ESTIMATING CROP EVAPOTRANSPIRATION USING A REMOTE SENSING-ENERGY BALANCE MODEL

by

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A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Master of Science in Geography

Spring 2020

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ACKNOWLEDGMENTS

I would like to thank the entire Department of Geography and Spatial Sciences for accepting me after I applied to be a master’s student. Without this first step, I would not be where I am today. I would like to thank my committee, advisor Dr. Tracy DeLiberty, Dr. Dan Leathers, and Dr. Changming He, for their continuous guidance and expertise throughout this thesis.

I would also like to thank the staff from Delaware Environmental Observing System for providing me with the data necessary to complete this thesis. Director Kevin Brinson’s help and data throughout the past two years made this thesis possible.

Finally, I would like to thank the faculty at the University of Georgia’s Geography Department for starting me on this path.
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ABSTRACT

Evapotranspiration (ET) is the combination of transpiration from plants and evaporation from land surface sources of water. Accurate accounting of actual crop ET is critical in agricultural water management, especially in areas with intensive irrigation. Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) is a useful tool to spatially estimate actual evapotranspiration (ET\textsubscript{a}) using satellite imagery. Although METRIC has been a documented success in estimating ET\textsubscript{a} in regions around the world, especially the semi-arid regions of the western United States, it has not been applied in the Mid-Atlantic region of the United States or examined under different irrigation regimes like subsurface drip (SDI) and central pivot irrigation (CPI). This study compares cumulative ET\textsubscript{a} from corn and soybean crops under CPI and SDI crop fields and provides cumulative ET\textsubscript{a} images of the fields in southern Delaware. METRIC modeled land surface energy balance data and daily ET\textsubscript{a} (ET\textsubscript{METRIC}) were compared to in-situ observations of incoming solar radiation (R\textsubscript{\downarrow}), surface temperature (T\textsubscript{s}), net radiation (R\textsubscript{n}), soil heat flux (G), sensible heat flux (H), latent heat flux (LE), Eddy Covariance ET\textsubscript{a} (ET\textsubscript{EC}), and atmometer ET\textsubscript{a} (ET\textsubscript{atm}). Turbulent fluxes (H and LE) were adjusted to force energy balance closure using the Bowen ratio method. In-situ data measurements were fixed to a Delaware Environmental Observing System (DEOS) station bordering the SDI field in Warrington Farm, a University of Delaware owned irrigation research farm. METRIC analysis and validation were performed over various dates within the 2015, 2016, and 2017 growing seasons. Modeled values of R\textsubscript{\downarrow}, T\textsubscript{s}, G,
and \( LE \) agreed reasonably well with observations, while \( R_n \) and \( H \) yielded large biases. Biases in \( H \) are in part due to the internal design of METRIC of internal calibration, which absorb all other energy balance biases to yield accurate values of \( \text{ET}_a \). Daily time series of \( \text{ET}_{\text{METRIC}} \) from the 2016 study period agreed well with \( \text{ET}_{\text{EC}} \), indicated by moderate correlation \( (R^2 = 0.63) \) and low RMSE \( (0.75 \text{ mm day}^{-1}) \). Results from the 2017 study period were unfavorable \( (R^2 = 0.33, \text{ RMSE of } 1.13 \text{ mm day}^{-1}) \). Less than optimal Landsat coverage over the study area contributed to deviations from observations. Cumulative \( \text{ET}_{\text{METRIC}} \) was 1.5\% and 2.9\% greater than \( \text{ET}_{\text{EC}} \) for the 2016 and 2017 study periods, respectively. METRIC analysis was able to detect differences in cumulative \( \text{ET}_a \) of corn and soybean under the CPI system and SDI system. Results indicate that METRIC is a useful tool to create spatial estimates of \( \text{ET}_a \) in an agriculturally intensive area of the mid-Atlantic region.
Chapter 1

INTRODUCTION

1.1 Evapotranspiration and Surface Energy Balance

Primarily driven by solar radiation, the hydrologic cycle describes the continuous movement and phase changes of water between the land surface, ocean, and atmosphere. Water is evaporated from the oceans and land surfaces or transpired by vegetation, sublimated (solid to gas) from ice, transported by winds, and condensed into clouds where it eventually precipitates onto the land and ocean (Trenberth et al. 2006). Evaporation is the phase change from liquid water to water vapor and occurs over any open water body, residual moisture stored at or near soil surface, and water on objects such as plants or buildings. Transpiration is the loss of water vapor through pores in vegetation called stomata located in leaves, needles, or stems (Fisher et al. 2011). Plants self-regulate water vapor loss by closing their stomata when necessary, but also open their stomata for CO₂ absorption for photosynthesis. When stomata are open, water vapor is free to exit the plant and move into the atmosphere (Zeiger 1983). Evaporation over land and transpiration are usually estimated together in the form of evapotranspiration (ET). Winds in the atmosphere transport moisture around the world, where the liquid droplets or ice precipitate over the land or over the open ocean. Over
land, precipitation is either evaporated, transpired, sublimated, or flows back to the oceans as overland water or subsurface groundwater discharge, thus completing the hydrologic cycle (Huntington 2010).

The Earth’s land surface energy balance is inherently coupled to the hydrologic cycle by the ET process. The surface energy balance is defined as the equilibrium of energy fluxes at the earth’s surface, where the energy fluxes include the incoming and outgoing solar and terrestrial radiation (net radiation), energy conducted into the ground, energy convected into the atmosphere, and energy as it is consumed in the ET process. The surface energy balance is represented by the surface energy balance equation:

\[ R_n = LE + G + H \]  \hspace{1cm} (1)

where \( R_n \) is net radiation (difference between the incoming and outgoing fluxes), \( G \) is the ground heat flux conducted into the soil, \( H \) is sensible heat flux convected into the atmosphere, and \( LE \) is latent heat (energy) consumed by ET (Allen et al. 2007a).

Evaporation is the result of the differences in water vapor concentration from the surface to the overlying atmosphere, or a vapor pressure gradient, and is always associated with a transfer of latent heat. Common meteorological variables affect ET rates. Direct solar radiation and, to a lesser extent, the ambient air temperature provide the energy required for ET. The humidity of the overlying air controls the amount of additional water that can be evaporated. Wind speed affects the ability to replace
saturated air with drier air to continue ET (Allen et al. 1998). In other words, ET is constrained by the energy available (e.g. solar radiation and temperature) to turn liquid water into water vapor and by the capability of the surrounding air to transfer moisture away from the surface into the atmosphere (e.g. humidity and wind speed) (Zhang et al. 2016).

Evaporation occurs when there is a vapor pressure deficit between the surface and overlying atmosphere. Vapor pressure is the pressure exerted by water vapor, and has an upward limit called the saturation vapor pressure and is a function of temperature. In general, as temperature increases, the saturation vapor pressure increases. The proportional relationship between vapor pressure deficit and the evaporation rate is described by Dalton’s Law:

$$E \propto e_s^* - e_a$$

where $E$ is the evaporation rate, $e_s^*$ is the saturation vapor pressure of the surface, and $e_a$ is the vapor pressure of the overlying atmosphere. Latent heat from the surrounding environment is consumed in the evaporation process because energy from the environment is required to break the hydrogen bonds that hold water molecules together as liquid – when those bonds break, the water molecules enter the atmosphere as vapor thereby completing the transfer of energy from a liquid water surface to water vapor. As a result, the surface from which the water molecules evaporate from loses energy and is cooled (Fisher et al. 2011, Katul et al. 2012). The quantity of energy required to break the hydrogen bonds is the latent heat of vaporization. Because of the pairing between
the water balance and energy balance, the latent heat-water transfer is described by the latent heat transfer equation:

\[ LE = \lambda E \]  

where \( \lambda \) is the latent heat of vaporization measured in Joules kg\(^{-1}\) (J kg\(^{-1}\)).

Energy transferred upwards into the atmosphere by convection and downward into the soil by conduction are the sensible and soil heat fluxes, respectively. These fluxes are not associated with the phase changes of liquid water to water vapor. Sensible heat (\( H \)) fluxes depend on a measurable temperature difference over a vertical distance, or temperature gradient. This flux is proportional to the near surface air temperature gradient (Allen et al. 2007a). \( H \) is dependent on wind speed of the overlying atmosphere and surface characteristics such as vegetation density. Soil heat flux (\( G \)) is proportional to the vertical temperature gradient in the soil and depends on the soil’s ability to absorb energy (i.e. thermal conductivity) (Hartman 1994). The soil’s thermal conductivity depends on soil type and water content in the soil (Kalma et al. 2008). Since water has a much higher thermal conductivity than dry soil, soils with high water concentration have higher thermal conductivity than dry soils and a greater potential for higher soil heat flux. Naturally, when there is little moisture or vegetation, the sensible heat and ground heat fluxes dominates the surface energy balance.
1.2 Agriculture in Delaware

The agricultural sector in Delaware is a nearly $1.5 billion per year industry. According to the Census of Agriculture report by the United States Department of Agriculture (USDA), there were 2,302 farms in the state of Delaware in 2017, with 1616 of those farms used for cropland spanning 452,211 acres (1,830 km$^2$). Corn and soybean crops were the dominant crop types in Delaware, comprised of approximately 190,000 and 178,000 acres of agricultural land, respectively. From 2012 to 2017, the number of farms has decreased by 149 farms, overall annual sales have increased by $191,959,000, and average annual sales has increased by $117,032 per farm. The number of farms and land area of farmland has decreased as a result of changes in land use (i.e. urbanization), increased population growth. Further, advances in irrigation, farm equipment, fertilizer, and pesticides has allowed crop yield to increase despite the decreasing number of farms. The trend in Delaware farmland is part of a national trend of increased agricultural productivity and a consolidation of farmland (Awokuse et al. 2010). Irrigation use has also increased despite continually decreasing size of farms. From 2012 to 2017, irrigated farmland has increased by 15.1% and the number of farms utilizing irrigation has increased by 14.8%. From 1997 to 2017, irrigated farmland increased by 39.6% and the number of farms using irrigation increased by 42.3% (USDA-NASS, 2017).
Irrigation in Delaware primarily consists of central pivot irrigation (CPI). There is a general understanding that subsurface drip irrigation (SDI) systems are more efficient in delivering water directly to the crop than CPI systems. Frequent irrigation under an SDI system provides water directly to the root zone to satisfy immediate crop ET, which leaves the root zone soil below available water capacity. In-season rainfall may allow the root zone soil to reach available water capacity, thereby maximizing effective use of irrigation. Because SDI systems do not wet the soil surface or interact with the atmosphere, evaporative losses and surface runoff are minimized (Odhiambo and Irmak, 2015). CPI systems, however, interact directly with the atmosphere, canopy surface, and soil surface. Water from sprinkler irrigation can be directed away from the crop canopy by wind, be intercepted by the crop canopy, and wet the soil surface. Water that does not reach the root zone can assumed to be lost to evaporation. Further, water loss through evaporation under CPI systems is dependent on diurnal variation in weather conditions (Martinez-Cob et al. 2008). CPI systems must irrigate more than SDI systems to reach the same yield (Lamm and Trooien, 2003). It follows that fields irrigated by CPI leads to higher levels of growing season ET than fields irrigated by SDI.
1.4 In Situ Approaches to Estimate Evapotranspiration

Computing actual ET ($ET_a$) is essential for applications in areas such as agriculture (He et al. 2017), water resource management (Lian and Huang 2015), and water resource regulation (Allen et al. 2007b). Various methods for estimating $ET_a$ have been documented, including near-surface remote sensing instruments, hydrological or water balance models, and satellite remote sensing-energy balance models. Ground or near ground instrumentation can measure $ET_a$ at a point or plant scale (e.g. porometer, lysimeter) to landscape scale (~100m) (e.g. water balance). $ET_a$ for crops can be calculated using reference ET ($ET_r$) multiplied by a crop coefficient ($K_c$) curve. $ET_r$ represents the ET rate, or evaporative demand of the atmosphere, of a hypothetical, well-watered and uniform crop surface (usually alfalfa). $ET_r$ can be calculated using near surface meteorological data and the Food and Agricultural Organization (FAO) Penman-Monteith method. A $K_c$ curve represents the ratio of previously measured ET rates for a given crop to the $ET_r$ (Allen et al. 1998).

Among the many forms of near surface $ET_a$ measurement methods, the Eddy Covariance (EC) method is widely used. The EC method measures the covariance between the concentration of water vapor and the vertical component of the three-dimensional wind field. Instead of directly measuring $ET_a$, EC methods measure $LE$ fluctuations (flux) in units of energy. $LE$ fluxes are converted to volume (mass) units to estimate $ET_a$. The EC method also estimates $H$ flux. Among other environmental variables, $R_n$ and $G$ can be integrated in the EC method to improve flux calculations.
Accurate flux measurements (e.g. \( LE, H \), etc.) are one of the advantages of EC methods. Flux measurements can be made on several time (e.g. hour, day, and year) and spatial scales of around 100 – 2000 m, provided the landscape is mostly homogeneous (Burba and Anderson, 2012).

EC methods assume that the fluctuations in ET\(_a\) at a point are representative of upwind fluctuations as well, the terrain is horizontal and homogeneous, and EC towers themselves do not distort air flow and turbulence (Burba and Anderson, 2012). Ground instrumentation, such as EC, are useful for small scale deployment and measurement of ET\(_a\), but are also prone to environmental disturbances (animals, debris) and/or human error (improper site setup, setup in a heterogenous landscape, etc) which may lead to inaccuracies, and are not useful in determining ET\(_a\) over regional or greater spatial scales (Rana and Katerji 2000; Verstraeten et al. 2008).

One way to evaluate EC fluxes is the closure of the energy balance. The energy balance closure necessitates that the turbulent fluxes (i.e. \( LE \) and \( H \)) equal all other energy sinks and sources following the equation:

\[
LE + H = R_n - G - S - Q
\]

where \( S \) is the rate of change of heat storage between the soil surface and the EC instrument (ECI), and \( Q \) is the combination of all minor energy storage and metabolic terms (Wilson et al. 2002, Stoy et al. 2013). The \( Q \) terms are often considered negligible and are disregarded for long term energy balance closure studies. Imbalances between
the left- and right-hand sides of equation 4 may indicate inaccurate turbulent flux estimates. Statistical regression and energy balance ratio (EBR) are typical methods to evaluate the energy balance closure. The EBR is the ratio of cumulative or incremental turbulent fluxes (i.e. $H$ and $LE$) to net radiation minus soil heat flux. Studies utilizing the EBR and regression to measure energy balance closure across hundreds of EC sites show that the turbulent fluxes ($H + LE$) are usually underestimated by about 10 – 30% relative to the estimates of available energy ($R_n - G - S$) (Wilson et al. 2002). A study by Wilson et al. (2002) determined a mean imbalance of 20% for 22 sites totaling 50 total years of EC data. Stoy et al. (2013) found that out of the 173 ecosystems in the study, crops generally had the poorest energy balance ratio of 0.70 – 0.78 (70 – 78%), while evergreen broadleaf forests and savannahs had the highest energy balance ratio of 0.91 – 0.94 (91 – 94%). The authors point to landscape homogeneity in broadleaf forests and savannahs as the likely reason for nearly complete energy balance closure. Instrument biases, unknown or additional water vapor sources, energy sinks, and landscape heterogeneity are some potential causes of an imbalance in the energy balance closure (Wilson et al. 2002, Stoy et al. 2013).

Atmometers are simple and inexpensive instruments designed to emulate grass or alfalfa reference ET, denoted as $ET_o$ and $ET_r$, respectively, and are regularly used in agricultural settings. Atmometers consist of a ceramic evaporation plate (Bellani cup) covered by a green canvas, mounted on top of a cylindrical reservoir designed to represent atmospheric water demand (Broner and Law, 1991). The canvas’s green color
imitates the albedo of a crop so that the absorption of solar radiation by the atmometer is like that of a plant. The canvas also serves as a diffusion barrier that controls the evaporation rate, similar to the resistance of a plant leaf to transpire into the atmosphere (Irmak et al. 2005). Atmometers with the number 54 canvas are designed to emulate Penman-Monteith ET$_r$, and atmometers with the number 30 canvas are meant to emulate Penman-Monteith ET$_o$ (Irmak et al. 2005). Previous research has shown good agreement between the Penman-Monteith based reference ET calculations and atmometer based evaporation (Knox et al. 2011, Irmak et al. 2005). Because atmometers effectively measure ET$_r$, they can theoretically be multiplied by a $K_c$ curve to estimate crop ET$_a$.

