92, \(r^2\): 0.95), MSMN had a SEE of 0.39 mm d\(^{-1}\) (slope: 0.97, \(r^2\): 0.92) and LIND had a SEE of 0.86 mm d\(^{-1}\) (slope: 1.14, \(r^2\): 0.66). Sites in the high precipitation zone sites (CFNT, CFCT, MSMN) have lower departure than the site in the low precipitation zone (LIND).

The daily-interpolated ETa estimates were expected to be less accurate than ETa estimates for days of satellite overpass. Comparison of METRIC and EC daily ETa for the entire season resulted in SEE of 0.52 mm d\(^{-1}\) (slope: 0.89, \(r^2\): 0.84) at CFNT, 0.65 mm d\(^{-1}\) (slope: 1.1, \(r^2\): 0.83) at CFCT, 0.83 mm d\(^{-1}\) (slope: 0.79, \(r^2\): 0.6) at MSMN, and 0.49 mm d\(^{-1}\) (slope: 0.68, \(r^2\): 0.5) at LIND. These discrepancies were comparable to those obtained by Singh et al. (2011), who reported daily METRIC ETa with a SEE of 0.6 mm d\(^{-1}\) for dryland maize compared with EC measurements.

Table 2. Crop parameters for five different crops in this study

<table>
<thead>
<tr>
<th>Parameter†</th>
<th>Winter wheat</th>
<th>Spring barley</th>
<th>Spring garbanzo</th>
<th>Spring canola</th>
<th>Spring pea</th>
</tr>
</thead>
<tbody>
<tr>
<td>TUE (g of B kg(^{-1}) of transpiration) at 1 kPa</td>
<td>5.5</td>
<td>5.5</td>
<td>3.5</td>
<td>3.5</td>
<td>4</td>
</tr>
<tr>
<td>Unstressed HI, kg kg(^{-1})</td>
<td>0.48</td>
<td>0.48</td>
<td>0.35</td>
<td>(*)‡</td>
<td>0.35</td>
</tr>
<tr>
<td>Translocation Fraction</td>
<td>0.3</td>
<td>0.3</td>
<td>0.2</td>
<td>(*)‡</td>
<td>0.2</td>
</tr>
</tbody>
</table>

† TUE, transpiration use efficiency, HI, harvest index.
‡ (*) = This crop was incorporated into the soil before harvest.

Fig. 1. Comparison of mapping evapotranspiration at high resolution with Internalized calibration (METRIC) and eddy covariance (EC) methods estimates of actual evapotranspiration (ETa) (mm d\(^{-1}\)) for satellite overpass dates. Standard Error of the Estimate (SEE) were 0.27, 0.33, 0.39, and 0.86 mm d\(^{-1}\) for Cook Farm no-till (CFNT), Cook Farm conventional tillage (CFCT), Moscow Mountain (MSMN), and Lind (LIND) sites, respectively.
The 7-d moving average of EC and METRIC ET$_a$ for the three growing seasons and four sites of this study are shown in Fig. 2. Overall, METRIC ET$_a$ follows well the seasonal progression determined by EC and the results were comparable to Morton et al. (2013). Both EC measurements and METRIC ET$_a$ estimates have uncertainties. METRIC ET$_a$ includes an internal calibration to provide boundaries to ET$_a$ estimates and uses interpolation to approximate ET$_a$ between days of satellite overpasses. The EC ET$_a$ requires estimation of the changing area of land contributing to ET$_a$, and the method may underestimate ET$_a$ during stable and calm atmospheric conditions and be affected by energy balance closure errors (Allen, 2008; Mauder and Foken, 2006; Twine et al., 2000).

Table 3 presents the cumulative ET$_a$ at the study sites for three growing seasons and multiple crops. The departure range for cumulative estimates was 1 to 16% for CFCT, CFNT, and

<table>
<thead>
<tr>
<th>Site†</th>
<th>Year</th>
<th>Crop</th>
<th>METRIC ET$_a$ mm</th>
<th>EC ET$_a$ mm</th>
<th>Departure %</th>
<th>Crop year precipitation‡ mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFNT</td>
<td>2013</td>
<td>SG</td>
<td>322</td>
<td>333</td>
<td>–3.3</td>
<td>458</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>WW</td>
<td>407</td>
<td>427</td>
<td>–4.7</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>SC</td>
<td>386</td>
<td>345</td>
<td>11.9</td>
<td>414</td>
</tr>
<tr>
<td>CFCT</td>
<td>2013</td>
<td>SG</td>
<td>297</td>
<td>306</td>
<td>–2.9</td>
<td>458</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>WW</td>
<td>490</td>
<td>423</td>
<td>15.8</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>SC</td>
<td>410</td>
<td>360</td>
<td>13.9</td>
<td>414</td>
</tr>
<tr>
<td>LIND</td>
<td>2013</td>
<td>WW</td>
<td>290</td>
<td>235</td>
<td>23.4</td>
<td>277</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>Fallow</td>
<td>133</td>
<td>106</td>
<td>25.5</td>
<td>168</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>WW</td>
<td>161</td>
<td>151</td>
<td>6.6</td>
<td>196</td>
</tr>
<tr>
<td>MSMN</td>
<td>2013</td>
<td>SB</td>
<td>390</td>
<td>385</td>
<td>1.3</td>
<td>450</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>SP</td>
<td>470</td>
<td>438</td>
<td>7.3</td>
<td>455</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>WW</td>
<td>490</td>
<td>433</td>
<td>13.2</td>
<td>793</td>
</tr>
</tbody>
</table>

† CFNT, Cook Farm no-till; CFCT, Cook Farm conventional tillage; LIND, Lind; MSMN, Moscow Mountain near Moscow, ID; SG, spring garbanzo; WW, winter wheat; SC, spring canola; SB, spring barley; SP, spring pea.
‡ Crop year is 1 October to 30 September.

