2017

Estimating energy fluxes and evapotranspiration of corn and soybean with an unmanned aircraft system in Ames, Iowa

Áthila Gevaerd Montibeller

University of Northern Iowa

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ESTIMATING ENERGY FLUXES AND EVAPOTRANSPIRATION OF CORN AND SOYBEAN WITH AN UNMANNED AIRCRAFT SYSTEM IN AMES, IOWA

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

Master of Arts

Áthila Gevaerd Montibeller

University of Northern Iowa

July, 2017
ABSTRACT

Evapotranspiration (ET) is a key hydrological variable and has been studies to plan irrigation schedule, understand surface-atmospheric interactions, assess crop sensitivity to droughts, etc. On top of that, ET is a proxy for evaluating water availability in trees canopies and assess soil moisture content. The recent advent of the Unmanned Aircraft Systems (UAS) has presented new opportunities and challenges in mapping ET at a much finer scale and under various atmospheric conditions. In this research, we integrate traditional remote sensing techniques with the novel UAS technology to estimate ET and surface energy fluxes for a corn and soybean field near Ames, Iowa, in five different stages of crop development: establishment, vegetative, flowering, yield formation and ripening. Multispectral and thermal cameras onboard the UAS were used to collect imagery that served as primary data for running the Surface Energy Algorithm for Land (SEBAL) model that estimates ET as a residual of the surface energy budget. Other data and materials used for the development of this research include eddy covariance flux towers, meteorological data, leaf area index measured in-situ, ground control points and surface reflectance and surface albedo measured with a field spectroradiometer. The eddy covariance flux towers are managed by the United States Department of Agriculture (USDA) and their data were utilized for calibrating and validating the model. Each tower has an approximated fetch of approximately 200 meters, and 24 tower footprints calculated for each tower using the Flux Footprint Predictions (FFP) model, that accounts for surface roughness, wind speed and friction
velocity. The footprints were used to extract the mean value for each raster-energy flux that was compared with the observed values from the flux towers. Statistical methods for validating the energy fluxes produced by SEBAL include linear regression, residual plots, the root mean squared error, mean absolute error and confidence coefficient. The cross-comparison between observed and estimated values for the Net Radiation (Rn) showed an R squared of $R^2 = 0.71$, for the Soil Heat Flux (G) an agreement of $R^2 = 0.17$ for plate 1 and $R^2 = 0.22$ for plate 2, for the Sensible Heat Flux (H) $R^2 = 0.50$ and for the Latent Heat Flux (LE) an agreement of $R^2 = 0.82$. The findings also indicate that ET rates are reliant upon the stage of crop development, where the corn plot had higher ET rates up until the appearing of the tassel, rapidly declining afterwards. The soybean field had a more consistent rate of ET from May through September, possibly due to its extended length of growth. This research concludes that the SEBAL model can be integrated with a UAS platform for estimating ET and surface energy fluxes at very fine scale, however, atmospheric conditions still affect the accuracy and quality of remotely sensed data.
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This Study by: Áthila Gevaerd Montibeller


has been approved as meeting the thesis requirement for the

Degree of Master of Arts in Geography

Date  Dr. Bingqing Liang, Chair, Thesis Committee

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Date  Dr. Patrick P. Pease, Interim Dean, Graduate College
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<table>
<thead>
<tr>
<th>TABLE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Length of Crop Development for Corn in Central USA (in days)</td>
</tr>
<tr>
<td>2</td>
<td>Length of Crop Development for Soybean in Central USA (in days)</td>
</tr>
<tr>
<td>3</td>
<td>Multispectral Payload Specifications</td>
</tr>
<tr>
<td>4</td>
<td>thermoMAP Specifications</td>
</tr>
<tr>
<td>5</td>
<td>Corn Plot Field Work Time Table</td>
</tr>
<tr>
<td>6</td>
<td>Soybean Plot Field Work Time Table</td>
</tr>
<tr>
<td>7</td>
<td>Micrometeorological and Flux Data utilized in this Research</td>
</tr>
<tr>
<td>8</td>
<td>Thermal Imagery collected from Flight Campaign – thermoMAP</td>
</tr>
<tr>
<td>9</td>
<td>Multispectral Imagery collected from Flight Campaign - Cannon S110 and Sequoia</td>
</tr>
<tr>
<td>10</td>
<td>Integrated Surface Albedo per Field - May through September</td>
</tr>
<tr>
<td>11</td>
<td>Coefficient of Absorption per Field - May through September</td>
</tr>
<tr>
<td>12</td>
<td>Root Mean Squared Error (RMSE) per Energy Flux for the Corn and Soybean Fields</td>
</tr>
<tr>
<td>13</td>
<td>Mean Absolute Error (MAE) per Energy Flux for the Corn and Soybean Fields</td>
</tr>
<tr>
<td>14</td>
<td>Confidence Coefficient R Squared per Energy Flux for the Corn and Soybean Fields</td>
</tr>
<tr>
<td>FIGURE</td>
<td>PAGE</td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>28</td>
</tr>
<tr>
<td>4</td>
<td>29</td>
</tr>
<tr>
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<td>30</td>
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<td>32</td>
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<td>33</td>
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<td>9</td>
<td>34</td>
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<tr>
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<td>36</td>
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<td>36</td>
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<td>12</td>
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<tr>
<td>15</td>
<td>48</td>
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<td>16</td>
<td>50</td>
</tr>
<tr>
<td>17</td>
<td>51</td>
</tr>
<tr>
<td>18</td>
<td>53</td>
</tr>
<tr>
<td>19</td>
<td>57</td>
</tr>
</tbody>
</table>
20 dT\_cold vs. T\_cold and dT\_hot vs. T\_ho

21 thermoMAP Temperature Mosaic and Replicated Features, on July 15

22 Sequoia Surface Reflectance Mosaic, fault lines and
mosaicking issues, on August 18

23 Cannon S110 NIR - Red Band Empirical Line Calibration

24 Cannon S110 NIR - NIR Band Empirical Line Calibration

25 Sequoia Sesnor - Red Band Empirical Line Calibration

26 Sequoia Sensor - NIR Band Empirical Line Calibration

27 thermoMAP - Empirical Line Calibration Model

28 Measurement of Reflected Light from Soybeans Canopy on August 3rd

29 White REference Radiance on June 27

30 Corn Canopy Radiance on Jun 27

31 Surface Albedo per plot from May 18 to Setptember 1

32 Flux Tower 10 Energy Balance Before Closure

33 Flux Tower 11 Energy Balance Before Closure

34 Sensible Heat Flux - Flux Footprint Temporal Evolution for the First Flight at
Approximately 10:45 A.M.

35 Sensible Heat Flux - Flux Footprint Temporal Evolution for the Second Flight at
Approximately 11:45 A.M.

36 Latent Heat Flux - Flux Footprint Temporal Evolution for the First Flight at
Approximately 10:45 A.M.
38 Net Radiation (Rn) Regression Model: Observed vs. Estimated................................. 99
39 Net Radiation (Rn) Residual Plot .................................................................................. 100
40 Net Radiation Temporal Evolution for the First Flight at Approximately 10:15 A.M. ................................................................................................................................. 101
41 Net Radiation Temporal Evolution for the Second Flight at Approximately 11:45 A.M. ................................................................................................................................. 102
42 Soil Heat Flux (G) - Plate 1 - Regression Model: Observed vs. Estimated.................... 104
43 Soil Heat Flux (G) Plate 1: Residual Plot ...................................................................... 105
44 Soil Heat Flux (G) Plate 2 - Regression Model: Observed vs. Estimated..................... 105
45 Soil Heat Flux (G) Plate 2 - Residual Plot .................................................................... 106
46 Soil Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M. ................................................................................................................................. 107
48 Leaf Area Index for the Growing Season - Corn and Soybean .................................. 110
49 Soil Heat Flux Rates from May through September (Plate1) ...................................... 111
50 Soil Heat Flux Rates from May through September (Plate2) ...................................... 111
51 Evaporative Pan at Study Site ..................................................................................... 114
52 Sensible Heat Flux Regression Model: Estimated vs. Observed............................... 115
53 Sensible Heat Flux Residual Plot ............................................................................... 116
54 Sensible Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M.