1.5 Remote Sensing-Surface Energy Balance Models

Satellite remote Sensing - surface energy balance (RSEB) models are the earliest remote sensing-based estimation of ET$_a$ (Zhang et al. 2016). RSEB models treat the land surface as an electrical analogue in that the heat fluxes are controlled by resistances that depend on local atmospheric qualities and internal properties of the land surface and vegetation (Kalma et al. 2008). For example, the sensible heat flux is dependent on the resistances caused by surface roughness and near surface winds. Among the RSEB models for estimating ET$_a$, Surface Energy Balance System (SEBS) (Su 2002), Simplified Surface Energy Balance Index (S-SEBI) (Roerink et al. 2000), Simplified Surface Energy Balance for operational applications (SSEBop) (Senay et al. 2013),
Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al. 1998a), and SEBAL’s descendant Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) (Allen et al. 2007a) are widely used. RSEB models have advanced throughout the years with the inclusion of new satellites offering more usable products (e.g. surface reflectance from Landsat 8), automated methods to reduce time necessary to prepare inputs and user-related errors (Bhattarai et al. 2017), and adaptations for model application in heterogeneous environments (e.g. diverse terrain, forests, etc.) (Santos et al. 2012, Oliveira et al. 2018).

Early iterations of RSEB models were usually only suitable for local applications due to their dependence on local calibration, thus making repeatability a major obstacle in widespread application (Zhang et al. 2016). Further, the radiometric surface temperatures obtained from a satellite image can be significantly different from the aerodynamic temperature that is responsible for the sensible heat flux component of the energy balance (Singh and Irmak 2011). To overcome these issues, Bastiaanssen et al. (1998) developed the SEBAL algorithm. SEBAL estimates the surface energy components at local and regional scales with minimum ground data and utilizes internal calibration within each satellite image (Liou and Kar 2014). The major advancement of the SEBAL method involves methods to remove the need for completely accurate surface temperature. SEBAL uses a near-surface temperature gradient for estimating sensible heat flux, which is indexed to the radiometric surface temperature using a linear relationship (Allen et al. 2007a). The use of the near-surface temperature gradient
reduces potential biases inherent in the estimation of factors such as surface temperature, surface roughness, and final ET calculation (Bhattarai et al. 2017).

RSEB models have important advantages over near surface instrumentation in that they can estimate ET\textsubscript{a} over a larger spatial scale and over heterogeneous surfaces to produce high resolution images (Kite and Droogers 2000). Further, ET\textsubscript{a} data can be spatially represented through geographic information systems (GIS) to show data that is not apparent using near surface instrumentation. RSEB are also more cost-effective than ground instrumentation as ground instrumentation is confined to a small area and requires resources and financial capital to establish and maintain (Makin et al. 2000). RSEB models are widely repeatable since many have a low requirement for meteorological data and are well documented to have reasonable accuracy (Zhang et al. 2016). RSEB models can provide spatial ET\textsubscript{a} information to address several diverse research topics, potentially useful in legislation, planning, water rights management, and topics related to environmental concerns (Makin et al. 2000).

Despite the well documented success of RSEB models to estimate ET\textsubscript{a}, inherent limitations exist. Many prominent RSEB models operate on an image by image basis and thus are termed “snapshot” models. One issue with snapshot models is their inability to capture evaporation signals from precipitation and irrigation events occurring between satellite overpass dates (Allen and Hendrickx 2010). ET\textsubscript{a} may be biased high when the satellite overpass follows an irrigation or precipitation event or biased low preceding an irrigation or precipitation event. Since a cloud-free image is
necessary for successful operation of snapshot models, ET_a may often be biased low. Satellite remote sensing derived ET_a values are instantaneous and require temporal extrapolation to daily and longer time scales using additional assumptions, methods, and gap-filling techniques. RSEB models are also susceptible to the uncertainties in the estimations of surface and air temperatures (Zhang et al. 2016).

The limitation of frequent satellite coverage is another issue associated with RSEB models. Satellites providing high spatial resolution imagery usually have lower temporal frequency. Conversely, low spatial resolution imagery usually has higher temporal frequency (Kalma et al. 2008). This limits the practicality for applications using RSEB models in areas that require frequent monitoring of water usage. However, attempts to solve the temporal resolution issue are ongoing. At least one study, by Bhattarai et al. (2015), attempted to solve the low temporal resolution issue associated with Landsat by incorporating the higher temporal resolution MODIS imagery. For the study, the authors used vegetation temperature condition index (VTCI) maps derived from MODIS and ET_rF (i.e. the ratio of instantaneous ET_a to alfalfa-based reference ET) maps derived from METRIC using Landsat 5 images to develop a “fusion model” for estimating growing season ET_a for two sites in the southeastern US under limited Landsat data availability conditions. A more detailed summary of METRIC is in the following sections.
1.6 METRIC

SEBAL represents a major advancement in the ability to use satellite remote sensing to estimate ET\textsubscript{a}. Both SEBAL and METRIC rely on theoretical and physical relationships to calculate empirical coefficients to make the process of estimating ET\textsubscript{a} repeatable across a range of environments (Bastiaanssen et al. 1998, Allen et al. 2007a). SEBAL’s successor METRIC utilizes some of SEBAL’s innovative methods but expands upon critical steps in the surface energy balance and ET\textsubscript{a} estimations. METRIC deviates from SEBAL in part because of its use of near surface meteorological data to calculate ET\textsubscript{r} (or ET\textsubscript{o}) to establish extreme surface energy balance conditions for each satellite image. ET\textsubscript{r} also functions to allow for the extrapolation of ET\textsubscript{a} from instantaneous ET\textsubscript{a} at the time of satellite overpass to longer time periods, such as daily, seasonal, and annual ET\textsubscript{a}. Ground based calculations of ET\textsubscript{r} using local meteorological data calibrates each image used in METRIC. The use of ET\textsubscript{r} also aligns METRIC estimations of ET\textsubscript{a} with the K\textsubscript{c} approach for estimating crop water use. Further, METRIC does not require knowledge of crop type and includes adjustments for mountainous terrain. (Allen et al. 2007a).

At their foundation, METRIC and SEBAL estimate ET\textsubscript{a} by calculating the energy balance at the surface, where the energy used in the ET process is calculated as a residual of the surface energy balance equation. Remote sensing-surface energy balance models rearrange and combine equations 1 and 3 to calculate LE as a residual of the net radiation (\(R_n\)), soil heat flux (\(G\)), and sensible heat flux (\(H\)):
\[ \lambda E = LE = R_n - G - H \] (5)

METRIC was designed to produce high resolution (30 m) \( \text{ET}_a \) derived images using Landsat imagery that is practical for monitoring at field scales (Allen et al. 2013), although it has been applied to larger spatial scales using MODIS imagery (Trezza et al. 2013). METRIC utilizes short wave and long wave thermal images from a satellite, specifically Landsat or MODIS, a digital elevation model (DEM), and ground-based meteorological data measured near or within the area (Allen et al. 2007a). Specific bands from Landsat or MODIS are obtained in the calculation of different components of METRIC such as albedo (bands 1 – 5 and 7 for Landsat 7), and the normalized difference vegetation index (NDVI) (bands 3 and 4 for Landsat 7), which is used in the calculation of outgoing long wave radiation. A DEM is incorporated in METRIC to account for effects of terrain on processes such as aerodynamic transport.

Meteorological data is required to calculate \( \text{ET}_r \) or \( \text{ET}_o \).

Full operation of METRIC includes the selection of “hot” and “cold” pixels (i.e. anchor pixels or termed endmember selection) to establish extreme \( \text{ET}_a \) conditions for each satellite image, which serve to internally calibrate the surface energy balance of each image and estimate the near surface temperature gradient. This internal calibration is termed CIMEC (calibration using inverse modeling at extreme conditions). Both MERIC and SEBAL utilize the CIMEC method. The utility of hot and cold pixels is that they aid in internally calibrating \( H \) to reduce potential biases associated with the calculation of intermediate variables such as surface temperature, albedo, net radiation,
and soil heat flux (Allen et al. 2011). A hot pixel usually represents dry and bare soil, where $LE$ is zero or close to zero and surface temperature is at a maximum for the satellite image. A cold pixel usually entails a well-watered agricultural field, where $H$ is zero or close to zero and $LE$ is at a maximum in the image, and surface temperature is at a minimum for the image (Allen et al. 2011; Singh and Irmak 2011). The surface energy balance is calculated at the hot and cold pixel locations, then the energy balance components (i.e. $R_n$, $G$, $LE$) at the extreme conditions are used in the calculation of $H$ at the extreme conditions, which is subsequently used in the calculation of $dT$ and $H$ for the study area. Recent advancements to METRIC and other surface energy balance models have automated the selection of hot and cold pixels, which has reduced the time demand for the user, reduced the chance of bias that is possible by manual endmember selection, and slightly increased the accuracy of ET$_a$ calculations (Bhattarai et al. 2017). A more detailed explanation of METRIC functions is included in the methods section, in Allen et al. (2007a), and Allen et al. (2011).
Chapter 2

LITERATURE REVIEW

2.1 Intercomparing RSEB Models

Prominent satellite RSEB models to estimate ET\textsubscript{a}, including SEBAL, METRIC, SEBS, and SSEBop, have been scrutinized and intercompared over the past few decades. Numerous studies have been published detailing the biases, limitations, and benefits inherent in each model.

Bhattarai et al. (2016) compared daily ET\textsubscript{a} acquired by five surface energy balance models over mixed-agricultural surface in the humid subtropical climate of Florida, USA. They found that SEBS was consistently the best model compared to Eddy Covariance estimates, and that SEBAL and METRIC did slightly worse. A similar study by Wagle et al. (2017) over high biomass sorghum in Oklahoma, USA found that all five surface energy balance models overestimated ET\textsubscript{a} under extremely dry conditions, and that seasonal ET\textsubscript{a} from METRIC, SEBAL, and SEBS were higher than seasonal ET\textsubscript{a} from Eddy Covariance estimations. METRIC overestimated ET\textsubscript{a} by approximately 25 and 30% for the 2012 and 2013 growing seasons, respectively, whereas SEBAL overestimated ET\textsubscript{a} by approximately 12 and 16% for the 2012 and 2013 growing seasons, respectively. He et al. (2017) applied METRIC over an almond orchard in California and compared ET\textsubscript{a} estimates to field measurements. METRIC
estimated ET_a compared well to Eddy Covariance data for both daily and monthly ET_a estimates, with an R^2 of 0.87 and 0.90, respectively.

A study by Liaqat and Choi (2015) compared METRIC and SEBS derived surface energy balance fluxes and daily ET_a to fluxes and ET_a obtained by EC methods over four different sites across eastern Asia. Two grassland sites were in north China and southern Mongolia, and two cropland sites were in Japan and South Korea. Both models estimated R_n reasonably well, with a RMSE of 39 and 21 Wm^{-2} for METRIC and SEBS, respectively. METRIC outperformed SEBS in its calculation of G, with RMSE of 46 Wm^{-2} and 125 Wm^{-2}, respectively. The usage of albedo and other parameters (e.g. NDVI) in the calculation of G for METRIC allows for the capture of changing soil moisture conditions and in vegetation structure over time. SEBS outperformed METRIC in its calculation of H in part due to the method in which METRIC calculates H, which absorbs biases from all other energy balance components. After adjustments were made to enclose the surface energy balance for the EC measurements, daily METRIC-ET_a showed a RMSE of 0.64 mm day^{-1}, whereas SEBS had a RMSE of 0.80 mm day^{-1} (Liaqat and Choi 2015).

2.2 METRIC: Corn and Soybean Applications

METRIC and similar surface energy balance models have been applied over various agricultural fields, including multiple crop and orchard types. Because soybeans and corn are the major crop types in Delaware in terms of cropland area and yield,
studies that focus on METRIC’s ability to estimate ET_a and other intermediate components, such as H, surface temperature (T_s), or leaf area index (LAI), over these types of agricultural fields are particularly important.

Many studies involving METRIC compare METRIC-derived ET_a to ground measurements of ET_a, commonly estimated using EC measurements. However, a study by Choi et al. (2009) compared surface energy balance fluxes (e.g. H, LE, G, R_n) estimated from three remote sensing-surface energy balance models, including METRIC, to meteorological flux (METFLUX) tower-derived fluxes over a corn and soybean agricultural landscape in Iowa. The study found that all three models performed well for estimates of R_n and G, with METRIC-derived fluxes yielding the lowest root mean square error (RMSE) of 19 Wm^{-2} and small negative bias for both fluxes. H and LE fluxes for METRIC had large negative biases of -63 Wm^{-2} and -55 Wm^{-2}, respectively, and large RMSE of 80 Wm^{-2} and 78 Wm^{-2}, respectively. The authors explain that the large errors in H and LE for this study may be attributed to the lack of ideal hot pixels for every satellite image processed. Their study highlights the importance of hot and cold pixels to the operation of METRIC and other models that utilize them (Choi et al. 2009). A study by Singh and Irmak (2011) further investigated the accuracy of METRIC-derived H and LE flux as compared to a Bowen ratio energy balance system over a corn and soybean agricultural field. Like Choi et al. (2009), the authors found that METRIC performed well for estimations of R_n and G, showing RMSE of 52 W and 24 Wm^{-2}, respectively, but large RMSE for estimates of H and LE.
Large errors in estimates of $H$ were attributed to residual moisture from antecedent rainfall at the “hot” pixel. Residual moisture at the hot pixel will cause an underestimation of $H$ and an overestimation of $LE$, which will increase error in the calculation of $ET_a$. To reduce the RMSE, the authors modified METRIC to incorporate a Priestley-Taylor equation in the calculation of $H$ at the cold and hot pixels to compensate for high residual moisture content in the image. The modified METRIC approach reduced the RMSE of $H$ from 122 to 54 Wm$^{-2}$ and of $LE$ from 163 Wm$^{-2}$ to 106 Wm$^{-2}$. The RMSE of daily $ET_a$ also decreased from 1.7 mm day$^{-1}$ to 1.1 mm day$^{-1}$ (Singh and Irmak 2011).

Studies investigating METRIC’s effectiveness at estimating $ET_a$ or other METRIC-derived variables over corn and soybean agricultural land have shown that METRIC can produce estimates with low error when compared to ground measurements. Singh and Senay (2016) compared $ET_a$ acquired from four surface energy balance models, including METRIC and SSEBop, to EC estimated $ET_a$ over three cropland (maize and soybean) sites in Nebraska, USA. METRIC consistently performed among the best out of the four models, with a correlation coefficient ($R^2$) ranging from 0.88 to 0.95, a MAE from 0.71 to 0.98 mm day$^{-1}$, and a RMSE from 0.84 to 1.06 mm day$^{-1}$. The largest errors for METRIC occurred over the third site in the study. The authors attributed larger errors over the third site to the nonirrigated condition of the site. As originally described by Allen et al. (2011), the assumption of a constant value for $ET_rF$, which is used for the extrapolation of instantaneous $ET_a$ to
daily ET\(_a\), may not be valid during the afternoon in nonirrigated or water limited conditions. For afternoons with nonirrigated or water limited conditions, ET\(_F\) would be lower than the assumed constant value due to decreases in ET\(_a\) throughout the day. METRIC-derived ET\(_a\) tied SSEBop for the highest average R\(^2\) value across all three sites with a value of 0.92 (Singh and Senay 2016).