Fig. 2. Comparison of daily mapping evapotranspiration at high resolution with internalized calibration (METRIC) and eddy covariance (EC) actual evapotranspiration (EC ET$_a$) for four sites and three growing seasons (SB-spring barley, SP-spring pea, WW-winter wheat, SG-spring garbanzo, SC-spring canola).
MSMN (high precipitation sites) and 6 to 25% for LIND (low precipitation site). For remotely sensed ET, larger departures are associated with low ET conditions and lower errors are associated with high ET conditions (Gowda et al., 2007).

**Seasonal Crop Biomass Evolution**

The evolution of AGB estimated by METRIC-CropSyst and the observed values are shown in Fig. 3. The observed AGB had a large variation among samples. The CFCT and CFNT sites had winter wheat (WW) in 2014, and spring garbanzo (SG) and spring canola (SC) in 2013 and 2015, and only differed in tillage management. The overall seasonal trend of observed and estimated evolution of AGB agreed generally well for all crops at both sites. Sites MSMN and LIND, the highest and lowest precipitation sites, also showed good agreement. The 2013 growth of WW at Lind could not be calculated because a sizeable amount of growth occurred before the first satellite image was available. For 2015 WW at Lind, we used the second biomass measurement (18 March) as a starting point for the METRIC-CropSyst AGB estimation.

Table 4 presents statistics of estimated aboveground biomass compared to average AGB measured at various times throughout the season (Fig. 3). Overall, WW SEE were higher and $R^2$ were lower than those of spring crops, except for MSMN 2015 ($R^2 = 0.99$). The lower performance of WW could be attributed to image limitations during winter. However, as shown in Fig. 3, the tracking of biomass evolution is good at CFCT and CFNT for most of the season, except for the last two observations that appear anomalous (a pause in growth followed by a large increase). The $R^2$ for WW in LIND 2015 and spring pea in MSMN 2014 were definitely low (0.76 and 0.78, respectively). Overall, the AGB measurements showed large variation (Waldo et al., 2016).

**Grain Yield Comparisons**

METRIC-CropSyst grain yield estimates and measurements are compared in Fig. 4. For the 2015 growing season, we did not have grain yield at CFCT and CFNT because spring canola was plowed into the soil that year. At MSMN, the WW yield
reported for 2015 was extremely low, not commensurate with visual observations and growing conditions, and most likely erroneous. For LIND, METRIC-CropSyst yield estimates could not be made because of the difficulty associated with insufficient seasonal coverage of the available satellite images. The estimated yield errors in 2013 were 15.2, –13.3, and 1.4% at CFNT, CFCT, and MSMN, respectively. The corresponding errors in 2014 were 0.6, 4.8, and 32.8% in 2014. Based on four 1-m² samples, observed yield presented large variation caused by crop heterogeneity (Chi et al., 2016). METRIC-CropSyst biomass production and yields were based on ETa estimates over an area of several pixels (900 m² each). Overall, the higher-yielding cereals showed lower errors than legumes. The large error obtained for MSMN 2014 was commensurate with the lower fit obtained for AGB.

**FINAL CONSIDERATIONS**

The purpose of this study was to provide a proof of concept of combining METRIC ETa estimates with simple algorithms extracted from the CropSyst model. With some deficiencies, METRIC-CropSyst performed reasonably well in estimating seasonal trends of ETa and biomass, and yields at harvest. However, it must be recognized that the low frequency of satellite images and the presence of clouds that partially or completely negated the usability of images, particularly for winter crops, are current challenges. The approach should benefit from the availability of more frequent satellite images and complementary air-borne imagery to increase the temporal density of data. Also, data from Lower Earth Orbit satellites offer great promise. Another challenge to the application of METRIC-CropSyst is the availability of daily weather data with sufficient spatial density over a region of interest. This constrain has been removed to some degree by the availability of a dataset of daily high-spatial resolution (4 by 4 km) surface meteorological data covering the contiguous United States from 1979-yesterday (GRIDMET, http://www.climatologylab.org/gridmet.html). This dataset, updated daily, provides the necessary weather data to support EEFlux (https://eeflux-level1.appspot.com), an implementation of METRIC that provides ETa data from 1984 to present and for nearly every land area on the contiguous United States.

**CONCLUSIONS**

Comparisons of METRIC and EC ETa at four sites showed reasonable agreement. The METRIC ETa values had SEE of ~0.4 mm d⁻¹ on satellite-overpass days, increasing to a maximum of 0.8 mm d⁻¹ for seasonal estimates at MSMN. Similarly, the SEE at LIND, CFNT, and CFCT was ~ 0.3 mm d⁻¹ for
satellite-overpass days and ~0.6 mm d−1 for seasonal estimates. METRIC-CropSyst was able to produce estimates of the growth of biomass and grain yield that were in good agreement with observations for both winter and spring crops.

Our results support the feasibility of the use of METRIC-CropSyst for high-resolution (30 by 30 m) yield estimation that can be readily extended to larger scales. Limitations to the approach include the paucity of satellite images (currently one overpass every 16 d) and the presence of clouds that partially or completely negate the usability of some images. Satellite overpasses with high-resolution images at weekly intervals would be highly desirable. In addition, the use of aerial images, including images collected with relatively inexpensive unmanned aerial systems, could provide complementary data for METRIC-CropSyst estimations.

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