55 Sensible Heat Flux Temporal Evolution for the Second Flight at Approximately 11:45 A.M.

56 Latent Heat Flux Regression Model: Observed vs. Estimated

57 Latent Heat Flux Residual Plot

58 Latent Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M.

59 Latent Heat Flux Temporal Evolution for the Second Flight at Approximately 11:45 A.M.

60 SEBAL ET Rates per Field (mm/h) – Flight 1 at ~10:45 A.M.

61 SEBAL ET Rates per Field (mm/h) – Flight 2 at ~11:45 A.M.

62 ET Temporal Evolution for the First Flight at Approximately 10:45 A.M.

63 ET Temporal Evolution for the Second Flight at Approximately 11:45 A.M.

64 NDVI – ET Correlation: Corn Field

65 NDVI – ET Correlation: Soybean Field

A1 Elevation Map

A2 Soils Map
CHAPTER 1

INTRODUCTION

1.1 Introduction

Chapter 1 covers background information on evapotranspiration (ET), surface energy fluxes and the most utilized methods for their estimation, including traditional field-based and remote sensing techniques. It also describes the research problem, the research goal and objectives, and importance of the study.

1.2 Research Background

Evapotranspiration (ET) is defined as the sum of evaporation, the return of water from a standing surface such as soil surface or a water body to the atmosphere, and transpiration, the return of water from within a plant leaf to the atmosphere. It is the process where water is transferred from the surface and/or vegetation to the atmosphere (Verstraeten, Veroustraete & Feyen, 2008), and represents the closing of the hydrologic cycle. The water exchange usually involves a change in water phase, from liquid to gas, where energy is absorbed and the surrounding areas are cooled (Liang, Li & Wang, 2012).
With the heavy reliance upon soil moisture and water availability, ET is a good measure of water consumption and water use (Kaplan, Myint, Fan & Brazel, 2014). Therefore, it is frequently applied to plan irrigation schedule, evaluate crop water stress, understand mass and heat exchange between the surface and the atmosphere, and monitor droughts (Allen, Tasumi & Trezza, 2007; Bastiaanssen, Menenti, Feddes & Holtslag, 1998; Eden, 2012; Park, 2015). Additionally, ET plays a key role in the hydrologic cycle, and it is an important variable on Earth’s climate (Watson & Burnett, 1993), recycling the solar energy through latent heat of vaporization.

There are a number of direct/field methods for estimating ET such as applying the so called reference evapotranspiration (ETo) and crop coefficient (Kc) ratio, the Bowen Ratio, and the application of equipment including pan evaporators, lysimeters, eddy covariance flux towers and scintillometers (Allen, Tasumi & Trezza, 2002; Teixeira, 2010). Although these methods are known for being reliable, its measurement footprint scale, or field of view (FOV), is restricted to the upwind fetch area of the instrument being used (Singh & Senay, 2015). Their applications are therefore limited when local, regional and even global scale ET maps are required. To overcome these limitations, remote sensing techniques have been developed for estimating ET and surface energy fluxes over large areas. Most of these techniques are based on the modelling the surface energy budget, and estimate ET as the residual of the energy balance equation (Alvala & Gielow, 1993).

When remote sensing imagery are applied, the surface energy budget must be incorporated, through different physical models such as the Surface Energy Balance
Algorithms for Land (SEBAL), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), the Dual Temperature Difference (DTD) and the Priestley-Taylor Energy Balance model (TSEB-PT), amongst others (Allen, Tasumi & Trezza, 2007; Bastiaanssen, Menenti et al., 1998; Hoffmann et al., 2015).

These remote sensing energy balance models (RSEB) have as their foundation the partitioning of the available energy at the surface in four energy fluxes: Net Radiation (Rn), Soil Heat Flux (G), Sensible Heat Flux (H) and Latent Heat Flux (LE). The net radiation, often called as net flux, is the ratio between the incoming and outgoing solar energy at the Earth’s surface, and integrates albedo, outgoing longwave thermal radiation and incoming longwave thermal radiation, on top of the solar energy. Net radiation represents the available energy at the surface to be consumed by G, H and LE.; the soil heat flux (G) represents the ratio of heat energy that penetrates the soil surface in a downward movement through conduction; the sensible heat flux (H) is the transfer of heat energy from the surface to the atmosphere due to conduction and convection, by exchanging heat from the surface to the air above it, and the latent heat flux (LE) is the energy transferred from the surface to the atmosphere due to convection of water molecules that carry the energy absorbed to change phase.

Although spaceborne and airborne remote sensing has been widely used to estimate surface energy fluxes and ET, it still faces challenges when it comes to revisiting a target at a specific time, or when the atmospheric conditions are not favorable. Another limitation when using traditional spaceborne platforms such as Landsat, MODIS and
NOAA/AVHRR is related to their medium to coarse pixel size and scale of observation (Ruhoff et al., 2012; Singh, Herlin, Berroir & Bouzidi, 2005; Sun et al., 2011).

Unmanned Aircraft Systems (UAS) are on the emerging front of remote sensing, because they can obtain very fine pixel scale, fly under overcast weather conditions, revisit a target multiple times during a day, and provide a relatively cheaper-to-operate platform among others within the remote sensing context (Colomina & Molina, 2014). As a result, UAS is an ideal platform of remote sensing to perform vegetation monitoring, crop water stress, precision farming, and ET estimations (Lelong, 2008; Park, 2015; Hoffmann et al., 2015). As a fairly new technology, its potential on estimating ET is still under investigation, especially when an energy balance model such as SEBAL and METRIC are used.

The state of Iowa, located in the corn-belt region of the United States, is a global reference in the production of agricultural products such as soybeans and corn, and about 90% of its land area is designated for agricultural purposes (USDA, 2017). The state ranks first in production of corn and soybeans in the United States, a factor that emphasizes the importance of this commodity to the economy of the state and the country (Natural Resources Defense Council, 2016). One of the reasons for Iowa success in agriculture is its geography, most notably the soil composition, known as the “black gold” (Iowa Soils, 2016), a fertile loess, considered one of the most fertile soils in the world.