Reyes-González et al. (2017) compared METRIC-estimated ET\(_a\) with atmometer-derived measurements of ET\(_a\) over three corn field sites in eastern South Dakota for one growing season (2016). Because atmometers effectively measure ET\(_r\), measurements at three sites were adjusted using a crop coefficient curve to estimate crop ET\(_a\). The authors found that METRIC performed well compared to the atmometer, with R\(^2\)=0.87, an index of agreement of 0.84 (0 to 1; 1 indicates a perfect match), and a RMSE of 0.65 mm day\(^{-1}\). Comparisons between METRIC-derived daily ET\(_a\) and atmometer measurements showed that the largest differences were attributed to high wind speed values (>4 m s\(^{-1}\)) at the time of satellite overpass. The station with the highest elevation (574 m above sea level) and consistently higher wind speeds had the largest differences between METRIC-derived daily ET\(_a\) and atmometer ET\(_a\). Higher daily ET\(_a\) differences were also present earlier in the growing season when crop heights were low and higher winds influenced ET\(_a\) rates. As the growing season continued, differences decreased, possibly due to taller crops blocking higher wind conditions (Reyes-González et al. 2017).
A more recent study by Reyes-González et al. (2019) compared leaf area index (LAI), surface temperature ($T_s$), and ET$_a$ from METRIC to in situ measurements collected over a corn field in eastern South Dakota at the satellite overpass time. LAI was measured directly using a ceptometer, $T_s$ was measured with an infrared thermometer, and ET$_r$ was measured with an atmometer, which was converted to ET$_a$ by a crop coefficient curve. METRIC-derived LAI performed well when compared to ceptometer LAI measurements, with $R^2$ value of 0.76 and a RMSE of 0.59. However, the authors noted that comparing METRIC-derived LAI and ceptometer LAI is difficult due to ceptometer only measuring LAI for a few plants, whereas METRIC calculates LAI on a 30 m by 30 m resolution pixel. METRIC-LAI is also maximized at 6 while the ceptometer measured LAI ranging from 4.7 to 7.0. METRIC-$T_s$ showed a good correlation ($R^2 = 0.87$) with infrared thermometer $T_s$ measurements and yielded a RMSE of 1.24°C. Again, differences in infrared thermometer $T_s$ measurements and METRIC-$T_s$ were in part due to $T_s$ measurements taken only over a few plants and not the entire pixel. ET$_r$, as measured by the atmometer and converted to ET$_a$ using a crop coefficient curve, showed a good relationship to METRIC-ET$_a$ with $R^2$ of 0.89 and a RMSE of 0.71 mm day$^{-1}$. Like the results from Reyes-González et al. (2017), this study found that the largest differences occurred on days with high wind speed values. The largest departure between METRIC-ET$_a$ and atmometer ET$_a$ was 1.4 mm day$^{-1}$ at the time of satellite overpass with the highest wind speed of 5.9 m s$^{-1}$ (Reyes-González et al. 2019).
Several studies in the past decade have shown METRIC to be sufficiently accurate in estimating $ET_a$ and other variables (e.g. $T_s$, $H$, and $LAI$) when compared to near surface-based measurements. Some recent studies conducted for corn and/or soybean fields have not compared METRIC products to ground measurements to validate model output. Instead, these studies utilize METRIC for varying purposes and demonstrate the growing practicality and usability of METRIC and similar surface energy balance models. Khand et al. (2017) used METRIC to compare $ET_a$ between corn and soybean fields with and without subsurface drainage. Subsurface drainage systems are used to remove standing water from agricultural soils to promote optimal crop productivity. Although the authors found no statistically significant difference in $ET_a$ between the corn and soybean fields with subsurface drainage and fields without subsurface drainage, METRIC was able to detect small differences between drained and undrained fields. Differences between total $ET_a$ during the corn growing season was less than 5 mm. $ET_a$ for the undrained soybean field was 10% greater than that from the drained field (Khand et al. 2017a). A study by Baeumler et al. (2019) used METRIC to estimate $ET_a$ of wetlands, soybean, corn, and native prairie grasses in Minnesota to answer the broader question of whether recent increases in streamflow are primarily from increased precipitation or decreased ET from conversion of small grains and prairie grass to current row crop agriculture. Results showed only small variations in seasonal $ET_a$ between the different landscapes. The authors concluded that increases in streamflow are due to recent increases in precipitation in the Upper Midwest from 50 to 100 mm and not decreases in ET (Baeumler et al. 2019).
2.3 METRIC: other applications

Studies that use METRIC over corn and soybean agricultural fields only represent a portion of the documented literature overall. It is important to examine how METRIC has been modified and performed when applied to different crops, orchards and over diverse landscapes throughout the world. Some studies have used calibrated algorithms beyond the original METRIC model design to better represent the study area and reduce error.

METRIC was originally designed for relatively homogeneous landscapes of row crops, so additional calibration has been required to apply METRIC to a more complex canopy structure such as an apple or olive orchard. Santos et al. (2012) optimized momentum roughness length ($Z_{om}$) estimates using the Perrier Function (Perrier 1982) based on LAI and tree canopy structure for sparse trees. Due to the success of Santos et al. (2012) for improving $ET_a$ estimates, the Perrier method for calculating $Z_{om}$ has been replicated by Pôças et al. (2014), de la Fuente-Sáiz et al. (2017), Numata et al. (2017), and others. de la Fuente-Sáiz et al. (2017) calibrated some intermediate components of METRIC (e.g. LAI, $Z_{om}$, and $G$) using specific sub-models to reduce error when compared to in situ measurements taken over an apple orchard in central Chile. The incorporation of the sub-models for LAI, $G$, and the Perrier function for $Z_{om}$ was intended to better represent the canopy structure of an apple orchard than the original algorithms as described in Allen et al. (2007a). Recalibrated functions for the intermediate components showed improvement from original METRIC algorithms. The
recalibrated estimations reduced the mean absolute error (MAE) of LAI from 1.16 to 0.15 m$^2$ m$^{-2}$, $Z_{om}$ from 0.21 to 0.03 m, and $G$ from 23 to 14 Wm$^{-2}$ (de la Fuente-Sáiz et al. 2017). Other modifications to METRIC procedures have involved changes in operations such as changes in hot and cold pixel selection. Oliveira et al. (2018) used a more intensive albedo model to improve $R_n$ and ET$_a$ estimates over two heterogeneous landscapes in south-central Brazil when compared to EC measurements. METRIC performed well overall, with an $R^2$ of 0.94 for $R_n$ and $R^2$ of 0.94 and 0.88 for ET$_a$ for the two sites. Bhattarai et al. (2017) developed an automated hot and cold pixel selection approach using an exhaustive search algorithm (ESA) based on surface temperature and NDVI. The authors tested the approach by comparing ET$_a$ obtained from METRIC runs using the manual and automated hot and cold pixel selection approaches. The two different methods of hot and cold pixel selection yielded similar ET$_a$ results when compared to EC measurements. The authors noted that the automation process improves efficiency in terms of time and can lead to more objective selection of hot and cold pixels. Olmedo et al. (2016) describes hot and cold pixel selection based on $T_s$, NDVI, LAI, and $Z_{om}$ and detail the METRIC algorithms written in the statistical R environment.

METRIC has also been used for non-agricultural applications. Liebert et al. (2016) used METRIC to track changes in ET$_a$ before and after the introduction of a biological control of tamarisk, an invasive tree, along the Lower Virgin River in Nevada, USA. METRIC estimated a decrease in annual average ET from 1245 mm
year$^{-1}$ to 1041 mm year$^{-1}$ as a result of the introduction of the biological control. Carrillo-Rojas et al. (2016) applied METRIC with both MODIS and Landsat imagery over a complex Andean terrain in southern Ecuador, South America and compared the monthly and annual results to a MODIS-based global ET product called MOD16, and a simple water balance equation. Landsat-based METRIC showed good agreement with the water balance approach with a mean bias error $<8$ mm month$^{-1}$ and an annual deviation $<17\%$. Khand et al. (2017b) adapted METRIC to an environment in the southern Amazon to estimate ET$_a$ and compared results to EC estimates. The purpose of their study was to characterize the ET$_a$ dynamics during the dry season over a region with a complex annual precipitation pattern. The modified METRIC model reduced the RMSE from 0.77 mm day$^{-1}$ to 0.35 mm day$^{-1}$ and improved $R^2=0.70$ to $R^2=0.73$. They demonstrated the ability to adapt METRIC to a more humid climate in the southern Amazon. Jaafar and Ahmad (2019) used SEBAL and METRIC to create a 34-year time series of ET$_a$ to aid in quantifying groundwater discharge for the Bekaa Valley in Lebanon. The authors produced nearly 600 ET$_a$ maps using archived Landsat data from Landsat 4, 5, 7, and 8. They estimated annual and average annual ET$_a$, which was incorporated into a water balance analysis that showed a decrease in ground water storage. The ET$_a$ analysis showed an increase in irrigated agriculture over the last five years of the time series (Jaafar and Ahmad 2019).
2.4 Research Objectives

Many METRIC-based studies in the United States have been focused on study areas in the mid-western and western states in part due to the presence of a large agricultural industry coupled with the need to track water usage in water-scarce regions. To the best of our knowledge, the published literature is devoid of studies that have applied METRIC over the mid-Atlantic or northeastern regions of the United States, or validated METRIC output in this region using in-situ instrumentation, including Eddy Covariance and atmometer. Further, no study has utilized the METRIC model to compare seasonal crop water usage under central pivot irrigated and subsurface drip irrigated cropland. In Delaware, quantifying ET$_a$ for an agricultural area is of interest due to the presence of a significant agricultural industry and increasing rates of irrigation. The objectives of this study were to: (1) quantify daily, cumulative, and seasonal evapotranspiration for corn and soybean crops for an irrigation research farm in Sussex County, Delaware; (2) compare water demand for crops under a subsurface drip irrigated (SDI) and a central pivot irrigated (CPI) irrigation regime; (3) validate intermediate components of METRIC, including surface temperature, incoming solar radiation, net radiation, and soil heat flux using in-situ measurements; and (4) validate sensible heat flux, latent heat flux, and daily, cumulative, and seasonal evapotranspiration from METRIC using eddy covariance and atmometer data.
Chapter 3

MATERIALS AND METHODS

3.1 Study Area

3.1.1 Delaware and Sussex County

This study focuses on three growing seasons during 2015, 2016, and 2017 for the Warrington Irrigation Research Farm, located in Sussex County, Delaware, United States (US) (Figure 3.1). Delaware is in the northern two-thirds of the Delmarva Peninsula, which is comprised of a portion of Delaware, Maryland, and Virginia. Delaware is bordered by the US states of Maryland, Pennsylvania, and New Jersey. Delaware is the second smallest US state with a land area of approximately 5133 km\(^2\), and is comprised of three counties: New Castle, Kent, and Sussex. According to a 2015 report by the National Resources Inventory, ‘non-Federal cropland’ accounted for a plurality of land cover use at 26.02\%, followed by forest, water, and developed land (i.e. urban and transportation) at 22.61, 19.79, and 19.39\%, respectively. The major water features that border Delaware are the Atlantic Ocean and Delaware Bay. The Chesapeake Bay is the major water feature bordering the western side of the Delmarva Peninsula, but does not border Delaware.
Figure 3.1: Warrington Farm within Sussex County, Delaware
Delaware is in a transition zone between a humid subtropical climate to the south and a humid continental climate to the north. The Köppen climate classification for Delaware is Mild Temperate-fully humid with hot summers (Chen and Chen, 2013). The average annual temperature in Delaware from 1980 to 2018 was 13.17 °C (55.7 °F), with slightly higher temperatures along the coast. The average annual precipitation over the same time period was 1136.65 mm (44.75 in.). Annual precipitation in Delaware is variable from year-to-year.

Sussex County is the southernmost and largest county in Delaware, with an area of approximately 2429 km$^2$. The 20-year (2000 – 2019) average annual temperature in Sussex County is 13.9°C (57 °F). Cropland is the dominant land use type in the county, followed by forested wetlands, residential, then mixed forest. Towards the eastern portion of the county, bays, tidal wetlands, mixed forest, and residential land cover types make up a larger portion of the total land area, though cropland is still a major land cover type. Rehoboth Bay and Indian River Bay, two large inland bays, and their surrounding tidal wetlands, are the main natural features on the eastern portion of the county. Beyond the two inland bays is a stretch of coastline bordering the Atlantic Ocean. Delaware Bay borders the northeastern coast of Sussex County. Corn and soybean are the dominant crop types in Sussex County. Corn and soybean agricultural land is comprised of approximately 112,000 and 90,000 acres, respectively (USDA-NASS, 2017).
3.1.2 Warrington Farm Description

Warrington Farm is located approximately 15 km from the coastline and nearly 6.5 km south of Harbeson, Delaware and is composed of 95 acres of agricultural land and 41 acres of woodland. Warrington Farm was donated to the University of Delaware (UD) in 1992 by Everett Warrington. In 1995, Warrington Farm was outfitted with a 232 meter, four-span central pivot irrigation (CPI) system to provide irrigation and support research on pea, lima bean, sweet corn, and pickling cucumbers. A variable rate irrigation (VRI) system was implemented in 2001 to the existing CPI system to improve yields and irrigation efficiency. 11 years later in 2012, an 18 acre, 42-zone subsurface drip irrigation (SDI) plot was added to the UD owned Warrington Farm property. Additional upgrades in 2012 include the addition of 4-inch and 8-inch wells, and a shift to a Global Positioning System (GPS)-based irrigation system that allows for control of individual nozzles.

The CPI fields are in the upper-right portion of the Warrington Farm border and are bordered by ditches and roads to the west, southwest, and south and by more cropland to the east. Undeveloped shrubland borders the CPI fields to the north. A narrow dirt and grass access road to the center of the pivot bisects the northern and southern portions of the CPI fields. The northern CPI field and southern CPI field will hereafter be referred to as CPI north and CPI south, respectively. The SDI fields are bordered by woodlands/forest to the north, northwest, and west, and by ditches and roads to the northeast, east, and south. Like the CPI fields, a narrow dirt and grass road divides the northern and southern portions of the SDI fields. Manifolds that deliver
water to the SDI system are positioned along the access road. The northern SDI field and southern SDI field will be referred to as SDI north and SDI south, respectively.

The Delaware Environmental Observing System (DEOS) is a group of over 80 environmental monitoring platforms that provide real-time, high quality data on environmental and meteorological conditions throughout Delaware and into portions of southeastern Pennsylvania. The main DEOS station used in this study is the Harbeson station (ID: DWAR) (Figure 3.2). DWAR is located at 38.68°N and 75.25°W at roughly 10 meters above sea level. Within the farm, DWAR is positioned on the southern edge of the SDI north field along the access road. Measuring instruments attached to DWAR are approximately 2 meters above ground. The DWAR station was mounted with the Eddy Covariance instrumentation (ECI) (Figure 3.3), which collected the validation data used in this study. The atmometer representing the SDI field was mounted on the ground to the side of DWAR on the edge of the SDI field. A soil analysis conducted on November 11, 2016 near DWAR found the soil texture to be loamy sand consisting of 80% sand, 12% silt, and 8% clay. Field capacity was 0.163 m$^3$ m$^{-3}$ and wilting point was 0.077 m$^3$ m$^{-3}$. The time periods for each growing season when EC data were collected and processed, the atmometer observation period, and the date ranges of the satellite images are summarized in Tables 3.1 and 3.2.
Figure 3.2: Harbeson Meteorological Station (DWAR). Retrieved from http://www.deos.udel.edu/station/index.php?station=DWAR
Figure 3.3: Eddy Covariance Instrument (top right) fixed to DWAR.
Table 3.1: Summary of first and last date, day of year (DOY), number of days and Landsat images used for the 2016 and 2017 study time periods for METRIC and Eddy Covariance analysis.

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<td>End Date</td>
<td>9/13/2016</td>
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</tr>
<tr>
<td><strong>METRIC</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Start Date</td>
<td>4/6/2016</td>
<td>6/12/2017</td>
</tr>
<tr>
<td>End Date</td>
<td>9/13/2016</td>
<td>10/18/2017</td>
</tr>
<tr>
<td>Start DOY</td>
<td>97</td>
<td>163</td>
</tr>
<tr>
<td>End DOY</td>
<td>257</td>
<td>291</td>
</tr>
<tr>
<td># of Days</td>
<td>161</td>
<td>129</td>
</tr>
<tr>
<td># of Images</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td><strong>Overlap</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Start Date</td>
<td>4/30/2016</td>
<td>6/12/2017</td>
</tr>
<tr>
<td>End Date</td>
<td>9/13/2016</td>
<td>10/18/2017</td>
</tr>
<tr>
<td>Start DOY</td>
<td>121</td>
<td>163</td>
</tr>
<tr>
<td>End DOY</td>
<td>257</td>
<td>291</td>
</tr>
<tr>
<td># of Days</td>
<td>137</td>
<td>129</td>
</tr>
<tr>
<td>Discarded Days</td>
<td>5/19, 9/1</td>
<td>None</td>
</tr>
<tr>
<td># of Days (total)</td>
<td>135</td>
<td>129</td>
</tr>
</tbody>
</table>
Table 3.2: Summary of first and last date, day of year (DOY), number of days and Landsat images used for the 2015 study time period for METRIC and atmometer analysis.

<table>
<thead>
<tr>
<th></th>
<th>Atmometer</th>
<th>METRIC</th>
<th>Overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Start Date</strong></td>
<td>6/20/2015</td>
<td>5/22/2015</td>
<td>6/20/2015</td>
</tr>
<tr>
<td><strong>End Date</strong></td>
<td>9/16/2015</td>
<td>8/26/2015</td>
<td>8/26/2015</td>
</tr>
<tr>
<td><strong>Start DOY</strong></td>
<td>171</td>
<td>142</td>
<td>171</td>
</tr>
<tr>
<td><strong>End DOY</strong></td>
<td>260</td>
<td>238</td>
<td>238</td>
</tr>
<tr>
<td><strong># of Days</strong></td>
<td>90</td>
<td>97</td>
<td>68</td>
</tr>
<tr>
<td><strong># of Images</strong></td>
<td></td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>

The SDI and CPI fields are under a crop rotation schedule of corn, full season soybean, and a double crop of wheat and soybean. Crop cover data for the SDI and CPI fields was identified using the Cropland Data Layer (CDL), a 30-meter resolution satellite-based crop cover dataset provided by the United States Department of Agriculture-National Agricultural Statistics Service (USDA-NASS). Crop types for
each growing season for the north and south portions of the SDI and CPI fields are summarized in Table 3.3.

Table 3.3: Dominant crop type for the SDI and CPI north and south fields of 2015, 2016, and 2017.

<table>
<thead>
<tr>
<th>Year</th>
<th>SDI north</th>
<th>SDI south</th>
<th>CPI north</th>
<th>CPI south</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>soybean</td>
<td>corn</td>
<td>soybean</td>
<td>corn</td>
</tr>
<tr>
<td>2016</td>
<td>corn</td>
<td>soybean</td>
<td>corn</td>
<td>soybean</td>
</tr>
<tr>
<td>2017</td>
<td>soybean</td>
<td>corn</td>
<td>soybean</td>
<td>corn</td>
</tr>
</tbody>
</table>

3.2 METRIC Input Data

3.2.1 Landsat Images

The 30 by 30-meter resolution of images collected by Landsat 8’s Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) allows ET to be mapped at the field scale. At this resolution, surface or near surfaced-based measurements of ET can be used to validate METRIC-based ET ($ET_{METRIC}$)

Altogether, 17 nearly cloud free Landsat 8 images were chosen for the 2015, 2016 and 2017 growing seasons. The images were selected based on the relative lack of cloud cover for the entire scene, complete lack of cloud cover for the Warrington Farm area, and date range within Delaware’s growing season and the Eddy Covariance data.
Because one Landsat path/row captures scenes over southern Delaware, all images were acquired along path 14 and row 33. The Landsat 8 OLI/TIRS Level-1 and Level-2 Surface Reflectance data were downloaded from United States Geological Survey (USGS) archives in Earth Explorer (https://earthexplorer.usgs.gov/). Bad pixel values, including clouds and cloud shadows, were removed using the 8-bit LandsatLook Quality Image band. Only scenes with less than 20% land cloud cover were used. Table 3.4 summarizes all Landsat 8 images included in the analysis.

Table 3.4: Landsat 8 image summary, including day of year (DOY), days from last (DFL) image, and % land cloud cover (L-CC).

<table>
<thead>
<tr>
<th>Count</th>
<th>Year</th>
<th>Date</th>
<th>DOY</th>
<th>DFL</th>
<th>L-CC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2015</td>
<td>5/22/15</td>
<td>142</td>
<td>NA</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>2015</td>
<td>6/7/15</td>
<td>158</td>
<td>16</td>
<td>9.1</td>
</tr>
<tr>
<td>3</td>
<td>2015</td>
<td>7/25/15</td>
<td>206</td>
<td>48</td>
<td>12.04</td>
</tr>
<tr>
<td>4</td>
<td>2015</td>
<td>8/26/15</td>
<td>238</td>
<td>32</td>
<td>5.77</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>4/6/16</td>
<td>97</td>
<td>NA</td>
<td>0.04</td>
</tr>
<tr>
<td>2</td>
<td>2016</td>
<td>5/8/16</td>
<td>129</td>
<td>32</td>
<td>9.86</td>
</tr>
<tr>
<td>3</td>
<td>2016</td>
<td>6/9/16</td>
<td>161</td>
<td>32</td>
<td>3.77</td>
</tr>
<tr>
<td>4</td>
<td>2016</td>
<td>7/11/16</td>
<td>193</td>
<td>32</td>
<td>17.58</td>
</tr>
<tr>
<td>5</td>
<td>2016</td>
<td>8/12/16</td>
<td>225</td>
<td>32</td>
<td>1.16</td>
</tr>
<tr>
<td>6</td>
<td>2016</td>
<td>8/28/16</td>
<td>241</td>
<td>16</td>
<td>1.99</td>
</tr>
<tr>
<td>7</td>
<td>2016</td>
<td>9/13/16</td>
<td>257</td>
<td>16</td>
<td>12.93</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>6/12/17</td>
<td>163</td>
<td>NA</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>2017</td>
<td>6/28/17</td>
<td>179</td>
<td>16</td>
<td>1.22</td>
</tr>
<tr>
<td>3</td>
<td>2017</td>
<td>7/30/17</td>
<td>211</td>
<td>32</td>
<td>0.1</td>
</tr>
<tr>
<td>4</td>
<td>2017</td>
<td>8/31/17</td>
<td>243</td>
<td>32</td>
<td>7.82</td>
</tr>
<tr>
<td>5*</td>
<td>2017</td>
<td>10/2/17</td>
<td>275</td>
<td>32</td>
<td>1.05</td>
</tr>
<tr>
<td>6</td>
<td>2017</td>
<td>10/18/17</td>
<td>291</td>
<td>16</td>
<td>0.06</td>
</tr>
</tbody>
</table>
3.2.2 Delaware Environmental Observing System (DEOS)

DEOS stations measure hourly or shorter meteorological variables that are required in the METRIC algorithms. Additionally, many DEOS stations calculate daily reference ET using a modified FAO Penman-Monteith equation for a hypothetical, well-watered grass reference surface \( \text{ET}_o \) (Allen et al. 1998):

\[
\text{ET}_o = \frac{(0.408\Delta (R_n - G) + \gamma \left(\frac{900}{(T_a + 273)}\right) u (e_{a*} - e_a)) / \left(\Delta + \gamma (1 + 0.34u)\right)}{
\Delta + \gamma (1 + 0.34u)\right)} \tag{6}
\]

Where \( \text{ET}_o \) is daily grass reference ET (mm day\(^{-1}\)), \( R_n \) is net radiation (MJ m\(^{-2}\) day\(^{-1}\)), \( G \) is soil heat flux (MJ m\(^{-2}\) day\(^{-1}\)), \( T_a \) is air temperature (°C), \( u \) is wind speed (m s\(^{-1}\)), \( e_{a*} \) is saturation vapor pressure (kPa), \( e_a \) is actual vapor pressure (kPa), \( \Delta \) is the slope of the vapor pressure curve (kPa °C\(^{-1}\)), and \( \gamma \) is the psychometric constant (kPa °C\(^{-1}\)).

The Harbeson DEOS station (ID: DWAR) is located within Warrington Farms between two subsurface drip irrigated (SDI) agricultural fields. Meteorological data in five-minute increments were collected from DWAR for the 2015, 2016, and 2017 growing seasons as inputs in the METRIC algorithms. The METRIC model requires hourly or shorter meteorological data for the Landsat overpass date to estimate daily \( \text{ET}_{\text{METRIC}} \). This study used five-minute meteorological data over the 24-hour period from the dates of satellite images, apart from October 2, 2017. On October 2nd, the incoming solar radiation measuring instrument was obstructed during the time of satellite overpass date, resulting in an unrepresentative instantaneous \( \text{ET}_o \) value.
Georgetown station (ID: DGES), a DEOS station located approximately 18 km away from DWAR, was used instead.

Meteorological inputs to METRIC include incoming solar radiation (W m⁻²), air temperature (°C), wind speed (m s⁻¹), and relative humidity (%). The use of five-minute meteorological data rather than hourly data allows for a more precise calculation of instantaneous ET₀ at the time of satellite overpass, which is essential in the estimation of H and extrapolation of instantaneous ET_METRIC to daily ET_METRIC. Daily ET₀ collected from DWAR was used to extrapolate the instantaneous to daily ET_METRIC and longer time periods.

3.3 Eddy Covariance

Raw eddy covariance (EC) data were processed in EddyPro software (LI-COR Inc., Lincoln, NE, USA) to produce 30-minute averaged ET (ET_EC) and flux components (i.e. Rₙ, H, LE, and G). The ECIs were mounted 2 meters above ground attached to the DWAR meteorological station during the 2015, 2016, and 2017 growing seasons. Turbulent flux and ET_EC data for 2015 was discarded due to unrealistic estimates of H, Rₙ, G, and other data recorded at DWAR for 2015 were still used in this study. A sonic anemometer measured the orthogonal wind and an open-path mid-infrared absorption gas analyzer measured water vapor at a sampling rate of 10 Hertz (Hz). Covariance of the vertical wind speed, water vapor density, and virtual air
temperature were used to compute 5-minute averages of the latent heat and sensible heat fluxes.

Environmental data recorded during the EC data collection periods were integrated into the processing of raw EC data, including global radiation (W m\(^{-2}\)), ambient air temperature (°C), surface temperature (°C), soil water content (m\(^3\) m\(^{-3}\)), rainfall (m), relative humidity (%), net radiation (W m\(^{-2}\)), and soil heat flux (W m\(^{-2}\)). The inclusion of this data improves flux measurements in part by replacing estimated variables with measured variables.

Energy balance closure is an indicator of how close the ECI is to capturing the land surface energy balance (LSEB) for a given time period. Following Wilson et al. (2002), the energy balance closure of the flux data was evaluated using the cumulative energy balance ratio (EBR) and an ordinary linear regression (OLR). The EBR is the ratio of cumulative \(H\) and \(LE\) to \(R_n\) and \(G\):

\[
\text{EBR} = \frac{\Sigma (H + LE)}{\Sigma (R_n - G)}
\]  

(7)

where \(\Sigma (H + LE)\) is the cumulative sensible and latent heat fluxes and \(\Sigma (R_n - G)\) is the cumulative available energy at the surface. A perfect energy balance closure would result in an EBR of 1, while any value below 1 would indicate an underestimation of \(H\), \(LE\) or both assuming \(R_n\) and \(G\) were correctly measured.

Closure of the energy balance is an ongoing dilemma in the EC method. Procedures to force closure of the energy balance (i.e. force EBR = 1) are common among studies that utilize EC data for validation. This study used a correction factor
(CF) derived from the Bowen Ratio ($\beta$) method as described in Twine et al. (2000) and used in Dhungel and Barber (2018). The $\beta$ method preserves the $\beta$ (i.e. $H/LE$) for the 30 minute fluxes and partitions the remaining available energy to the turbulent fluxes:

$$ CF = \frac{(R_n - G)}{(H + LE)} $$

$R_n$ less than 50 Wm$^{-2}$ was assumed to be before and after sunrise and sunset, respectively, and was not used to compute the CF. To remove statistical outliers, CFs beyond ± 3.5 standard deviation (SD) based on a 14-day running mean window were removed. The CF was multiplied by the $LE$ and $H$ fluxes, then the corrected $LE$ and $H$ fluxes were screened for statistical outliers using the same procedure above and filled by simple linear interpolation if the missing data gap did not exceed 10 consecutive missing 30-minute averages. The resulting $LE$ fluxes were used to calculate 30 minute and daily ET$_{EC}$ that were used in analysis. Finally, ET$_{EC}$ and turbulent flux values during periods of low turbulence (friction velocity: $u^* < 0.15$ m s$^{-1}$) were discarded from analysis. Some days in the EC time series were removed due to a lack of data. The EBR and the OLR for the 2016 and 2017 growing seasons were calculated before and after the quality controls were implemented.

3.4 Atmometer

The atmometer was covered with number 30 green canvas to simulate ET$_o$ (Figure 3.4). The observation period for the atmometer was from June 20, 2015, to September 3, 2015. Canopy height for the SDI field was taken once every two weeks.
from May 6 to September 6. Every time canopy height was taken, the atmometer was adjusted to be at level with the canopy height. The atmometer was deployed June 19 and data collection began on June 20. The $K_c$ curve was calculated based on the FAO-56 single crop coefficient method. Measured crop height was used to estimate crop growth stages and their length in days. Tabulated $K_c$ values for grain corn were selected and matched with the crop growth stages. Linear interpolation between $K_c$ values produced a daily $K_c$ curve. Daily $\text{ET}_a$ is obtained by multiplying daily atmometer-measured $\text{ET}_o (\text{ET}_{o, \text{atm}})$ by the daily $K_c$ value:

$$\text{ET}_{\text{atm}} = \text{ET}_{o, \text{atm}} \times K_c$$

(9)

Where $\text{ET}_{\text{atm}}$ is daily $\text{ET}_a$ as calculated using atmometer data.
3.5 METRIC Model

3.5.1 METRIC Implementation

The METRIC model is coded in multiple languages and implemented in GIS software. This research utilized the ‘water’ package (version 0.8) written in an R environment. The ‘water’ package has advantages for the user in that a user has the option to select from multiple methods to compute the surface energy balance.
components. The ‘water’ package contains functions to read in satellite and meteorological data and the equations to implement the METRIC model. A user-defined area of interest (AOI) is used to clip out a portion of the Landsat scene. This study used a shapefile delineating Sussex County, Delaware boundary to define the AOI. The ‘water’ package’s meteorological data requirements for METRIC include incoming solar radiation, temperature, vapor pressure, relative humidity, and wind speed at hourly or shorter intervals. The primary Landsat 8 satellite inputs are the Level-1 (not atmospherically corrected) thermal, red, and near-infrared bands, Level-2 (atmospherically corrected) surface reflectance of blue, green, red, near-infrared, and shortwave infrared (SIR) bands 1 and 2. The Landsat metadata file is used to compute instantaneous ET$_o$ and determine meteorological conditions, including wind speed and incoming solar radiation, at the time of satellite overpass. The Shuttle Radar Topography Mission (SRTM) 1-arc-second digital elevation model (DEM) with 30-meter resolution is used to adjust the surface temperature of each Landsat pixel. SRTM is also used to compute slope and aspect and solar angles (latitude, declination, hour angle, and solar incidence angle) for the calculation of atmospheric transmissivity. A more detailed description of the ‘water’ package can be found in (Olmedo et al. 2016).

3.5.2 METRIC Description

METRIC is a complex Landsat-based surface energy balance model that estimates evapotranspiration at the field scale. METRIC estimates actual
evapotranspiration (ETₐ) for each pixel by taking the latent heat flux (LE) as a residual of the land surface energy balance (LSEB):

$$LE = R_n - G - H$$  \hspace{1cm} (10)  

where $LE$ is the latent heat flux consumed by ETₐ (W m⁻²), $R_n$ is net radiation (W m⁻²), $G$ is soil heat flux (W m⁻²), and $H$ is the sensible heat flux (W m⁻²). All LSEB components are determined at the time of satellite overpass. LSEB closure (i.e. all available energy is allocated to the $LE$, $G$, and $H$ components and is equal to $R_n$) is an assumption in the METRIC model. Other energy balance components, such as physical and biochemical energy storage in the crop canopy, are negligible and are not incorporated into the METRIC model (Khand et al. 2017).

$R_n$ is the net radiant energy available at the surface and is the primary source of energy for ETₐ. $R_n$ is computed by subtracting all outgoing radiative fluxes from all incoming radiative fluxes:

$$R_n = R_{S\downarrow} - \alpha R_{S\downarrow} + R_{L\downarrow} - R_{L\uparrow} - (1 - \varepsilon_o) R_{L\downarrow}$$  \hspace{1cm} (11)  

where $R_{S\downarrow}$ is incoming shortwave radiation (W m⁻²), $\alpha$ is surface albedo (dimensionless), $R_{L\downarrow}$ is incoming longwave radiation (W m⁻²), $R_{L\uparrow}$ is outgoing longwave radiation (W m⁻²), $\varepsilon_o$ is broadband surface thermal emissivity (dimensionless). $(1 - \varepsilon_o) R_{L\downarrow}$ is the fraction of incoming long-wave radiation emitted from the surface. $R_{S\downarrow}$, the primary input to $R_n$, is computed as:

$$R_{S\downarrow} = (G_{sc} \cos \theta_{rel} \tau_{sw})/ d^2$$  \hspace{1cm} (12)
where $G_{sc}$ is the solar constant (1367 Wm$^{-2}$), $\theta_{rel}$ is the solar incidence angle, $d^2$ is the squared of the relative Earth-Sun distance, and $\tau_{sw}$ is broad-band atmospheric transmissivity.

$R_L \uparrow$ is driven by surface temperature and surface emissivity and is computed using the Stefan-Boltzmann equation:

$$R_L \uparrow = \varepsilon_o \sigma T_s^4$$

(13)

where $\sigma$ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ Wm$^{-2}$K$^{-4}$).

$R_L \downarrow$ is the downward thermal radiation flux originating from the atmosphere and is computed using the Stefan-Boltzmann equation:

$$R_L \downarrow = \varepsilon_a \sigma T_a^4$$

(14)

where $\varepsilon_a$ is the atmospheric emissivity, and $T_a$ is the near-surface air temperature.

Surface temperature is often used as a substitute for the $T_a$ term. The ‘water’ package uses surface temperature as in input in equation 14 rather than $T_a$.

$G$ is the rate of heat stored in the soil and vegetation. Because METRIC does not rely on land classification or crop type, $G$ is estimated from ancillary satellite products such as the soil adjusted vegetation index (SAVI) to compute the leaf area index (LAI). METRIC computes $G$ as a ratio of $G/R_n$ using a method developed for general agricultural soils:
\[
G/R_n = 0.05 + 0.18e^{-0.521 \text{LAI}}
\]
\(\text{LAI} > 0.5\) \hspace{1cm} (15a)

\[
G/R_n = 1.80 \left( T_s - 273.15 \right)/R_n + 0.084
\]
\(\text{LAI} < 0.5\) \hspace{1cm} (15b)

where \(T_s\) is surface temperature (K), and LAI is leaf area index (dimensionless).

Equation 15a suggests that \(G\) decreases with increasing LAI due to increased shading from the crop canopy. LAI is calculated from the ‘metric2010’ equation from the ‘water’ package based on the soil adjusted vegetation index (SAVI). Equation 15b suggests that \(G\) increases in proportion to \(T_s\). \(T_s\) was calculated based on the ‘Split Window’ (SW) algorithm included in the ‘water’ package from Jimenez-Munoz et al. (2014). The SW algorithm incorporates brightness temperatures from bands 10 and 11 of Landsat 8, mean emissivity, and total atmospheric water vapor content.