Corn is planted and cultivated worldwide, in regions where precipitation ranges from 300 to 5000 millimeters year round, in which the amount of water consumed by a
tillage during its cycle is about 600mm (Magalhaes & Duraes, 2006). In Iowa, most of the corn planted is grain, with some small portions of the land area destined for the planting of sweet corn (Official Website of Iowa Corn, 2016). The development stages of corn, from breaking through the soil until it reaches maturity, are divided in vegetative (V) and reproductive stages (R), and further subdivided as V(n), V(n), V(n) until V(n), in which (n) represents the presence of the leaf collars (Ritchie., 1993). There are 17 to 22 V stages before the tassel emergence (Mueller & Sisson, 2011), where VE represents the emergence of the shoot from the soil, and VT the presence of the tassel. For the reproductive stage, R1 is defined as silking, period which the silks emerge beyond the tip of the ear husk, whereas the other R stages are related to the development of the kernels on the ears (O’Keeffe, 2009). The life cycle of corn is complex, with some stages of development overlapping each other, and some parts the plant might be developing, and while in others might be dying (O’Keeffe, 2009).

Corn is an efficient crop type regarding water consumption and dry matter production, where maximum production of medium grain crop requires between 500 and 800 mm of water, depending on the climate and the region (FAO - Water Development and Management). The plant physiology is directly affected by the water supply and demand. The consequences of water shortage in the soil or high evaporative demand can affect the growing and development of the plant, attenuating and reducing the yield (Magalhaes & Duraes, 2006). Table 1 and picture 1 depict the different stages of crop development for corn (grain) and their respective crop coefficient (Kc).
Table 1. *Length of Crop Development for Corn in Central USA (in days)*

<table>
<thead>
<tr>
<th>Crop Characteristics</th>
<th>Initial Stage (in days)</th>
<th>Mid-Season (in days)</th>
<th>Late Stage (in days)</th>
<th>Total (in days)</th>
<th>Plant Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage length</td>
<td>25</td>
<td>40</td>
<td>40</td>
<td>35</td>
<td>135</td>
</tr>
<tr>
<td>Crop Coefficient</td>
<td>0.30</td>
<td>&gt;&gt;</td>
<td>1.2</td>
<td>0.5</td>
<td>-</td>
</tr>
</tbody>
</table>

*Kc*


*Figure 1. Stages of Development and the Crop Coefficient (Kc) - Corn*

Soybeans (*Glycine Max*) is one of the most important world crops, and its cultivation is mainly related with oil and protein production (FAO Water Development and Management, 2016). Soybeans has been cultivated for over three millennia in Asia, and today it can be found being produced in every continent, most notably in the United States, Brazil, Argentina, China and India (Soy Facts, 2016). Originally from temperate climate, soya is highly adaptive to a wide range of climatic regions, although for an optimal development the medium air temperature must fall in between 20 and 35 degrees Celsius, and an annual precipitation between 700 to 1200 mm is recommended for hydrological needs (Diehl & Junquetti, 2016).

The development stages of soybeans can overlap within a field, and a growth stage begins when more than 50% of the plants are at or beyond that stage (Soybeans Field Guide, 2011). Soybeans growth stages are divided in two main stages of development: (V) vegetative and the (R) reproductive stage (CAMARA, 1997). Vegetative (V) vegetative stages are subdivided into VE (Emergence), VC (unrolled unifoliate leaves), and V(n) represents the unrolled trifoliate leaf, in which (n) is the number of unrolled trifoliate leaves (Farias 2007; Soybeans Field Guide, 2011).

The absence of water or the excess of it, during the vegetative period, can retard growth. During this growing period, flowering and yield formation are the most affected stages and sensitive to water deficits (FAO Water Development Management, 2016). Figure 2 and Table 2 depicts stages of growth and crop coefficients used for soybeans water management (FAO Water Development and Management, 2016).
Figure 2. Stages of Development and the Crop Coefficient (Kc) - Soybean


Table 2. Length of Crop Development for Soybean in Central USA (in days)

<table>
<thead>
<tr>
<th>Crop Characteristics</th>
<th>Initial Stage Length (in days)</th>
<th>Crop Development</th>
<th>Middle-Season</th>
<th>Late</th>
<th>Total</th>
<th>Plant Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop</td>
<td>20</td>
<td>30/35</td>
<td>60</td>
<td>25</td>
<td>140</td>
<td>May</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.5</td>
<td>&gt;&gt;</td>
<td>1.15</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Source: Allen et al. (1998).
Considering its agricultural-based economy and landscape, it makes important to understand how changes in land use and land cover affect the transport and exchange of moisture and energy between the surface and the atmosphere. Hydrologic processes such as ET have a key role in the management of water resources, as well as being an indicator for land degradation, water uptake and water stress (Allen, Tasumi & Trezza, 2007; Allen et al., 1998; Park, 2015). Although most of Iowa’s agriculture is not reliant upon irrigation, the management of water resources and knowledge about crop water consumption is vital for the sustainable use of this resource. Also, there is an increasing concern towards climate change and its effects over weather patterns and the possible increase of climatic threats and unpredictable climatic phenomena such as droughts and floods, considering that these phenomena can pose severe damage to agriculture. Moreover, the increasing in the global population and the demand for food could intensify the need for a more efficient crop production, where the responsible use of water resources must be taken into account and become a major component of environmental issues.

1.3 Research Problem

The land cover in agricultural landscapes such as in Iowa is constantly changing, and such changes directly affect the transport of energy and mass between the surface and the atmosphere. Vegetation cover, surface albedo, land surface temperature, surface
roughness and aerodynamic resistance to heat transfer are some of the parameters that are directly affected by changing the land cover. Land surface energy and ET fluxes depend upon these parameters and the rate to which they change. Estimating these fluxes can tells us about regional and climatic patterns, as well as water availability and water consumption. Well-established field methods for estimating ET such as scintillometers and lysimeters, although reliable, do not provide continuous information of ET for an entire field.

Traditional remote sensing platforms and methods to estimate ET face challenges when high spatial resolution and the need for multiple and flexible revisiting time are in need. Moreover, spaceborne and airborne platforms can stumble into unstable atmospheric conditions and cloudy skies, making the imagery collection at times impossible.

1.4 Research Goal, Objectives

This research goal is to integrate traditional remote sensing methods and techniques to fixed-wing UAS for estimating crop ET and energy fluxes in different stages of crop development. The specific objectives are:
a. Evaluate the performance of the SEBAL model to estimate and map surface energy fluxes and ET as a residual of the energy balance equation for the corn and soybean fields;

b. Estimate the water consumption (ET) on a plot level for the corn and soybean fields in different stages of crop development;

c. Establish a workflow for collecting field data and imagery for generating ET and surface energy fluxes maps;

d. Compare and validate the estimated ET and surface energy fluxes with the measured Rn, G, H and LE from the eddy covariance flux towers in the corn and soybean fields.