\(H\) is the convective heat loss from the land surface to the atmosphere. METRIC calibrates \(H\) for each satellite image based on an aerodynamic function:

\[
H = \rho_{\text{air}}C_p \left[ dT/r_{\text{ah}} \right]
\] (16)

where \(\rho_{\text{air}}\) is air density (kg m\(^{-3}\)), \(C_p\) is specific heat of air at constant pressure (J kg\(^{-1}\) K\(^{-1}\)), \(dT\) is the near surface temperature gradient (K), and \(r_{\text{ah}}\) is aerodynamic resistance (s m\(^{-1}\)) between two near surface heights (\(z_1\) and \(z_2\)) computed as a function of aerodynamic roughness for each pixel.
The METRIC model employs the Calibration using Inverse Modeling of Extreme Conditions (CIMEC) procedure to calibrate $H$. The CIMEC approach assumes a linear relationship between $dT$ and $T_s$:

$$dT = a + bT_s^{datum}$$

(17)

where $a$ and $b$ are empirically determined constants for a given satellite image, and $T_s^{datum}$ is surface temperature adjusted to each pixel using a DEM. The constants $a$ and $b$ are unique for each satellite image and are calculated using extreme values derived from representative ‘hot’ and ‘cold’ pixels. The constants $a$ and $b$ from equation 17 are determined by solving equation 9 at the hot and cold pixels in the AOI:

$$a = (dT_{\text{hot}} - dT_{\text{cold}})/(T_s^{datum \text{ hot}} - T_s^{datum \text{ cold}})$$

(18a)

$$b = (dT_{\text{hot}} - a)/T_s^{datum \text{ hot}}$$

(18b)

where $dT_{\text{hot/cold}}$ are the temperature gradients at the hot and cold pixels and $T_s^{datum \text{ hot/cold}}$ are the surface temperatures at the hot and cold pixels. $dT_{\text{hot/cold}}$ is computed by solving for the LSEB at the hot and cold pixel under some assumptions about the extreme values for $LE$. Solving for the LSEB at the two hot and cold pixels calibrates METRIC by setting extreme values for $ET_a$.

The selection of the hot and cold pixels is critical for calibration of METRIC to each satellite image. This study utilized an automated hot and cold pixel selection method included in the ‘water’ package. The selection method locates pixels with the highest and lowest surface temperatures (i.e. hottest and coldest) that have surface
characteristics within discrete ranges of albedo, LAI, Normalized Difference Vegetation Index (NDVI), and momentum roughness length ($Z_{om}$).

After the hot and cold pixel selection process, a maximum value for instantaneous $E_{Ta}$ must be specified. Previous research has shown that the wettest agricultural fields that are at full canopy cover have $E_{Ta}$ rates that are about 5% greater than the (alfalfa) $E_{Tr}$ rates, and 20 - 30% greater than the (grass) $E_{To}$ rates (Allen et al. 2011). $E_{Tr}$ is greater than $E_{To}$ because it represents alfalfa, which is a more water intensive plant than grass. This can occur when agricultural fields are at full cover and have wet soil beneath the crop canopy due to recent wetting by precipitation or irrigation. In METRIC, this is reflected by solving for $E_{Ta}$ at the cold pixel using the instantaneous $E_{To}$ value:

$$E_{Ta\ cold} = (E_{Ta\ cold}/E_{To}) \ E_{To} \quad (19)$$

where $E_{Ta\ cold}$ is the instantaneous $E_{Ta}$ at the cold pixel, $E_{To}$ is the instantaneous grass reference ET (mm hour$^{-1}$), and the term $(E_{Ta\ cold}/E_{To})$ is the pre-defined ratio of $E_{Ta}$ at the cold pixel to reference ET (e.g. 1.05 – 1.3), otherwise known as the reference ET fraction ($E_{ToF_{cold}}$). From $E_{Ta\ cold}$, the $LE$ component of the LSEB can be solved for the cold pixel. $E_{Ta}$ at the cold pixel calibrates METRIC by establishing a maximum $E_{Ta}$ rate for the AOI. An exception to this condition occurs in the early part of the growing season or in the non-growing season when the $E_{Ta}$ rates for a given agricultural field is much less than the instantaneous $E_{To}$. During these periods, a simple NDVI-based approach as suggested by Allen et al. (2007a) can be used to compute $E_{ToF_{cold}}$: 
ET_{F;\text{cold}} = 1.25 \text{NDVI}_{\text{cold}} \quad (20)

where NDVI_{cold} is the NDVI at the cold pixel. This study utilized equation 20 due to the contrasting crop development period for the SDI and CPI fields. NDVI and LAI values derived from Landsat images used in this study provide evidence that the corn and soybean crops of the SDI field were at different development stages on either side of the EC tower throughout the study periods (Figures 3.5, 3.6, 3.7). Differing crop types combined with distinct crop growth stages may result in different estimates of ET_{METRIC} when compared to ET_{EC} because the flux footprint often overlapped with the bare or nearly bare portion of the SDI field. The flux footprint captured both developing corn or soybean crops and nearly developed or fully developed corn and soybean crops for the same image date.
Figure 3.5: NDVI and LAI of SDI pixels representing corn and soybean for Landsat 8 images used in the 2015 analysis.
Figure 3.6: NDVI and LAI of SDI pixels representing corn and soybean for Landsat 8 images used in the 2016 analysis.
Figure 3.7: NDVI and LAI of SDI pixels representing corn and soybean for Landsat 8 images used in the 2017 analysis.

3.6 Calculation of Actual ET

Instantaneous ET ($ET_{\text{inst}}$) was determined for each pixel in the AOI at the time of satellite overpass by converting $LE$ to $ET$:
\[ ET_{\text{inst}} = 3600 \left( \frac{\text{LE}}{\lambda \rho_w} \right) \]  

where \( ET_{\text{inst}} \) is instantaneous ET (\( \text{mm h}^{-1} \)), 3600 converts from seconds to hours, \( \rho_w \) is the density of water (~1000 kg m\(^{-3}\)), and \( \lambda \) is the latent heat of vaporization (J kg\(^{-1}\)). \( \lambda \) is the heat absorbed when a kilogram of water evaporates:

\[ \lambda = [2.501 \times 0.00236 (T_s - 273.15)] \times 10^6 \]  

Daily and longer values for ET are more useful than instantaneous values. To extrapolate to longer time periods, the ratio of \( ET_{\text{inst}} \) to \( ET_o \) was calculated as:

\[ ET_o F = \frac{ET_{\text{inst}}}{ET_o} \]  

where \( ET_o F \) is the reference ET fraction or crop coefficient (\( K_c \)), and \( ET_o \) is the instantaneous grass reference ET (\( \text{mm hour}^{-1} \)) computed using meteorological data at time of satellite overpass. Values for \( ET_o F \) usually range from 0 at extremely dry pixels to above 1.0 at extremely wet pixels. \( ET_o F \) values above 1.0 generally represent wetlands and forests. Because \( ET_o F \) is assumed to be constant throughout the day, daily \( ET_a \) values for each pixel were calculated by multiplying daily \( ET_o \) as follows:

\[ ET_{\text{METRIC}} = ET_o F \times ET_o \]  

where \( ET_{\text{METRIC}} \) is the daily ET as calculated by METRIC (\( \text{mm day}^{-1} \)), and \( ET_o \) is the cumulative daily grass reference ET (\( \text{mm day}^{-1} \)) recorded at DWAR.

Daily and seasonal maps and values of \( ET_{\text{METRIC}} \) are useful to quantify water consumption by crops. Daily \( ET_{\text{METRIC}} \) images were created by performing temporal
linear interpolation of ET_oF images between Landsat image dates, then multiplying
daily ET_o from the DWAR station by the corresponding ET_oF image. Daily images of
ET\(_{\text{METRIC}}\) were summed to produce seasonal ET\(_{\text{METRIC}}\) images. Daily ET\(_{\text{METRIC}}\) values
were produced by performing a temporal linear interpolation of spatially averaged ET_oF
pixels representing crop types and multiplying by the respective daily ET_o. Cumulative
sums of ET\(_{\text{METRIC}}\) were calculated for each crop type.

### 3.7 Pixel Selection

Crop ET was estimated using all available Landsat 8 images (17) for each year.
Crop cover type was identified using the Cropland Data Layer (CDL), a 30-meter
resolution satellite-based crop cover dataset provided by the United States Department
of Agriculture-National Agricultural Statistics Service (USDA-NASS). The 30-meter
resolution of CDL matches well with 30-meter resolution of Landsat-based METRIC
outputs. Crop types were chosen for analysis using the CDL layer over the Warrington
Farm SDI and CPI fields. Bordering pixels representing different crop types, along with
the surrounding pixels representing non-agricultural areas (e.g. forest and road) were
excluded by creating a 60 meter buffer zone to negate the inclusion of mixed pixels.
Additionally, if a pixel representing a crop type intersected the access road through the
SDI field, the pixel was removed from analysis
3.8 METRIC Validation

For METRIC-EC comparison, turbulent fluxes and ET\textsubscript{METRIC} were averaged over the modeled source-area/footprint. The EC footprint is the upwind area that contributes to the measured fluxes. The 2-D flux footprint climatology for each growing season was modeled using the Flux Footprint Prediction online tool (Kljun et al. 2015). ET\textsubscript{a}F pixels representing the 2-D flux footprint climatology were spatially averaged. Temporal linear interpolation was performed on the averaged ET\textsubscript{a}F pixels, then the averaged pixels were multiplied by the respective daily ET\textsubscript{o} collected at DWAR. Multiple Landsat derived ET\textsubscript{METRIC} pixels were able to generally represent the source area of an Eddy Covariance tower and enabled a comparison of ET.

Due to the continuous variability of meteorological conditions governing the flux footprint, 13 daily flux footprints representing conditions for each image date were modeled to compare EC turbulent fluxes (\(H\) and \(LE\)) and daily ET\textsubscript{EC} and ET\textsubscript{METRIC}. The flux footprint climatology overlaps with surfaces other than the SDI fields, including a small portion of the road and grassy areas surrounding the field. Therefore, the evaluation of ET\textsubscript{METRIC} using ET\textsubscript{EC} is performed over an agricultural/mixed land use surface, which has implications for uncertainties and errors for the EC data. METRIC validation with variables taken at DWAR (e.g. \(R_n\), \(G\), \(T_s\), and incoming solar radiation) was done using the single pixel including the station.
For METRIC-atmometer comparison, daily ET\textsubscript{METRIC} derived from the pixels averaged over the SDI and CPI corn fields for the 2015 growing season were compared to daily ET\textsubscript{atm}. Daily ET\textsubscript{o} at DWAR was also compared against daily ET\textsubscript{o, atm}.

Statistical comparison between intermediate components of METRIC and measured values, and daily and cumulative sum of ET\textsubscript{METRIC}, ET\textsubscript{EC}, and ET\textsubscript{atm} was performed using bias (i.e. Modeled – Observed), Mean Bias Error (MBE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination ($R^2$), and Willmott Index of Agreement (IOA). The data used for comparison is summarized in Table 3.7.
Table 3.5: METRIC-derived incoming solar radiation ($R_s\downarrow$), net radiation ($R_n$), soil heat flux ($G$), surface temperature ($T_s$) extracted for comparison over the pixel representing DWAR and sensible heat flux ($H$), latent heat flux ($LE$), daily actual ET ($ET_a$), and instantaneous ET ($ET_{inst}$) averaged over the daily flux footprint.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_s\downarrow$ (Wm$^{-2}$)</td>
<td>DWAR</td>
</tr>
<tr>
<td>$R_n$ (Wm$^{-2}$)</td>
<td>Pixel</td>
</tr>
<tr>
<td>$G$ (Wm$^{-2}$)</td>
<td></td>
</tr>
<tr>
<td>$T_s$ (K)</td>
<td></td>
</tr>
<tr>
<td>$H$ (Wm$^{-2}$)</td>
<td>Flux</td>
</tr>
<tr>
<td>$LE$ (Wm$^{-2}$)</td>
<td></td>
</tr>
<tr>
<td>$ET_a$ (mm day$^{-1}$)</td>
<td>Footprint</td>
</tr>
<tr>
<td>$ET_{inst}$ (mm hour$^{-1}$)</td>
<td></td>
</tr>
</tbody>
</table>
Chapter 4

RESULTS AND DISCUSSION

4.1 Harbeson Meteorological Data

Annual and monthly average temperature and total precipitation from DWAR for 2015, 2016, and 2017 were compared to the 1981 – 2010 climatology from DGES. Average annual temperatures for all three years were similar to the 30-year average. Average temperature for 2015 was nearly 1°C below normal, while 2016 and 2017 were slightly above normal. September 2015 was the largest departure with an average temperature of 9°C below normal. Apart from the comparatively cold month of September in 2015, monthly temperatures from May to September of all three years did not deviate more than ±2.5°C from normal. The highest total rainfall occurred in 2016 with 1336.5 mm, followed by 2017 and 2015 with 1186.1 mm, and 1065.0 mm, respectively. Total annual precipitation was variable from year to year relative to the normal. Precipitation for 2015, 2016, and 2017 was 128 mm below, 143 mm above, and 7 mm below normal, respectively. 2016’s high precipitation is attributed to an unusually wet September that had a precipitation total of 448 mm, which was 329 mm above average for that month. Roughly 95% of September 2016’s precipitation fell outside of the study period (i.e. after September 13).

Monthly and annual $\text{ET}_o$ recorded at DWAR (Table 4.1) shows that $\text{ET}_o$ generally increases to maximums in summer months (i.e. May through July), then
decreases to a minimum in December during the three study years. The total annual ET₀ was 951.6 mm, 1016.8 mm, and 1018.7 mm for 2015, 2016, and 2017, respectively.

The highest monthly ET₀ occurred in May for 2015, July for 2016, and June for 2017. Incoming solar radiation, the dominant driver for ET rates in humid climates (Allen et al. 2011) and an input in the FAO-56 modified Penman-Monteith ET₀ equation, was greatest for the months with the highest ET₀. On average for the three years of study, ET₀ from May to September account for 63% of ET₀ for the year.

Table 4.1: Monthly and annual (total) grass reference ET (ET₀) of 2015, 2016, and 2017 recorded at DWAR.

<table>
<thead>
<tr>
<th>ET₀ (mm)</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>30.1</td>
<td>35.0</td>
<td>31.9</td>
</tr>
<tr>
<td>February</td>
<td>32.3</td>
<td>43.2</td>
<td>52.7</td>
</tr>
<tr>
<td>March</td>
<td>55.4</td>
<td>81.6</td>
<td>77.0</td>
</tr>
<tr>
<td>April</td>
<td>77.7</td>
<td>98.8</td>
<td>106.3</td>
</tr>
<tr>
<td>May</td>
<td>149.8</td>
<td>101.6</td>
<td>118.5</td>
</tr>
<tr>
<td>June</td>
<td>132.1</td>
<td>145.0</td>
<td>152.1</td>
</tr>
<tr>
<td>July</td>
<td>136.4</td>
<td>148.0</td>
<td>142.4</td>
</tr>
<tr>
<td>August</td>
<td>127.1</td>
<td>140.0</td>
<td>116.8</td>
</tr>
<tr>
<td>September</td>
<td>93.1</td>
<td>83.7</td>
<td>87.9</td>
</tr>
<tr>
<td>October</td>
<td>41.9</td>
<td>63.2</td>
<td>64.0</td>
</tr>
<tr>
<td>November</td>
<td>36.8</td>
<td>43.5</td>
<td>41.3</td>
</tr>
<tr>
<td>December</td>
<td>28.9</td>
<td>33.2</td>
<td>27.8</td>
</tr>
<tr>
<td>Total</td>
<td>941.6</td>
<td>1016.8</td>
<td>1018.7</td>
</tr>
</tbody>
</table>
4.2 Turbulent Flux Correction

The $\beta$ method to force energy balance closure redistributes available energy to $LE$ and $H$ by preserving the $\beta$. If the $LE$ or $H$ fluxes are under or overestimated, the $\beta$ method will lead to an under or overcorrected turbulent flux estimate. Figures A.1 and A.2 show the 2015 uncorrected and $\beta$ corrected $LE$ and $H$ fluxes plotted separately against available energy ($R_n - G$). Due to a severe underestimation of $H$, the $\beta$ was unrealistically small (0.029). In contrast, the $\beta$ of the uncorrected cumulative turbulent fluxes for 2016 and 2017 was 0.69 and 0.61, respectively. The $\beta$ method for 2015 led to an over adjustment to the $LE$ fluxes, hence an overestimate of ET$_{EC}$. Because of this, 2015’s turbulent fluxes and ET$_{EC}$ were discarded from comparison with ET$_{METRIC}$. Other in-situ measurements (e.g. incoming shortwave radiation, $R_n$, $G$, and $T_s$) were not discarded.