1.5 Significance of this Study

The significance of this study relies on the fact that little has been done in the sense of estimating and mapping surface energy fluxes and ET using UAS. This technology is still new in the field of remote sensing, although much potential has been seen when applied to agriculture, vegetation monitoring, land use land cover changes, irrigation management, etc. The use of surface energy balance models such as SEBAL had been widely explored by scientists using traditional spaceborne and airborne platforms, but its application to low altitude remote sensing UAS with a sub-metric spatial resolution is still unknown.
On top of that, this research aims to create a workflow to estimate and map ET to a state where most of its land area is used for agriculture purposes, therefore understanding physical processes of mass and energy exchange are of great importance to a wide range of applications.

Finally, this study hopes to contribute with the scientific community, in a sense that monitoring the landscape is an important step for preserving and securing the sustainable use of natural resources.

1.6 Thesis Structure

This thesis is structured as follows: Chapter 1 introduces the background information about ET, surface energy fluxes and estimation approaches, research problem, goals and objectives. Chapter 2 reviews previous literature in the Earth surface energy budget, estimation of ET using spaceborne and airborne remote sensing, and the use of UAS for environmental analysis, vegetation monitoring and estimating ET. Chapter 3 describes the study area, materials and methods utilized. Chapter 4 discusses the results and Chapter 5 concludes the research with the most important findings.
CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter reviews the existent literature in the topics of the Earth’s surface energy budget, remote sensing energy balance models for estimating energy fluxes and ET, and UAS application towards vegetation monitoring, water consumption modelling and precision agriculture.

2.2 Earth Surface Energy Budget

Earth’s climate and all life inhabiting this planet rely on the incoming solar radiation, and all of the physical and biological processes occurring on Earth are dependent on this same energy (Monteith & Unsworth, 1990). Every day a given place on Earth receives shortwave radiation from the sun, making its temperature to rise. At this point, molecules start to vibrate, emitting longwave thermal energy and starting a cooling process. If there was no cooling process, e.g. if absorption was the only ongoing process, the temperature of this place would rise continuously. This process of incoming and outgoing radiation fluxes is known as the Earth’s Energy Budget.

The solar energy that heats up the surface can be partitioned in four energy fluxes: net radiation (Rn), soil heat flux (G), sensible heat flux (H) and latent heat flux (LE). The
relationship between these fluxes can be seen on equation 1, whereby $H$ and $LE$ represent the transfer of mass and energy from the surface to the atmosphere through the movement of rising air and water vapor, through turbulent fluxes, also called eddies, and $Rn$ and $G$ represent the available energy for $H$ and $LE$ to happen.

$$R_n - G - H - LE = 0$$  \hspace{1cm} (1)

Conversion from tropical forest to grassland can greatly affect micrometeorological climate and systems, and its impacts were evaluated by the modelling and partitioning of the surface energy budget to understand the effects of each one of these energy fluxes in the surface temperature and albedo on rainy days. These information are crucial for general circulation models as they represent the main surface-atmospheric processes, i.e. radiative transfer and the formation of clouds and precipitation (Alvala & Gielow, 1993).

The impacts of vegetation cover and leaf area index (LAI) on soil heat flux ($G$) were investigated and assessed by applying two land-surface models: the Biosphere-Atmosphere Transfer Scheme (BATS) and the IAP94. One of the findings include that the topmost part of the plant canopy intercepted more solar radiation and have a higher temperature than the canopy mean, irradiating more thermal infrared radiation than those underneath. Also, it was found that with a lower LAI there is less available energy to warm the vegetation, as the canopy temperature decreases with lower values of LAI (Yang, Dai, Dickinson & Shuttleworth, 1999).
Seasonal variation on mass (H$_2$O) and energy of a semi-deciduous forest in Brazil were characterized by modelling the energy balance model using micrometeorological measurements of latent and sensible heat flux (LE and H), as well as canopy conductance. The investigation was concerned with the more gradual decline in sap flux density and LE in comparison with the canopy and leaf conductance in the dry season. The use of eddy covariance and remote sensing techniques were not in full agreement with field measurements of sap flow. The findings include that deep water reserves in the root zone can support high rates of LE and ET as well as sap flux in the absence of precipitation (Vourlitis et al., 2008).

The exchange of energy, water and carbon between continents and the atmosphere and the global atmospheric general circulation models (AGCMs) are based in the partition of the surface energy budget, and it was found that the fluxes of H and LE have profound impacts in the weather and climate (Sellers, 1997). The sensible heat flux (H) that is released from the surface raises the temperature of the overlying air that warms the planetary boundary layer (ABL). In the other hand, the latent heat flux (LE) brings moisture and energy back to the atmosphere that initiates the process of cloud formation and precipitation.

An experiment during the International Rice Experiment (IREX) to observe the partition of energy over a rice paddy in Japan found that in the flooded areas of the field 65 – 79% of the available energy (Rn) was consumed by the water to evaporate, i.e, latent heat flux (LE). It was noticed that this amount corresponds to potential
evapotranspiration rates (ETa), with a daily ET corresponding to 4.5 mm per day under
drained conditions and 5.0 mm per day under flooded conditions.

Land surface parametrizations (LPs) were integrated with a surface energy
balance model to estimate heat exchange between land surface and the atmosphere and
atmospheric turbulent fluxes from satellite data. The investigations were concerned with
the exchange of latent heat flux, to be said as the most important process in the
determination of energy and mass exchange between the surface and the atmosphere
among hydrosphere, atmosphere and biosphere (Su, 2002).


Mapping ET can be difficult, time consuming and costly when using traditional
techniques such as the eddy covariance (EC), the Bowen Ratio (BR) and the use of
lysimeters, once they have a limited footprint to which they estimate ET (Liou & Kar,
2014). Remote sensing imagery and energy balance models can be used to estimate and
map ET in various scale range, depending on the type of platform and sensors used, and
the altitude on which they are imaging.

Spatially distributed ET is an important variable to be taken into account in a wide
range of applications, such as for assessing soil moisture content, evaluating crop water
stress, monitoring droughts, measuring water consumption, etc. (Eden, 2012; Kaplan et
al., 2014; Verstraeten et al., 2008). Moreover, ET maps have been used to plan irrigation
and preserve water resources, besides been utilized to asses issues related with water
rights and use in semi-arid areas (Allen, Tasumi & Trezza, 2007). Because ET is an important variable for the hydrologic components of Earth, it makes it of great value to have this information in a spatially distributed context, such as those produced from remote sensing imagery, to assess its variability across the landscape and different land cover types.

The use of remote sensing imagery and techniques to retrieve ET is fundamentally an indirect method where ET is estimated based on the spectral curve of wavelengths in the visible, near infrared and thermal infrared emitted and reflected from surface variables, such as clouds, vegetation indexes, the surface temperature, and the surface radiant fluxes (Liang et al., 2012; Liou & Kar, 2014).

Over the past decades, most of the remote sensing techniques developed to estimate and map ET are satellite-based (Allen, Tasumi, Morse & Trezza, 2007; Bastiaanssen, Pelgrum et al., 1998; Kustas & Norman, 1997), and are restricted to the use of medium to coarse spatial resolution sensors such as the Landsat Thematic Mapper (TM), Terra/MODIS, and the NOAA/AVHRR (Ruhoff et al., 2012; Singh et al., 2005; Sun et al., 2011). The possibilities of mapping and monitoring land use land cover types with high spatial resolution, multiple flights in a day and under various atmospheric and weather conditions has been explored in recent years with the advent of the Unmanned Aircraft Systems (UAS) (Berni, Zarco-Tejada, Suarez & Fereres, 2009; Hoffmann et al., 2015).