The energy balance closure using the EBR and coefficients from the OLR analysis for 2016 and 2017 before and after quality control procedures are summarized in Table 4.2. The uncorrected EBR for 2016 was 1.37, suggesting that the sum of the $H$ and $LE$ fluxes were greater than available energy. The $\beta$ method reduced the EBR to a nearly perfect closure of 1.001. The slope and intercept of the uncorrected 2016 data was 0.99 and 26.70 Wm$^{-2}$, respectively. After correction, the slope was increased to 1.0 and the intercept was reduced to 0.14 Wm$^{-2}$. $R^2$ for 2016 improved from 0.63 to 1.0. Similarly, the uncorrected EBR for 2017 was greater than 1 (1.27), showing that for this year, the sum of the $H$ and $LE$ fluxes were also greater than available energy. Using the
The \( \beta \) method, the slope and intercept of the uncorrected data for 2017 was modified from 0.93 to 0.99, and 23.06 Wm\(^{-2}\) to 1.28 Wm\(^{-2}\), respectively. \( R^2 \) increased from 0.76 to 0.98. Figures A.3 and A.4 shows uncorrected and corrected turbulent fluxes \((H + LE)\) against available energy \((R_n - G)\) for 2016 and 2017. The uncorrected turbulent fluxes plotted against available energy for both years show significant scatter around the 1:1 line while following correction, the data nearly matched the 1:1 line.

Table 4.2: Results of energy balance closure procedure, including number of 30 minute energy balance fluxes (n).

<table>
<thead>
<tr>
<th>Initial</th>
<th>n</th>
<th>intercept</th>
<th>slope</th>
<th>( R^2 )</th>
<th>EBR</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>6333</td>
<td>26.70</td>
<td>0.99</td>
<td>0.63</td>
<td>1.37</td>
</tr>
<tr>
<td>2017</td>
<td>6107</td>
<td>23.06</td>
<td>0.93</td>
<td>0.76</td>
<td>1.27</td>
</tr>
<tr>
<td>Final</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2016</td>
<td>3870</td>
<td>0.14</td>
<td>1.0</td>
<td>1.0</td>
<td>1.00</td>
</tr>
<tr>
<td>2017</td>
<td>3654</td>
<td>1.28</td>
<td>1.0</td>
<td>0.98</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Values from the OLR and \( R^2 \) of the uncorrected turbulent fluxes for this study are slightly higher than those reported in Wilson et al. (2002) with the slopes for both the 2016 and 2017 study periods (> 0.9) whereas the \( R^2 \) was on the lower end for 2016 and near the middle for 2017 in comparison to the results from Wilson et al. (2002).
Results of energy balance closure (i.e. EBR) for this study are unlike results reported by Stoy et al. (2013), which found that cropland had on average among the lowest energy balance closure (0.70 – 0.78) of all landscapes in their study. This is relevant because the corrected \( LE \) and \( H \) fluxes are based on uncorrected \( LE \) and \( H \) fluxes.

To force energy balance closure, the \( \beta \) method brings about uncertainties in the corrected turbulent fluxes. The \( \beta \) method does not account for errors and uncertainties in \( R_n \) and \( G \). Thus, errors in \( R_n \), \( G \), or both are propagated into the correction method (Teixiera and Bastiaanssen, 2012). Even if available energy observations are correct, the source area (i.e. area over which observations are taken) often differs from \( H \) and \( LE \) estimates over the flux footprint, so \( R_n \) and \( G \) are likely not representative of the flux footprint (Wilson et al. 2002). This is likely true since \( R_n \) and \( G \) were measured at DWAR and the flux footprint frequently represented turbulent fluxes over SDI corn and/or soybean crops. Further, the \( \beta \) method assumes that \( H \) and \( LE \) have the same level in confidence (i.e. one turbulent flux term is not more inaccurate than the other) (Teixiera and Bastiaanssen, 2012). Other potential causes of uncertainty include a lack of measurement between the soil surface and level of flux measurements \( (S) \), advection from source areas dissimilar to the crop canopy, or additional energy sinks \( (Q) \) (e.g. photosynthesis), which may be large in high yield crops such as corn (Wilson et al. 2002).
4.3 METRIC Comparison using In-Situ Data

ET\textsubscript{a} from latent heat flux is calculated as the residual from all other surface energy balance components in the METRIC model. Thus, the final estimation of ET\textsubscript{a} is only as accurate as the combination of all other energy balance components (Allen et al. 2007a). The intermediate components of METRIC were extracted from the pixel containing the Harbeson weather station (DWAR) at each satellite overpass and compared to in-situ observations recorded at DWAR. The pixel representing DWAR comprises both agricultural land and the dirt road that bisects the SDI fields. Thus, the pixel captures land surfaces with potentially vastly different surface characteristics such as albedo, LAI, and surface temperature. Turbulent fluxes were averaged over the daily flux footprint. Like the pixel representing DWAR, the flux footprints were often considered over heterogeneous landscapes. 16 Landsat image derived fluxes from METRIC from the 2015, 2016, and 2017 study periods were used to compare \( G, T_s, R_{S\downarrow} \), and \( R_n \). 12 Landsat images from the 2016 and 2017 study periods were used to compare \( H \) and \( LE \), ET\textsubscript{inst}, and ET\textsubscript{a} from day of satellite overpass. Tables 4.3, A.3, A.4, and A.5 summarize the mean bias error (MBE), mean absolute error (MAE), and root mean squared error (RMSE) of each component.
Table 4.3: 2015, 2016, and 2017 study periods combined mean bias error (MBE), mean absolute error (MAE), and root mean squared error (RMSE) of modeled variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>G (Wm$^{-2}$)</td>
<td>28.69</td>
<td>32.36</td>
<td>38.94</td>
</tr>
<tr>
<td>H* (Wm$^{-2}$)</td>
<td>151.93</td>
<td>153.21</td>
<td>181.53</td>
</tr>
<tr>
<td>LE* (Wm$^{-2}$)</td>
<td>53.45</td>
<td>89.08</td>
<td>102.90</td>
</tr>
<tr>
<td>T_s (K)</td>
<td>8.21</td>
<td>8.21</td>
<td>8.73</td>
</tr>
<tr>
<td>R_n (Wm$^{-2}$)</td>
<td>225.96</td>
<td>225.96</td>
<td>227.72</td>
</tr>
<tr>
<td>R_s ↓ (Wm$^{-2}$)</td>
<td>35.51</td>
<td>39.46</td>
<td>47.40</td>
</tr>
<tr>
<td>ET a* (mm day$^{-1}$)</td>
<td>0.25</td>
<td>0.85</td>
<td>1.01</td>
</tr>
<tr>
<td>ET inst* (mm hour$^{-1}$)</td>
<td>-0.01</td>
<td>0.13</td>
<td>0.15</td>
</tr>
</tbody>
</table>

* Results from 2016 and 2017 study periods only

4.3.1 Solar Radiation

Incoming solar (shortwave) radiation ($R_s ↓$) represent the primary energy input in the estimation of net radiation and is the dominant factor controlling ET in humid climates (Allen et al. 2007a: Allen et al. 2011). Modeled $R_s ↓$ extracted from the pixel containing DWAR are compared to $R_s ↓$ observations recorded at DWAR (Figure 4.1). All but two data points (from the 2015 study period) were above the 1:1 line indicating that METRIC-derived $R_s ↓$ was generally greater than observations. Greater incoming solar radiation leads to more energy available for net radiation and ultimately the ET process. However, given a strong correlation ($R^2 = 0.83$), a low MBE, MAE, and RMSE (35.51, 39.46, and 47.40 Wm$^{-2}$, respectively), modeled $R_s ↓$ agreed well with observations. Biases in $R_s ↓$ may be caused by the errors in albedo or in the calculation.
of broad-band atmospheric transmissivity calculated in the METRIC model, which relies on vapor pressure from weather station measurements to calculate precipitable water vapor. These results are slightly worse than those reported by Liaqat and Choi (2015), who found an $R^2$ of 0.99, MBE of 17 Wm$^{-2}$, and a RMSE of 21 Wm$^{-2}$ over multiple sites in arid regions of southeast Asia.

**Figure 4.1**: Modeled incoming solar radiation plotted against observations from a pyranometer.
4.3.2 Surface Temperature

Surface temperature ($T_s$) is integral to the METRIC model calculation of outgoing longwave radiation ($R_L\uparrow$), incoming longwave radiation ($R_L\downarrow$), sensible heat flux through the calibration of hot and cold pixels, and soil heat flux equations. METRIC-derived $T_s$ compared well to observations recorded at DWAR ($R^2 = 0.68$) (Figure 4.2), but tended above the 1:1 line, signifying that modeled pixel $T_s$ was greater during all satellite overpasses than observed $T_s$ at DWAR. Greater surface temperature indicates that more energy is allocated to $R_L\uparrow$ and $R_L\downarrow$ (equations 13 and 14). Per equation 15b (METRIC-modeled soil heat flux), modeled $T_s$ values that are biased hot increases the soil heat flux values with LAI < 0.5 (i.e. little vegetation). These results are slightly worse than Reyes-González et al. (2019), who compared infrared thermometer-measured $T_s$ of corn in eastern South Dakota with METRIC-derived $T_s$. The authors found better correlation ($R^2 = 0.87$) and lower RMSE (1.24°C). The lower performance of the current study is unsurprising given the mixed landcover pixel (i.e. agriculture and dirt road) that incorporates DWAR.
4.3.3 Net Radiation

Net radiation ($R_n$) is the sum of $G$, $H$, and $LE$ at the surface and is calculated from satellite-measured narrowband reflectance and $T_s$ (Allen et al. 2007a). Modeled $R_n$ considerably overestimated observed $R_n$ for all overpass dates (Figure 4.3), leading to large MBE, MAE, and RMSE, but showed reasonably well correlation ($R^2 = 0.77$). These large positive biases are unusual among METRIC-based studies but may be explained in part by positive biases of $R_s\downarrow$ and $T_s$, errors in albedo, and/or differences in spatial resolution between the Landsat pixel and observations (Liaqat and Choi 2015).
4.3.4 Soil Heat Flux

Soil heat flux \( G \) is the rate of energy storage into the soil and vegetation from conduction (Allen et al. 2007a). \( G \) is obtained based on equations that calculate the ratio
of $G$ to $R_n$, then multiplied by $R_n$ to estimate $G$. $G$ is often the smallest surface energy balance component of METRIC applications. Modeled $G$ showed a poor correlation against measured $G$ in the soil below DWAR station (Figure 4.4) and frequently overestimated $G$ but had relatively low bias statistics. Landsat images from the 2016 study period had considerably lower bias statistics than images from 2015 and 2017. From equation 15, a ‘hot’ bias in $T_s$ likely contributed to higher $G$ when LAI < 0.5. Despite the weak correlation, these results compare well to other studies that validate METRIC-derived $G$. Liaqat and Choi (2015) found a RMSE of 46 Wm$^{-2}$, compared to the current study with an overall RMSE of 39 Wm$^{-2}$. The authors note that METRIC’s usage of vegetation indices and albedo capture changing soil moisture and vegetation structure over time, likely leading to high accuracy of $G$ (Liaqat and Choi 2015). Other studies yielded better results. Choi et al. (2009) found a RMSE of 19 Wm$^{-2}$, and Singh and Irmak (2011) found a RMSE of 24 Wm$^{-2}$. The current study’s result is satisfactory given the mixed land use pixel over which DWAR is located. Further, errors in METRIC-derived $G$ can be associated with different measurement scales between Landsat resolution and ground-based observations (Fuente-Sáiz et al. 2017).
Figure 4.4 Modeled soil heat flux plotted against observations.

4.3.5 Sensible Heat Flux

Sensible heat flux ($H$) is the energy convected into the atmosphere by a near surface temperature gradient (Allen et al. 2007a). $H$ is frequently the most difficult energy flux to model in RSEB models. $H$ is estimated in METRIC based on a pixel-unique near surface temperature gradient, surface roughness, and wind speed using buoyancy corrections. METRIC was designed to have $H$ absorb all intermediate estimation errors and biases from the other energy balance fluxes (Allen et al. 2007a). Spatially averaged pixels of METRIC-estimated $H$ over the daily flux footprint is
compared to EC estimated $H$ (Figure 4.5). METRIC overestimated $H$ and showed a poor correlation compared to observations. Thus, the three study period’s combined MBE, MAE, and RMSE were 151.93, 153.21, 181.53 Wm$^{-2}$, respectively. Although these biases are large, other studies found the MAE and RMSE of $H$ to be above 100 Wm$^{-2}$. Results from Oliveira et al. (2018) found the MAE and RMSE of METRIC-derived $H$ to be approximately 87, 87, and 112 Wm$^{-2}$ and 101, 101, and 178 Wm$^{-2}$, respectively, across three sites. The overall high biases in $H$ were caused in part by its design. METRIC utilizes the process known as ‘calibration using inverse modeling at extreme conditions’ (CIMEC) to calibrate the energy balance through the estimation of $H$ by inversely solving the energy balance at two extreme thermal and hydrologic conditions (i.e. hot/dry and cold/wet pixels) using surface based reference ET. This serves in part to prevent outliers of $H$. The CIMEC process imbeds all biases of $R_\alpha$, $G$, and other intermediate components into the estimation of $H$ (Allen et al. 2011). The calibration of $H$ is highly sensitive to the selection of hot and cold pixels and the hydrologic conditions at the pixels (Singh and Irmak 2011). In addition to errors in METRIC, it is likely there are errors in $H$ estimation from the EC data.
4.3.6 Latent Heat Flux

The latent heat flux ($LE$) is the energy consumed during the ET process. In METRIC, $LE$ is estimated as the residual of $R_n$, $H$, and $G$ (equation 10). Spatially averaged pixels of METRIC-estimated $LE$ from the daily flux footprint show poor correlation with EC-derived $LE$ ($R^2 = 0.18$) (Figure 4.6) over the 2016 and 2017 study periods but showed relatively low bias statistics. METRIC analysis from the 2016 study period agreed better with EC-$LE$ than from the 2017 study period. Thus, ET$_{inst}$ and daily ET$_a$ from days of satellite overpass showed better agreement for the 2016 METRIC
analysis than the 2017 analysis. Better agreement of ET\textsubscript{inst} and ET\textsubscript{a} for the 2016 study period is reflected in lower MBE, MAE, and RMSE. One drawback of the METRIC model is that LE is calculated as a residual of the other energy balance components so LE is only as accurate as the combination of \( R_n, G, \) and \( H \). Thus, it relies on hot and cold pixel selection. Choi et al. (2009) found a RMSE of 19 Wm\(^{-2}\), and Singh and Irmak (2011) found a RMSE of 24 Wm\(^{-2}\).

Figure 4.6: Modeled latent heat flux plotted against observations.
4.4 Validation of ET\textsubscript{METRIC} with ET\textsubscript{EC}

Validation of ET\textsubscript{METRIC} using ET\textsubscript{EC} allows users of METRIC to gauge the model’s efficacy in ET\textsubscript{a} modeling, assuming ET\textsubscript{EC} is accurate. In general, daily ET\textsubscript{a} estimates from METRIC and the EC method were low during the early months of the study periods (growing seasons) then increased into July and August. After peaks in mid-July, daily ET\textsubscript{a} decreased towards the end of the study periods as crops reached maturity. In the case of the 2017 study period, METRIC analysis overlaps with soybean harvest, after which ET\textsubscript{a} values were around 1.0 mm day\textsuperscript{-1}. Tables 4.4 and 4.5 summarize ET\textsubscript{METRIC} and ET\textsubscript{EC} time series for the 2016 and 2017 study periods.

The 2016 study period began on April 30 and ended on September 13, with two days of discarded data (n = 135), and the 2017 study period began on June 12 and ended on October 18 (n = 129). Average daily ET\textsubscript{METRIC} was close to ET\textsubscript{EC}, resulting in an MBE of 0.04 and 0.07 mm day\textsuperscript{-1} for the 2016 and 2017 study periods, respectively. Daily ET\textsubscript{METRIC} for 2016 plotted against daily ET\textsubscript{EC} shows that METRIC data tended around the 1:1 line (Figure 4.7), with an R\textsuperscript{2} of 0.63. The 2017 METRIC analysis showed less correlation with field data (Figure 4.8), resulting in an R\textsuperscript{2} of 0.33. Moderate agreement for 2016 is also based on a relatively low RMSE (0.75 mm day\textsuperscript{-1}) and higher IOA (0.67). In contrast, 2017 showed a comparatively high RMSE of 1.13 mm day\textsuperscript{-1} and a lower IOA (0.53). Singh and Irmak (2011) reported a RMSE of 1.7 mm day\textsuperscript{-1} over a corn and soybean field. Correlations from the current study are worse than those reported by Singh and Senay (2016), who found R\textsuperscript{2} values from 0.88 to 0.95 over three
corn and soybean sites in Nebraska, USA, although their analysis only considered ET_{METRIC} during the day of satellite overpass. Metrics from other studies match closely with the current results, including a MAE ranging from 0.71 to 0.98 mm day\(^{-1}\), and RMSE ranging from 0.84 to 1.06 mm day\(^{-1}\) (see section 2.2) (Singh and Senay 2016). It is important to note that the comparison of daily ET_{METRIC} is limited by the accuracy of ET_{EC}, which is likely reduced due to the heterogenous nature of the landscape surrounding DWAR. Further, the flux footprint climatology over which ET_{METRIC} is averaged is constantly changing with time and often overlaps with heterogenous land surfaces (e.g. dirt road, paved road, agricultural field, etc.). Another source of error results from the Landsat overpass frequency which is limited by only one path/row capturing the entire Delmarva Peninsula, and cloud cover made many images unusable. Trezza et al. (2016) found that limiting METRIC analysis to two Landsat satellites over one path/row underestimated growing season ET\(_a\) by approximately 8% on average compared to METRIC analysis with two satellites over two path/rows. The ideal conditions for frequent Landsat-based ET\(_a\) monitoring include two satellites covering two overlapping path/rows leading to a return period of 4 days (Trezza et al. 2016), assuming all images are usable. Because the current study lacked an additional and overlapping path/row and did not utilize Landsat 7 images, the highest return period was 16 days, but was frequently 32 days, or one image every month. September 2017 was devoid of usable Landsat images.
Table 4.4: Comparison of daily ET_{METRIC} and daily ET_{EC} for the 2016 and 2017 study period, including number of days, mean ET_{EC}, mean ET_{METRIC}, standard deviation of ET_{EC}, and standard deviation of ET_{METRIC}.

<table>
<thead>
<tr>
<th>Year</th>
<th># of days</th>
<th>EC mean</th>
<th>METRIC mean</th>
<th>SD EC</th>
<th>SD METRIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>135</td>
<td>2.60</td>
<td>2.61</td>
<td>1.11</td>
<td>1.22</td>
</tr>
<tr>
<td>2017</td>
<td>129</td>
<td>2.56</td>
<td>2.63</td>
<td>1.19</td>
<td>1.25</td>
</tr>
</tbody>
</table>

Table 4.5: Year, mean bias error (MBE), mean absolute error (MAE), coefficient of determination ($R^2$), and index of agreement (IOA).

<table>
<thead>
<tr>
<th>Year</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
<th>$R^2$</th>
<th>IOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>0.04</td>
<td>0.60</td>
<td>0.75</td>
<td>0.63</td>
<td>0.67</td>
</tr>
<tr>
<td>2017</td>
<td>0.07</td>
<td>0.91</td>
<td>1.13</td>
<td>0.33</td>
<td>0.53</td>
</tr>
</tbody>
</table>
Figure 4.7: 2016 modeled daily time series $ET_{\text{METRIC}}$ plotted against observations.
Figure 4.8: 2017 modeled daily time series ET\textsubscript{METRIC} plotted against observations.

Daily ET\textsubscript{METRIC} and ET\textsubscript{EC} in the 2016 study period remained relatively low throughout May, then steadily increases throughout June and mid-July. After mid-July, ET\textsubscript{METRIC} and ET\textsubscript{EC} steadily decreased to the end of the study period (September 13) as
crops reached maturity (Figure 4.9). Both ET\textsubscript{EC} and ET\textsubscript{METRIC} for the 2017 study period did not follow a clear pattern throughout the growing season (Figure 4.10). ET\textsubscript{METRIC} showed a distinct time period of high ET\textsubscript{a} values (> 3.0 mm day\textsuperscript{-1}) in late June through July, then decreased as soybeans reach maturity and are harvested. ET\textsubscript{EC} shows no apparent decrease in high ET\textsubscript{a} from late June to the end of August. Cumulative sums of daily ET\textsubscript{METRIC} and ET\textsubscript{EC} for 2016 and 2017 corresponded well throughout the study periods (Figures A.5, A.6). Cumulative ET\textsubscript{METRIC} for 2016 was 352.62 mm, which was 1.5% greater than the total ET\textsubscript{EC} of 347.32 mm. Cumulative ET\textsubscript{METRIC} for 2017 was 339.40 mm, which was 2.9% greater than ET\textsubscript{EC} (329.83 mm). Based on cumulative ET\textsubscript{a}, METRIC performed satisfactorily. Wagle et al. (2017) reported that METRIC overestimated cumulative ET\textsubscript{a} by 25% and 30% for sorghum over two growing seasons. Oliveira et al. (2018) found that METRIC overestimated ET\textsubscript{a} by 14% compared to EC data over a grassland site where grass was 4 – 5 meters tall. Interpolation of ET\textsubscript{a,F} between days with little or no cloud cover and ample solar energy for ET may cause an overestimation of cumulative ET\textsubscript{a} from METRIC when compared to ground measurements. Because cloudless or nearly cloudless (i.e. high solar radiation at the surface) images are a prerequisite for the METRIC model, METRIC misses cloudy days with overall lower ET\textsubscript{a}, leading to a systematic overestimation of ET\textsubscript{a} (Kjaersgaard et al. 2011, Wagle et al. 2017).
Figure 4.9: 2016 daily time series of ET_{METRIC} and ET_{EC}. Green bars represent Landsat 8 overpasses.
Figure 4.10: 2017 daily time series of $ET_{METRIC}$ and $ET_{EC}$. Green bars represent Landsat 8 overpasses.
Model biases (i.e. $\text{ET}_{\text{METRIC}} - \text{ET}_{\text{EC}}$) for 2016 and 2017 are shown in Figures 4.11 and 4.12. $\text{ET}_{\text{METRIC}}$ was typically greater during time periods of overall high $\text{ET}_a$, usually in July. Biases during the 2016 and 2017 analysis ranged from -2.0 mm day$^{-1}$ on May 15 to 2.1 mm day$^{-1}$ on July 12, and -2.9 mm day$^{-1}$ on August 20 to 2.6 mm day$^{-1}$ on June 20, respectively. Large positive biases for both study periods tended to occur from late June to mid-July. Large biases during the peak $\text{ET}_a$ months may be due to the systematic high $\text{ET}_a$ bias in METRIC, which may not be as pronounced during times with no or low crop cover when $\text{ET}_a$ is low regardless of cloud cover and comprised of mainly soil evaporation.
Figure 4.11: 2016 daily ET$_{\text{METRIC}}$ biases against ET$_{\text{EC}}$. Green bars represent Landsat 8 overpasses.
Figure 4.12: 2017 daily ET\textsubscript{METRIC} biases against ET\textsubscript{EC}. Green bars represent Landsat 8 overpasses.

4.5 ET\textsubscript{METRIC} and ET\textsubscript{atm} Comparison

Atmometers are a simple and inexpensive alternative to FAO Penman-Monteith equations to estimate ET\textsubscript{o}, as they do not require multiple meteorological inputs (Irmak et al. 2005). Because atmometers effectively measure reference ET, they can be multiplied by a K\textsubscript{c} curve to estimate ET\textsubscript{a}. This study utilized an atmometer covered with #30 green canvas to emulate grass reference ET. The atmometer was placed near the SDI corn field during the 2015 growing season. Atmometer-observed reference ET
(\(\text{ET}_o, \text{atm}\)) was multiplied by a \(K_c\) curve to yield a time series of atmometer-based actual ET (\(\text{ET}_{\text{atm}}\)). The daily time series of \(\text{ET}_{\text{atm}}\) was compared to \(\text{ET}_{\text{METRIC}}\) derived from the SDI corn field for a portion of the 2015 study period.

Daily \(\text{ET}_o, \text{atm}\) agreed moderately well with Penman-Monteith \(\text{ET}_o\) with an \(R^2\) of 0.59. \(\text{ET}_o\) ranged from 1.4 mm day\(^{-1}\) (June 27) to 6.3 mm day\(^{-1}\) (June 23) during the growing season. \(\text{ET}_o, \text{atm}\) varied from 0.25 mm day\(^{-1}\) on June 27 to 7.11 mm day\(^{-1}\) on July 26 (Figure 4.13) The largest negative bias of -2.11 mm day\(^{-1}\) occurred on July 26, while the largest positive bias of 3.01 mm day\(^{-1}\) occurred on July 1. Negative biases generally began occurring early in the study period (after July 15) when corn was at full height (2.85 meters), while positive biases generally present before July 15 (Figure 4.14). Positive biases early in the study period are likely attributable to differing heights between the instruments either mounted to the DWAR tower or the height of the atmometer. The atmometer was adjusted according to canopy height, while the DWAR instrumentation remained approximately 2 meters above ground, where it measured higher windspeed than near the surface. The cumulative grass reference ET collected from DWAR and measured by the atmometer was 296 and 298.2 mm, respectively.
Figure 4.13: Daily ET₀ and ETₐₜ m. o. Green bars represent Landsat 8 overpasses.
Comparison of daily ET\textsubscript{atm} as multiplied by the K\textsubscript{c} curve and daily ET\textsubscript{METRIC} from the SDI corn field for the 2015 growing season (Figures 4.15, 4.16), resulted in an average of 4.66 mm day\textsuperscript{-1} for ET\textsubscript{atm} and 3.75 mm day\textsuperscript{-1} for ET\textsubscript{METRIC}, respectively. Daily ET\textsubscript{METRIC} showed a good correlation with daily ET\textsubscript{atm} with an R\textsuperscript{2} of 0.83. However, the plotted data tended to be below the 1:1 line, indicating ET\textsubscript{atm} was generally greater than ET\textsubscript{METRIC}. This is reflected in a large RMSE of 1.48 mm day\textsuperscript{-1}, a MAE of 1.29 mm day\textsuperscript{-1}, and an MBE of -0.91 mm day\textsuperscript{-1}. Biases ranged from -3.35 mm day\textsuperscript{-1} on July 26 to 1.73 mm day\textsuperscript{-1} on July 1 (Figure 4.17). These extreme biases also coincide with the
largest negative and positive biases in grass reference ET. Negative biases commonly began to occur around July 5 and continued throughout the rest of the time period. Large negative biases after around July 5 are attributed to high $K_c$ values ranging from 1.01 to 1.2 from July 5 to August 17 (period of 44 days). The high tabulated $K_c$ values for the atmometer during this period is greater than ET$_{oF}$ values for METRIC ranging from 0.77 to 1.04 over the same time period. Further, the data collection period for the atmometer began when SDI corn was 1.2 meters tall and the $K_c$ value was above 0.5 and trending towards 1 and greater, so the atmometer did not capture ET from earlier in the growing season when ET was lower. From June 20 to August 26, cumulative ET$_{METRIC}$ for the time period was 254.97 mm, which was 24.88% less than cumulative ET$_{atm}$ (316.67 mm).
Figure 4.15: Daily time series of ET_{METRIC} and ET_{atm}. Green bars represent Landsat 8 overpasses.
Figure 4.16: Modeled daily time series ET\textsubscript{METRIC} plotted against ET\textsubscript{atm}.
This ET analysis using METRIC did not have an adequate Landsat 8 satellite image between June 7 and July 25, or a period of 48 days. Allen et al. (2007a) recommends at least one satellite image every month to create a representative ET<sub>oF</sub> curve for the growing season. During the peak growing season, more than one image every month is optimal to capture rapidly developing crops. Lacking an image in late June caused the METRIC analysis to miss ET information during a critical stage of crop development. When the crop canopy is rapidly growing, an additional satellite image during this 48 day period in late June would have added another vertex to the ET<sub>oF</sub> curve and more accurately represented SDI corn ET.
Similar results were reported by Reyes-González et al. (2017) and Reyes-González et al. (2019). Both studies reported good correlation ($R^2 > 0.8$) between ET$_{\text{METRIC}}$ and ET$_{\text{atm}}$. However, both studies also reported lower RMSE and higher IOA. This discrepancy is likely due to a critical time in the growing season (between June 7 and July 25) being devoid of a Landsat image from which to obtain an ET$_o$F data point. In addition, $K_c$ values were higher than the existing ET$_o$F curve during this time, leading to higher ET$_{\text{atm}}$. However, the two studies did not create daily time series of ET$_{\text{METRIC}}$. Thus, the authors’ ET$_a$ comparison was only considered over several image dates and did not compare seasonal ET$_a$ estimates. The two studies took place under climates unlike Delaware’s (North Dakota), used Number 54 green canvas for alfalfa reference ET (ET$_r$), and used a different $K_c$ curve method.

### 4.6 ET$_o$F and ET$_{\text{METRIC}}$ Maps

Field-by-field spatial estimates of ET$_a$ are one of the main benefits of METRIC. This study utilized 17 nearly cloud free Landsat 8 images acquired along path/row 14/33. Landsat images were clipped to the borders of Sussex County, then processed using the METRIC model. Maps of instantaneous ET$_o$F and daily ET$_{\text{METRIC}}$ are shown in Figures A.7 – A.12. Pixels with no value from cloud masking are shown as white patches within a County.

The ET$_o$F and ET$_{\text{METRIC}}$ images for each study time period show that water consumption from vegetation strongly differ based on images taken during the early,
late, or non-growing season to images taken during the peak growing season (i.e. late June and July). Pixels representing vegetation (e.g. agriculture, forest, etc.) respond with higher ET\textsubscript{oF} and ET\textsubscript{METRIC} in conjunction with the progression of the growing season. ET\textsubscript{oF} and ET\textsubscript{METRIC} in developed areas (e.g. towns, roads, etc.) and the sandy coastlines show little change throughout the study time period as would be expected.

Riparian areas, forests, wetlands, water bodies, and other natural vegetation areas have higher 24 hour ET\textsubscript{METRIC} than developed areas, including agriculture for images during the non-growing season. The contrast between these areas is clearly shown in, for example, the June 9, 2016 image. Low ET\textsubscript{METRIC}, as shown in red, is present for the pixels representing the developed lands, including some bare or nearly bare agricultural fields. High ET\textsubscript{METRIC}, shown in shades of blue, is visible for forests, including Redden State Forest (upper center), and riparian areas, such as Nanticoke River (lower left) and surrounding forests. The next image in 2016 on July 11 shows more widespread high ET\textsubscript{METRIC} values. This is due in part to corn and soybean, the dominant crop types in Sussex County, generally reaching peak water consumption/crop development during late June or July. Spatial patterns of ET\textsubscript{METRIC} outside of the peak growing seasons (e.g. on the 4/6/2016, 5/8/2016, 8/31/2017, 10/2/2017, and 10/18/2017 images) is generally lower and more homogenous.
4.7 Daily and Seasonal Crop ET\textsubscript{METRIC}: SDI and CPI

\( \text{ET}_0 \)F images derived from the Landsat based METRIC model are intended to represent information about crop development stages. Interpolating between ET\textsubscript{a}F images, or specific pixels, is similar to developing a \( K_c \) curve. Multiplying the interpolated ET\textsubscript{a}F images or pixels by respective daily \( \text{ET}_0 \) is done to obtain daily ET\textsubscript{METRIC}. Combining daily ET\textsubscript{METRIC} images creates a spatial estimation of seasonal ET\textsubscript{METRIC}, which is useful for quantifying crop water demand on a field-by-field basis. The METRIC method is a way to accurately replicate the \( K_c \) curve on a large spatial scale using Landsat imagery.

The 30 meter resolution of Landsat 8 imagery is suitable for spatial estimates of seasonal ET\textsubscript{a} using the METRIC model. Seasonal ET\textsubscript{METRIC} images for each study period were clipped to represent Warrington Farm (703 pixels). The resultant images provide estimated seasonal ET\textsubscript{METRIC} information of the CPI and SDI fields, including bordering forested, residential, and utility land surfaces. Figures 4.18, 4.19, and 4.20 show the seasonal ET\textsubscript{METRIC} values for Warrington Farm. Seasonal ET\textsubscript{METRIC} images for each study period show similar patterns. The forested area to the northwest of the SDI field consistently have the highest seasonal ET\textsubscript{METRIC}, while pixels mostly representing roads, homes, and nearly bare land have the lowest seasonal ET\textsubscript{METRIC}. The circular shape of the CPI fields shows up well, and clearly has higher seasonal ET\textsubscript{METRIC} than the rectangular SDI fields. The relatively small area of the SDI field makes accurate
seasonal ET_{METRIC} estimation difficult because of mixed pixels, or pixels representing two distinct surface types (e.g. forest and agriculture).

Figure 4.18: 2015 cumulative ET_{METRIC} for Warrington Farm. Black lines signify the SDI fields (bottom left) and CPI fields (center right).