To this day, there are a number of methods and algorithms used to produce ET estimates from remotely sensed imagery. These methods can be categorized as (a)
residual methods, that estimates ET as a residual of the surface energy budget; (b) Ts-VI space methods, which is based in the distribution of Ts vs VI pixels on a scatterplot; (c) empirical models, that often require local calibration and measurements; and the (d) Penman-Monteith equation, recommended by the Food and Agriculture Organization (FAO) to estimate ET (Liang et al., 2012).

Among these, most notably used models are the Surface Energy Algorithms for Land (SEBAL), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), the Dual Temperature Difference (DTD), the Priestley-Taylor TSEB (TSEB-PT), and the S-ReSET model (Allen, Tasumi & Trezza., 2007; Bastiaanssen, 1995; Hoffmann et al., 2015; Kaplan et al., 2014).

Residual methods combine empirical and physical relationships to estimate surface energy fluxes (sensible heat flux, soil heat flux, and the net radiation) using remote sensing imagery. After these variables are obtained, ET is estimated as a residual of the surface energy budget equation (1) (Nouri, Beecham, Anderson, Hassanli & Kazemi, 2014). SEBAL and METRIC are residual based methods, where ET is estimated as a residual of the energy balance equation, computed by subtracting surface energy fluxes (H) and (G) from the available energy at the surface (Rn). The remaining energy, i.e. the residual, is the energy used for ET to occur. These models require minimum ground data, along with digital imagery acquired by a sensor measuring in the visible, near-infrared and thermal infrared spectrum (Liou & Kar, 2014).
2.4 Surface Energy Balance Algorithms for Land (SEBAL)

The Surface Energy Balance Algorithm for Land - SEBAL, was originally developed by Bastiaanssen (1995), to estimate and map surface energy fluxes for local and regional scale using Landsat TM images (Ruhoff et al., 2012). SEBAL is a physically based algorithm that uses surface temperature $T_s$, surface reflectance $\rho$, and the normalized difference vegetation index (NDVI) and their interrelationships to derive surface fluxes for a wide range of land cover types (Bastiaanssen, Menenti et al., 1998). SEBAL is a well-known and intensively used algorithm to estimate actual ET (ETa), and considered one of the most promising approaches currently available for local and regional approaches with minimum ground data, representing an intermediate approach using both empirical relationships and physical parameterizations (Liou & Kar, 2014).

The algorithm has been validated under different climatic conditions, in different land cover types and across different regions of the world, such as in Turkey, India, Pakistan, United States, China and Brazil (Bastiaanssen, 2000; Bastiaanssen, Ahmad & Chemin, 2002; Ruhoff et al., 2012; Singh & Senay, 2015 and Sun et al., 2011). SEBAL is based on the surface energy balance and its primary input data consists of remotely sensed imagery, that are used to estimate and partition the surface energy budget among net radiation, soil heat flux, sensible heat flux and latent heat of vaporization flux (Sun et al., 2011). Gautam, Steele, Hopkins and Sharp (2006) estimated components of the energy balance equation applying the SEBAL model over Landsat TM imagery, at the Devils Lake basin in North Dakota. Their study aimed to determine how the surface
water in the basin can be utilized via sprinklers irrigation compared with non-irrigated crops and to evaluate effects of irrigation on representative soil map units within the study. Their findings include ET maps over the region, a proxy for soil moisture content. Bastiaanssen and Ali (2003) combined the photosynthetically active radiation (PAR) model from Monteith (1972) with the light use efficiency model by Field, Randerson, and Malmström (1995) and the SEBAL model (Bastiaanssen, Pelgrum et al., 1998) to estimate crop growth under irrigation, in the Indus Basin, Pakistan. They used AVHRR imagery and modeled variables such as NDVI, APAR (Absorbed Photosynthetically Active Radiation) and fraction of ET to describe spatial-temporal variability in land wetness conditions. Their findings include the formulation of a new combined model for biomass growth, suitable for various spaceborne platforms such as Landsat, CBERS and ASTER. French et al. (2005) applied two energy balance models to estimate energy fluxes using ASTER imagery, the SEBAL and the TSEB models, during the Soil Moisture Atmosphere Coupling Experiment (SMACEX), in central Iowa. Their study estimated the net radiation, soil and sensible heat fluxes, and the latent heat flux, and validated their findings with measured fluxes at the ground with eddy covariance towers. From this study, the authors have found good agreement in between the models to estimate energy fluxes with ASTER imagery. Teixeira, Bastiaanssen, Ahmad and Bos (2009) applied the SEBAL model using Landsat TM imagery to estimate albedo, surface temperature, atmospheric and surface emissivity, soil heat flux, surface roughness, net radiation, air temperature gradients, sensible heat flux, latent heat flux and evaporative fraction, in the semi-arid region of the Low-Middle Sao Francisco River basin, in Brazil.
Their findings were calibrated and validated using flux sites from agro-meteorological stations within the study area.

**2.5 Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC)**

Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) is a satellite-based image-processing model for calculating evapotranspiration (ET) as a residual of the surface energy balance (Allen, Tasumi & Trezza, 2007). METRIC is a variant of the SEBAL model, with the innovative aspect of using weather-based reference ET to tie down satellite-based actual ET (Singh & Senay, 2015). ETo is calculated in METRIC by using the standardized ASCE Penman-Monteith equation for the alfalfa reference (ETr) to calibrate the surface energy fluxes computed by the model (Allen, Tasumi & Trezza, 2007).

Allen, Tasumi, Morse and Trezza (2007) compared ET estimated by METRIC with ET measured by a lysimeter near the town of Montpelier, Idaho, in which Landsat scenes were processed into ET maps. In this study, daily ET was computed by applying an extrapolation of the evaporative fraction (EF) from the image to the remaining 24h period. Their findings pointed a difference of only 4% between the estimated by METRIC and the lysimeter. The Water Resources Research Institute (IWRRI) and the University of Idaho re-calibrated hydrologic ground-water models for the Snake River Plain aquifer, in Idaho, using spatial-ET maps computed with METRIC, where the
estimation of depletions from the acquirer's caused by pumping were considerably enhanced, improving estimates of recharge (Allen, Tasumi, Morse & Trezza, 2007).

Trezza, Allen and Tasumi (2013) have made use of the METRIC model to map ET using MODIS and Landsat imagery, for the Middle Rio Grande Valley, New Mexico. With MODIS, the authors have found challenges in performing the internalized calibration of the model due to the spatial resolution, in the thermal and shortwave bands. Their values for extrapolated annual ET from the MODIS-METRIC ET mapping was of 1,045 mm, and the annual ET average for the Landsat-METRIC ET mapping measured 1,067 mm.

Silva Oliveira and Moreira (2016) have applied METRIC to estimate surface energy fluxes and ET for sugarcane in Sao Paulo state, Brazil, utilizing Landsat imagery from 2005 to 2007. Energy fluxes were validated with ground truth fluxes obtained by eddy covariance flux towers, achieving a confidence level of 95% with the estimate net radiation. Soil heat flux was underestimated by 34%, and latent heat flux was estimated with a confidence level of 95%, showing an R square of 0.86 compared with the EC values.

Most of the SEBAL and METRIC applications to estimate energy fluxes and ET has been done using governmental spaceborne platforms, with medium to coarse spatial resolution. To this date, little or none has been published with respect to the use of the SEBAL model to estimate ET using UAS. The use of these models with UAS thermal imagery is still little explored.
2.6 Unmanned Aircraft Systems - UAS

UAS is said to be a composition of systems that are brought up together, in order to accomplish a mission or a goal, and so, there are a number of different systems, one for each combination of technologies or application (Colomina & Molina, 2014), whereas for Simelli and Tsagaris (2015) UAS are aerial vehicles made up of light composite and can be remotely controlled or fly autonomously through software controlled flight-plans. The definition for UAS still seems to be vague in literature, most likely due to the innovative component UAS are bringing to the scientific and commercial communities. To this date, there are a number of different UAS platforms, for very specific to more general applications. These include rotary or fixed wing, single or multi-rotor, and remotely or autopilot platforms (Colomina & Molina, 2014).

UAS has been mainly used for military purposes for the past years, especially for surveillance and reconnaissance missions, where as recent as 2004, only about 2% of the operating UAS were operating in the civil market (Laliberte, 2009). Among the different acronyms for this new technology, the term UAS was adopted by the United States Department of Defense, and the Civil Aviation Authority of the United Kingdom (Colomina & Molina, 2014).

The past recent years in the field of remote sensing and photogrammetry have experienced the emergence of the new unmanned aerial systems technology, that have several advantages over traditional remote sensing platforms such as satellites or airborne missions, such as the quick deployment, multiple and fast turnarounds, less costly and
safer than an airborne mission, and they can retrieve sub-meter pixel resolution images (Berni et al., 2009; Laliberte 2009).

The use of UAS has been increasingly promoted in the past years, as the new hot spot of remote sensing and photogrammetry applications. Examples include the use of UAS to monitor vegetation (Berni et al., 2009; Hoffmann et al., 2015 and Zarco-Tejada et al., 2013), to assess landslides (Peterman, 2015; Rau, Jhan, Lo & Lin, 2012), to perform flood monitoring (Abdelkader, Shaqura, Claudel & Gueaieb, 2013; Feng, Liu & Gong, 2015). Lelong (2008) estimated biophysical parameters from small wheat plots over a growing season, near Toulouse, France, using a fixed wing UAS and two digital commercial cameras with instrument adaptations, a CANON EOS 350D and a SONY DSC-F828. Their cameras collected imagery in the visible and near infrared spectrum, (400-850 nm), and were used to retrieve vegetation indexes such as NDVI, SAVI (Soil Adjusted Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index) and the GI (Greenness Index). Park (2015) mapped the Crop Water Stress Index (CWSI) over a nectarine orchard in the district of Victoria, Australia, as part of an experiment in the Stonefruit Field Laboratory. Their method used a thermal infrared camera an on board a multirotor UAS, where imaging was schedule at solar noon at clear sky conditions. The results were proved an efficient method to assess spatial variability of water stress across the entire nectarine orchard, using the high-resolution thermal infrared camera. Ortega-Farias et al. (2015) utilized UAS with high-resolution thermal imagery to produce high resolution ET maps, and develop a water stress monitoring method over olives and a vineyard in Chile. In this study case, an octocopter was flown in an altitude of about 60
meters above the soil surface, around the solar-noon (12:00 and 13:00), collecting thermal and multispectral imagery with a spatial resolution of 6 cm. They approached different energy balance models to estimate ET, with good statistical results retrieved when compared with the eddy covariance fluxes at the surface.

UAS can be used to estimate and map evapotranspiration in very fine scale and with flexible repeatability, for individual crop fields, which can benefit farmers to prevent yield losses as water stress can have a negative impact in the total yield, especially if in specific stages of development (FAO Water Development and Management Unit).

2.7 Conclusions

This chapter covered the existent literature in the topics of the earth energy budget, the existence and application of remote sensing energy balance models, and the use of UAS for precision agriculture, vegetation monitoring and water consumption modeling.
CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter covers describes the methods and material utilized in this research, including background information about the study area and the flux towers in it, as well as the UAS platform and payload, the eddy covariance method, a description about the field work, data pre-processing and the remote sensing energy balance model, as well as the method utilized to model the flux tower footprints. Each of the methods is thoroughly described below.

3.2 Study Area

The study area is a farm located southwest of Ames, in central Iowa, where the landscape is mainly agricultural and the farming of soybeans and corn is almost exclusive. The study area is of private ownership where two crop types are cultivated: corn and soybeans, and the farms are rotated every year. The site is currently being used by different research groups from institutions such as the USDA, the Iowa State University and the University of Northern Iowa, as three flux towers are installed in the soybean and corn fields. The flux towers are operated by the USDA. Figures 4, 5 and 6 depict the flux towers located within the study area.
The terrain is mostly flat with the presence of smooth hills, with a slope ranging from 0 to 2 percent. Other roughness’s with slopes ranging from to 2 to 5 percent can also be identified, as a typical feature from the Des Moines Lobe landform (SSURGO 1995; Iowa Department of Natural Resources 2016). The corn plot has a total area of approximately 61 acres, whereas the soybeans field dimensions are about 77 acres. A subset was created in order to reduce the size to about 26 acres to the corn field and 37 to for the soybean field, and facilitate the collection of auxiliary data such as ground control points, canopy radiance and reflectance from both fields.

The three flux towers located in the study area are spread such as the Flux 10 makes its observations from within the soybeans field, Flux 11 from within the corn field, and a third tower, Flux 30ft is located in between the fields at a different height. Towers 10 and 11 are located at a height of about 2 meters from the surface, and Flux 30ft makes observations at a height of about 10 meters from the surface.

The soils in the study area are characterized as loam, with some variations in the mineral composition. It can be found the Canisteo Clay Loam, the Webster Clay Loam, Clarion Loam, Nicollet Loam and the Hubster Loam (SSURGO, 1995). Climate is classified as Dfa according to the Koppen system, with a humid continental zone, hot summers, cold winters and wet spring.

Strong winds prevail in March and April, with the annual minimum occurring in July and August (NOAA, 2016; National Climatic Data Center, 2016). Precipitation is well distributed throughout the year, with highest concentration during spring and summer months. Temperature averages from -7 degrees Celsius on January, to 23 degrees
Celsius in July. Graph depicts precipitation distribution and temperature averages in Ames, IA, from 1985 to 2010.