5/22/2015 to 8/26/2015
Figure 4.19: 2016 cumulative ET\textsubscript{METRIC} for Warrington Farm. Black lines signify the SDI fields (bottom left) and CPI fields (center right).
Figure 4.20: 2017 cumulative ET\textsubscript{METRIC} for Warrington Farm. Black lines signify the SDI fields (bottom left) and CPI fields (center right).
4.7.1 ET₀F Curves and Cumulative ET_{METRIC}

The linearly interpolated ET₀F curves representing CPI and SDI corn and soybean fields for the 2015, 2016, and 2017 study periods are presented in Figures 4.21, 4.22, and 4.23. The METRIC model was able to capture ET information that showed there was overall greater average ET₀F from corn and soybean crops under a CPI system than an SDI system. Differences in the ET₀F curves directly translate to differences in seasonal crop ET_{METRIC}. This is confirmed with the METRIC analysis of corn and soybean crops which found the seasonal ET_{METRIC} was greater for corn and soybeans under a CPI system than under an SDI system (Table 4.8). Because the analysis for each growing season began and ended on different dates and had different date ranges, it is not practical to compare seasonal corn and soybean ET_{METRIC} between years. In general, corn and soybean under the CPI system had greater cumulative (seasonal) ET_{METRIC} than corn and soybean under the SDI system (Figures A.13, A.14, A.15).
Figure 4.21: 2015 temporal linear interpolated ET₀F curves for SDI and CPI crops.
Figure 4.22: 2016 temporal linear interpolated ET₀F curves for SDI and CPI crops.
Figure 4.23: 2017 temporal linear interpolated $ET_o F$ curves for SDI and CPI crops.
Table 4.6: Percentage greater of Cumulative ET\textsubscript{METRIC} for CPI crops than SDI crops.

<table>
<thead>
<tr>
<th>Year</th>
<th>Corn (%)</th>
<th>Soybean (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>21.0</td>
<td>24.9</td>
</tr>
<tr>
<td>2016</td>
<td>13.2</td>
<td>9.5</td>
</tr>
<tr>
<td>2017</td>
<td>4.0</td>
<td>1.1</td>
</tr>
</tbody>
</table>

4.7.1.1 2015

Out of all three study time periods, the 2015 study period had the least number of Landsat images, and the largest gap between overpass dates (48 days). Soybean and corn ET\textsubscript{oF} curves for 2015 had similar shapes throughout the growing season. ET\textsubscript{oF} values for all crops reached a minimum on the June 7\textsuperscript{th} Landsat overpass and a maximum on the July 25\textsuperscript{th} overpass. ET\textsubscript{oF} curves for CPI soybean and corn and SDI soybean had similar values from late May to mid-June, then began to diverge in late June. SDI soybean had the lowest values from early July to the end of the study period, and CPI corn had the highest values.

ET\textsubscript{oF} for SDI soybean was less than 0.8 throughout the study period. ET\textsubscript{oF} for CPI corn was greater than 1.0 from mid-July to mid-August. Average ET\textsubscript{oF} of CPI corn and soybean were 20.5\% and 25.1\% greater than SDI corn and soybean, respectively. METRIC analysis of seasonal ET\textsubscript{a} in 2015 showed this large contrast between the CPI and SDI crops. ET\textsubscript{METRIC} for CPI and SDI corn were 386.1 and 319.0 mm, respectively. ET\textsubscript{METRIC} for CPI and SDI soybean were 368.8 and 295.4 mm, respectively.
4.7.1.2 2016

The 2016 study period spanned 161 days from early April to mid-September and included 7 Landsat images. There was at least one satellite image for every month of the study period. The METRIC analysis captured ET information from before the summer growing season began to near the end of the growing season. \( E_{\text{T}0F} \) values of soybean for both fields reached minimums on the May 8\(^{\text{th}}\) Landsat overpass, and corn for both fields reached minimums on the June 9\(^{\text{th}}\) overpass. All crops reached \( E_{\text{T}0F} \) maximums on the July 11\(^{\text{th}}\) Landsat overpass. Like 2015, \( E_{\text{T}0F} \) curves for the 2016 period were similar in the early part of the study period then began to diverge in mid to late June. Early growing season similarity in \( E_{\text{T}0F} \) is likely due to fields being bare or nearly bare, thus sharing similar surface characteristics (e.g. albedo, temperature, roughness length, etc.) before crop emergence. Average \( E_{\text{T}0F} \) of CPI corn and soybean were 13.2\% and 9.8\% higher than SDI corn and soybean, respectively. The seasonal \( E_{\text{METRIC}} \) contrast in 2016 was less than for 2015. \( E_{\text{METRIC}} \) for CPI and SDI corn were 499.7 and 441.3 mm, respectively. \( E_{\text{METRIC}} \) for CPI and SDI soybean were 409.8 and 374.4 mm, respectively.

4.7.1.3 2017

The 2017 study period began later in the growing season than 2015 and 2016 and extended past the growing season into mid to late October. The 2017 study period was based on 6 Landsat images, with at least one image per month except in September. \( E_{\text{T}0F} \) curves of CPI corn and soybean were approximately equal to SDI corn and
soybean throughout the study period. Average ET$_{oF}$ of CPI corn and soybean were 3.6% and 2.0% larger than SDI corn and soybean, respectively. ET$_{oF}$ curves of CPI and SDI corn and soybean were nearly identical, with an R$^2=0.99$ and 0.97, respectively.

Seasonal ET$_{METRIC}$ for corn and soybeans were comparable for both irrigation systems. ET$_a$ for CPI and SDI corn were 421.4 and 405.1 mm, respectively. ET$_a$ for CPI and SDI soybean were 321.7 and 318.3 mm, respectively. One possible explanation for nearly identical seasonal ET$_{METRIC}$ is that rainfall recorded at DWAR during this growing season was 507.7 mm, which is greater than the highest seasonal crop ET$_a$ (i.e. CPI corn). Cumulative rainfall values for 2015 and 2016 were below the highest respective seasonal crop ET$_{METRIC}$. High rainfall in 2017 may have lessened the need for substantial irrigation, ensuring that both fields received roughly equal amounts of water.

It is important to note that this analysis does not consider the quantity of applied irrigation in the estimation of seasonal ET$_{METRIC}$ and cannot estimate the evaporation and transpiration components separately. Thus, this study cannot draw a conclusion about the efficiency of one irrigation system over another. More applications of METRIC, or a similar model, are necessary to determine seasonal ET$_{METRIC}$ differences between crops under a CPI and SDI system. However, this study shows that METRIC capture differences in seasonal ET$_a$, or crop water demand, between corn and soybean crops under an SDI and CPI regime.
Chapter 5

SUMMARY AND CONCLUSION

This study showed that METRIC is a useful tool to spatially estimate ETa and tracking changes in water demand in a humid climate. The METRIC model estimates instantaneous land-surface energy balance components ($R_{S\downarrow}$, $R_n$, $T_s$, $G$, $H$, $LE$) and daily and cumulative ETa ($ET_{\text{METRIC}}$) using 17 Landsat 8 images available within the 2015, 2016, and 2017 growing seasons concentrating the analysis over an irrigation research agricultural site (Warrington Farm) in Sussex County, Delaware. Results were compared to observations from the DEOS weather station (DWAR) fixed with an Eddy Covariance Instrument located near two subsurface drip irrigated (SDI) fields in Warrington Farm. Daily $ET_{\text{METRIC}}$ of corn in the SDI field was also compared to daily ETa estimated with an atmometer ($ET_{\text{atm}}$). The crop water demand of corn and soybean fields under two different irrigation systems – SDI and central pivot irrigated (CPI) fields – were related.

METRIC estimations of $R_{S\downarrow}$ and $T_s$ were greater than in-situ measurements, leading to an overall mean bias error (MBE) of 35.51 Wm$^{-2}$ and 8.21 K, respectively. Although $R_{S\downarrow}$ and $T_s$ showed good performance compared to observations, positive biases likely propagated to successive components of METRIC that are a function of $R_{S\downarrow}$ and $T_s$. Large biases from observations were found with $R_n$, leading to a RMSE of 227.72 Wm$^{-2}$. This is unusual among similar studies but is likely due in part to positive
biases in $R_S\downarrow$ and $T_s$, errors in modeled albedo, or differences in spatial resolution between the pixel and observations. METRIC-derived estimates of $G$ showed weak correlation with observations, but relatively low bias. Errors in $G$ are likely due to the differences in spatial resolution between the Landsat pixel and observations. METRIC biases in $R_S\downarrow$, $R_n$, $T_s$, and $G$ are to be expected due to the heterogeneous nature of the Landsat pixel that represents DWAR. Further, more observations over more pixels should be considered to assess the accuracy of METRIC-derived components of the surface energy balance.

$H$ and $LE$ estimated by METRIC and averaged over the flux footprint showed moderate biases compared to $\beta$ adjusted fluxes from Eddy Covariance data, leading to an overall MBE of 151.93 Wm$^{-2}$ and 53 Wm$^{-2}$. These results are in line with existing literature. For $H$, large biases are expected due to the CIMEC process that absorbs all intermittent biases from other parameters to produce accurate ET$\text{METRIC}$ images. However, these results are satisfactory given the course resolution of the Landsat pixels averaged over the daily flux footprint.

Daily ET$\text{METRIC}$ correlated reasonably well against ET$\text{EC}$ for the 2016 study period, but less so for the 2017 study period. The absence of a consistent usable Landsat 8 image every 16 days likely decreased the accuracy of the METRIC analysis. Most of Sussex County is not within an overlapping region of two adjacent Landsat path/rows, further limiting temporal and spatial coverage. To be operational in a frequently cloudy area, other methods should be incorporated to compensate for a lack of optimal Landsat
coverage. The accuracy of ET\text{METRIC} is also likely limited by the accuracy of ET\text{EC}.

Cumulative ET\text{METRIC} matched well with ET\text{EC} for both the 2016 and 2017 study periods, which is reflected in low MBE (0.04 and 0.07 mm day\textsuperscript{-1}). The small positive bias in daily ET\text{a} is possibly due to an inherent high-ET\text{a} bias of the METRIC model, especially during the peak growing season.

Cumulative ET\text{atm} was nearly 25% greater than ET\text{METRIC} but showed good correlation ($R^2 = 0.83$). The large difference in cumulative ET\text{a} was due in part to the high (> 1) $K_c$ values over a 44 day period. The lack of a Landsat 8 image from June 7 to July 25 caused the METRIC model to miss an ET\text{a,F} image during a critical time in the crop development stage.

This study showed that METRIC is able to provide acceptably accurate spatial ET\text{a} estimates and show differences in cumulative ET\text{a} between corn and soybean crops under an SDI and CPI irrigation regime. The use of the Cropland Data Layer allowed for the extraction of pixels representing different crop types, which would be useful in quantifying water demand over an area where the crop type would be unknown otherwise. Pixels representing corn and soybean crop extracted and spatially averaged for analysis. Maps of cumulative ET\text{METRIC} show that METRIC using Landsat imagery can capture spatial patterns within individual fields. However, it is more difficult to observe spatial patterns of the SDI fields due to its relatively small size. The absence of consistent usable Landsat 8 images is a drawback in practical applications of METRIC in humid areas with frequent cloud cover. Usable images are limited further because
most of Sussex County is not within an overlap of two path/rows. The integration of
other satellite images with higher temporal frequency would increase the practicality of
METRIC applications.
REFERENCES


69. “Warrington Farm: College of Agriculture and Natural Resources: University of Delaware.” *College of Agriculture and Natural Resources | University of Delaware*, www.udel.edu/academics/colleges/canr/carvel/warrington-farm/.
Table A.1: Meteorological conditions at instant of Landsat overpass, including time, incoming shortwave (solar) radiation, windspeed, relative humidity (RH), vapor pressure (ea), air temperature (T<sub>a</sub>), and grass reference ET (ET<sub>o</sub>)

<table>
<thead>
<tr>
<th>Date</th>
<th>DOY</th>
<th>Time (local)</th>
<th>Radiation (Wm&lt;sup&gt;-2&lt;/sup&gt;)</th>
<th>Wind (ms&lt;sup&gt;-1&lt;/sup&gt;)</th>
<th>RH (%)</th>
<th>ea (kPa)</th>
<th>T&lt;sub&gt;a&lt;/sub&gt; (°C)</th>
<th>ET&lt;sub&gt;o&lt;/sub&gt; (mmhour&lt;sup&gt;-1&lt;/sup&gt;)</th>
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<td>69.3</td>
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<td>39.58</td>
<td>1.5</td>
<td>27.99</td>
<td>0.6228</td>
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<td>48.38</td>
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Table A.2: Surface characteristic requirements for automated hot and cold pixel search algorithm (Olmedo et al. 2016).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cold Pixel</th>
<th>Hot Pixel</th>
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<tbody>
<tr>
<td>albedo</td>
<td>0.18 - 0.25</td>
<td>0.13 - 0.15</td>
</tr>
<tr>
<td>NDVI</td>
<td>0.76 - 0.84</td>
<td>0.10 - 0.28</td>
</tr>
<tr>
<td>LAI (m&lt;sup&gt;2&lt;/sup&gt; m&lt;sup&gt;-2&lt;/sup&gt;)</td>
<td>3.0 - 6.0</td>
<td>NA</td>
</tr>
<tr>
<td>Z&lt;sub&gt;om&lt;/sub&gt; (m)</td>
<td>0.03 - 0.08</td>
<td>≤ 0.005</td>
</tr>
</tbody>
</table>
Table A.3: 2015 mean bias error (MBE), mean absolute error (MAE), and root mean squared error (RMSE) of modeled variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G$ (Wm$^{-2}$)</td>
<td>40.34</td>
<td>40.34</td>
<td>41.89</td>
</tr>
<tr>
<td>$T_s$ (K)</td>
<td>7.63</td>
<td>7.63</td>
<td>7.66</td>
</tr>
<tr>
<td>$R_n$ (Wm$^{-2}$)</td>
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<td>229.97</td>
<td>230.65</td>
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<tr>
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<td>3.71</td>
<td>19.52</td>
<td>21.72</td>
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</table>

Table A.4: 2016 mean bias error (MBE), mean absolute error (MAE), and root mean squared error (RMSE) of modeled variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G$ (Wm$^{-2}$)</td>
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<td>21.01</td>
<td>25.82</td>
</tr>
<tr>
<td>$H$ (Wm$^{-2}$)</td>
<td>176.52</td>
<td>176.52</td>
<td>193.19</td>
</tr>
<tr>
<td>$LE$ (Wm$^{-2}$)</td>
<td>57.96</td>
<td>78.88</td>
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<tr>
<td>$T_s$ (K)</td>
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<td>7.46</td>
<td>7.78</td>
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<tr>
<td>$R_n$ (Wm$^{-2}$)</td>
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<td>237.79</td>
<td>240.49</td>
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<td>$R_s \downarrow$ (Wm$^{-2}$)</td>
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<td>52.11</td>
<td>58.84</td>
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<tr>
<td>ET$a$ (mm day$^{-1}$)</td>
<td>0.50</td>
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<td>ET$_{inst}$ (mm hour$^{-1}$)</td>
<td>-0.007</td>
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<td>0.11</td>
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Table A.5: 2017 mean bias error (MBE), mean absolute error (MAE), and root mean squared error (RMSE) of modeled variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G$ (Wm$^{-2}$)</td>
<td>37.49</td>
<td>38.40</td>
<td>46.99</td>
</tr>
<tr>
<td>$H$ (Wm$^{-2}$)</td>
<td>127.35</td>
<td>129.91</td>
<td>169.07</td>
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<tr>
<td>$LE$ (Wm$^{-2}$)</td>
<td>48.95</td>
<td>99.29</td>
<td>111.22</td>
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<tr>
<td>$T_s$ (K)</td>
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<td>9.35</td>
<td>10.18</td>
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<tr>
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<td>211.45</td>
<td>212.08</td>
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<td>40.11</td>
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<tr>
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<tr>
<td>ET$_{inst}$ (mm hour$^{-1}$)</td>
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</table>
Figure A.1: 2015 uncorrected turbulent fluxes plotted separately against available energy.
Figure A.2: 2015 corrected turbulent fluxes plotted separately against available energy.
Figure A.3: 2016 uncorrected and corrected turbulent fluxes plotted against available energy.
Figure A.4: 2017 uncorrected and corrected turbulent fluxes plotted against available energy.
Figure A.5: 2016 running sum of ET_{M} and ET_{EC}.
Figure A.6: 2017 running sum of ET (EC) and ET (METRIC).
Figure A.7: 2015 instantaneous ET$_o$F of Sussex County at time of Landsat 8 overpass.
Figure A.8: 2016 instantaneous ET₀F of Sussex County at time of Landsat overpass.
Figure A.9: 2017 instantaneous ET₀F of Sussex County at time of Landsat 8 overpass.
Figure A.10: 2015 daily ET$_{METRIC}$ of Sussex County for day of Landsat 8 overpass.
Figure A.11: 2016 daily ET\textsubscript{METRIC} of Sussex County for day of Landsat 8 overpass.
Figure A.12: 2017 daily ET\textsubscript{METRIC} of Sussex County for day of Landsat 8 overpass.
Figure A.13: 2015 running sum of ET_{METRIC} for SDI and CPI crops.
Figure A.14: 2016 running sum of ET_{METRIC} for SDI and CPI crops.
Figure A.15: 2017 running sum of ET_{METRIC} for SDI and CPI crops.