Figure 3. Map of the Study Area
**Figure 4.** Climate Graph for Ames, Iowa (1985 - 2010)

Source: National Centers for Environmental Information/Climate Data Online
Figure 5. USDA Flux Tower "Flux 30ft"
Figure 6. USDA Flux Tower "10"
3.3 Data Collection

3.3.1 UAS Payload

This session describes the UAS platform and the sensors and cameras utilized for this project, including the UAS eBee Ag developed by SenseFly, the modified Cannon S110 camera, the Sequoia Multispectral Sensor and the thermoMAP camera. The equipment and methods described in this session are the source of the most important data utilized in this project: multispectral and thermal imagery.
The UAS platform used in this study is the SenseFly eBee Ag (Figure 8), a fixed-wing UAS that can cover up to 12 square kilometers in a single flight, and attain a pixel resolution of 1.5 centimeters, when flown in the proper conditions. eBee Ag is a professional mapping drone that do not require flying skills, once the flight plan is programmed previous the actual flight mission on eMotion, a propriety UAS software. The platform weighs about 700 grams, and its wings are detachable (SenseFly, 2016). The drone has a built-in rotor that is activated by forward shaking the platform three times, and it takes altitude after being thrown in the air with rotor at full throttle.

Figure 8. SenseFly eBee Ag
Source: http://www.skyviv.net/wp-content/uploads/2016/05/ebeeshadow.png
eBee can be manually controlled and also automatically fly through waypoints if a pre-defined route is set. In this research, all of the flights and the waypoints were predefined in office, thus eliminating the need for manual piloting. Figure 8 illustrates the launching of eBee on May 18 at the study site.

Figure 9. Launching of eBee

The payload onboard eBee to collect the imagery required for this project involved three distinct devices of thermal and multispectral nature. Their characteristics and specifications are described in this section.
Multispectral Payload – Cannon NIR S110 and Sequoia Sensor

The multispectral payload utilized in this research are the modified Cannon NIR S110 camera, a 12 megapixels model that obtains imagery in the green (0.55), red (0.62 µm) and near infrared (0.85 µm) bands, and the Sequoia sensor designed by Parrot to capture light in the green, red, red-edge and near infrared ranges of spectrum. Sequoia differs from other multispectral cameras by retrieving reflectance integrating two devices: the sunshine sensor looking upwards and capturing irradiance in real time, and the body with its four individual multispectral sensors that captures light in the same wavelengths as the sunshine sensor, thus correcting the images for real time reflectance. Figures 10 and 11 depict the concept of real time reflectance and the band designations for the sunshine sensor and the body.
**Figure 10.** Sequoia Real-Time Reflectance Concept

Source:

**Figure 11.** Band Designation for the Sunshine sensor and the Sequoia Sensor

Source:
https://static1.squarespace.com/static/579a34a98419c24fccc684b3e0/147132037500/Sequoia_Datasheet_A4_V11.pdf
Cannon NIR S110 camera was utilized in the first two flights of the flight campaign, followed by the incorporation of the Sequoia sensor in the remaining days. Sequoia was chosen to substitute the Cannon camera due to its robustness and spectral range, besides being a more modern and complex sensor, considering its sunshine sensor that corrects reflectance values with real-time irradiance flux. Table 3 illustrates the specifications and technical features for Cannon NIR S110 and Sequoia sensor.

Table 3. Multispectral Payload Specifications

<table>
<thead>
<tr>
<th></th>
<th>Modified Cannon NIR S110</th>
<th>Sequoia Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial Resolution</td>
<td>3.5 cm (at 100m)</td>
<td>~17 cm (at 100m)</td>
</tr>
<tr>
<td>Spectral Resolution</td>
<td>Green (550 nm) Red (625 nm) Near Infrared (850 nm)</td>
<td>Green (550 nm) Red (660 nm) Red Edge (735 nm) Near Infrared (790 nm)</td>
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<tr>
<td>Radiometric Resolution</td>
<td>16 bit</td>
<td>16 bit</td>
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</table>

Thermal Camera – thermoMAP

Aside from the multispectral images, the thermal camera used in this project is also a product of SenseFly, and its features are described below. thermoMAP can be attached to the eBee to capture thermal videography, enabling the retrieval of thermal maps or mosaics (SenseFly, 2016). This camera is capable of taking pictures from the
surface temperature on a pixel basis, a crucial information and environmental variable for the estimation and interpretation of surface and atmospheric processes such as evaporative and convective fluxes.

Accurate measurements of the surface temperature can be complex to obtain, due to the nature of this range of the electromagnetic spectrum. Norman and Becker (1995) defines the land surface temperature (LST) as the thermodynamic, or the kinetic temperature of a body (Liang et al., 2012). Remote sensing is capable of inferring the temperature of a surface by measuring the emitted radiation of a given body, through a series of algorithms and equations that translate this radiation to a physical unit of kinetic temperature. Figure 12 depicts the band responses for thermoMAP, and Figure 13 the surface temperature variation from canopies, rows and the flux tower 11 on September 1st in the corn field.
Figure 12. thermoMAP band responses

Source: https://www.sensefly.com/drones/accessories.html

Table 4. thermoMAP Specifications

<table>
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<th>thermoMAP Camera</th>
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<tr>
<td>Spatial Resolution</td>
<td>14 cm (at 75m)</td>
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<tr>
<td>Spectral Resolution</td>
<td>~10 µm (wavelength peak)</td>
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<tr>
<td>Radiometric Resolution</td>
<td>16 bit</td>
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</table>
Six dates were pre-determined for acquiring imagery from the corn and soybean fields, aiming to observe different stages of crop development vegetative, flowering, yield formation and ripening, and the seasonal variation of evapotranspiration and energy fluxes. These dates were chosen taking in consideration the planting date for the corn and
the soybean fields, and the length of development as guided by the Food and Agriculture Organization (FAO, 2016). The dates imagery were acquired are displayed on Tables 5 and 6.
Table 5. *Corn Plot Field Work Time Table*

<table>
<thead>
<tr>
<th>Julian Day (2016)</th>
<th>Stages of Development</th>
<th>Growth Periods</th>
<th>Length of Development (in days)</th>
<th>Agricultural Calendar</th>
<th>Date of Imagery Acquisition</th>
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<td>Plant Day 0</td>
<td>Planting</td>
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<td>127</td>
<td>Initial Stage</td>
<td>Establishment</td>
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<td>Crop Development</td>
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<td>Mid-Season</td>
<td>Flowering</td>
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<td>June 30th</td>
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<td>222</td>
<td>Late Season</td>
<td>Yield Formation</td>
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<td>September 4th</td>
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<td>Ripening</td>
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<td>Harvest</td>
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Table 6. Soybean Plot Field Work Time Table

<table>
<thead>
<tr>
<th>Julian Day (2016)</th>
<th>Stages of Development</th>
<th>Growth Periods</th>
<th>Length of Development (in days)</th>
<th>Agricultural Calendar</th>
<th>Date of Imagery Acquisition</th>
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<td>Plant Day 0</td>
<td>Planting</td>
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<td>138</td>
<td>Initial Stage</td>
<td>Establishment</td>
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<td>May 7th</td>
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<td>Mid-Season</td>
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<td>248</td>
<td>Late Season</td>
<td>Ripening</td>
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<td>Harvest</td>
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</tbody>
</table>
3.3.3 Auxiliary Data

This session describes the equipment and techniques utilized for the data collection of auxiliary data necessary for the development of the project. As previously mentioned, the main data for the estimation of ET maps are the thermal and multispectral imagery. However, for the proper processing of the imagery and the modelling of ET maps, a number of techniques and equipment were utilized. The data collected include surface reflectance and the integrated surface albedo for the corn and soybean fields, the infrared temperature of calibration boards, leaf area index for the corn and soybean fields, and ground control points surveyed using a GPS survey grade receiver.

Surface Albedo and Surface Reflectance – ASD FieldSpec Pro

Surface albedo and surface reflectance are important variables for the development of this project and the accurate estimation of surface energy fluxes, and both variables were collected using the full range spectroradiometer FieldSpec Pro 3 by Analytical Spectral Devices (ASD), a portable device capable of collecting light energy reflected from the surface. This device has a fiber optic bundle that collects the light from a spectrum range of 350 to 2500 nanometers, with a spectral resolution that varies between 10 and 12 nanometers depending on the angle (ASD, 2017). Figure 14 depicts the equipment utilized in this research for obtaining surface albedo and surface reflectance, the ASD FieldSpec Pro 3.
Liang et al. (2012) defines surface albedo as the ratio between the reflected energy and the incident energy over a unit area, and this can be easily confused with reflectance. However, Allen, Tasumi & Trezza (2007) mentioned that the surface albedo represents the integrated reflectance across the short-wave spectrum (200 to 3200 nanometers). Therefore, the surface albedo can be seen as the ratio between the incident radiant flux by the reflect radiant flux from a surface, over a range of the electromagnetic spectrum. Nevertheless, albedo is a dimensionless measure ranging from 0 to 1.0 that indicates the amount of light reflected by a surface, where a surface with albedo close to zero indicates maximum absorption of light, and close to 1.0 indicates maximum reflectance and minimum absorption. Clouds and ice have a high albedo, and ocean water and forests have a low albedo, indicating the amount of solar light absorbed by these land covers. In this project, considering the equipment utilized and its spectral range, the surface albedo represents the ratio of incident irradiance and reflected radiance from 350
nm to 2500 nm. More information about this variable and its importance for calculating surface energy fluxes is described in section 3.4.

The measurement of the surface albedo was taken at the same time as the UAS was flown over the fields, in order to preserve the sun angle and the environmental conditions seen by the cameras FOV and the ASD pistol grip. The measurement was obtained following the technique proposed by Iqbal (1983), where the measured radiance from the area of interest is divided by the radiance beam from a white reference highly reflective. Considering that SEBAL estimates the surface albedo over a region as the product of the sum all optical bands and multiplying these bands with known coefficients that represent the solar intensity per band, multiple samples of the surface albedo were measured from each field, and a single value for the surface albedo was averaged for each plot.

Surface reflectance, in the other hand, is a dimensionless unit that represents the ratio of the radiant exitance to the irradiance (Liang et al., 2012). In contrast with the surface albedo, surface reflectance represents the ratio of the incident to the outgoing beam of light in a single wavelength, or in a single spectral interval. This variable was also collected through multiple marked sites within each crop field, and were utilized for the creation of an empirical line model to atmospherically correct the multispectral imagery retrieved by Sequoia and Cannon Cameras. Section 3.3 details this process with better detail.
To radiometrically calibrate the infrared temperature measured by the thermoMAP camera, observations of “ground-truth” infrared temperature were measured from known targets that were crafted prior to the fieldwork. These targets are plywood boards painted in white, light grey, dark grey and black and their temperature were measured with a handheld infrared thermometer Fluke 561r at the same time the UAS was flown over the fields, in order to preserve the sun angle and match the temperature observed by the handheld thermometer and the field of view of thermoMAP. In every flight mission during the six days of fieldwork, these boards had their temperature measured. Figure 15 illustrates the calibration boards.

The measured infrared temperature from each board were utilized to calibrate the thermal mosaics obtained by thermoMAP, regressing their values to the values obtained from the calibration boards. Section 3.4 discusses the calibration method in depth.
Leaf Area Index (LAI) is defined as a dimensionless variable and a ratio of leaf area per unit ground surface area (Zheng & Moskal, 2009) and indicates the area of ground that is occupied by plants, besides being an important structural property of vegetation (Liang et al., 2012). Considering the importance of leaves for mass and energy exchange between plants and the atmosphere, LAI is directly related with evapotranspiration rates, photosynthesis and gross primary productivity (Liang et al., 2012).
SEBAL utilizes LAI as a proxy variable for estimating surface roughness length ($z_0m$), friction velocity ($u^*$) and aerodynamic resistance to heat transfer ($ra_h$), thus an essential variable for the development of this research. LAI estimates from the soy and corn fields occurred throughout the growing season from May 23 through October 11 using a LAI-2200, a plant canopy analyzer from LI-COR Environment. LAI-2200 calculates LAI from radiation measurements made with a fisheye optical sensor. These measurements are made below the canopy, and LAI is obtained by calculating the amount of light that passes through the canopy using a radiative transfer model (LI-COR, 2014). For this research, LAI estimates were provided by the USDA office in Ames, Iowa.

Ground Control Points – Trimble R6 GPS Receiver

To accurately georeference the thermal and multispectral mosaics, ground control points were surveyed in the study area. Seven ground control points were distributed in between the two fields and measured with a survey grade GPS receiver from Trimble, the Trimble R6. This unit is capable of measuring coordinates with a horizontal and vertical accuracy under 1 centimeter, thus reducing geometric errors to the final georeferenced mosaic. Figure 16 illustrates the distribution of the control points within the study area.
Figure 16. Distribution of Ground Control Points within the Study Area

Figure 16 illustrates that the majority of the control points are spread in the center part of the imaged area. The homogeneity of the surface area in the corn field made it difficult for the allocation of visible points and identifiable features in the area. For visual identification and accurate georeferencing, wooden boards of about 60x60 centimeters were painted in black with an unpainted part in the middle, in order to locate its center from the multispectral and thermal images, considering that the painted parts of the boards absorb more heat and therefore are brighter than the other parts. That was done in order to preserve the center point of the GCP’s. Figure 17 depicts the surveying of one of
the ground control points, as well as the board utilized for visually identifying the points from the images taken.

Figure 17. Surveying Ground Control Points with the Trimble R6 GPS

Micrometeorological and Flux Data – Flux Towers and Eddy Covariance Method

Micrometeorological and flux data from three eddy covariance flux towers were utilized in this research for calibrating SEBAL in estimating ET. These towers
comprehend a robust set of complex equipment that iterate to observe specific variables and processes at the surface, with the so-called eddy covariance method. This method calculates the covariance of fluctuations in the vertical wind velocity and the physical quantity to be measured (Liang et al., 2012), and it is a popular method for measuring turbulent fluxes and the exchange of momentum, gases and energy between the surface and the atmosphere (Litvak, 2017). In simple terms, the eddy covariance method utilized by flux towers observe the fluctuation and mixing of gases and energy that is carried with the wind.

Among the many processes observed by flux towers, some include the latent heat flux, sensible heat flux and evapotranspiration, as well as other simple environmental variables such as temperature, wind speed, relative humidity and solar radiation. Flux towers and the eddy covariance method are an important source of data for calibrating remote sensing models and validating local and regional climate models (González-Dugo et al., 2012). Figure 18 illustrates two main equipment utilized by the eddy covariance method, a 3D Sonic Anemometer and an IR Gas Analyzer.

Other equipment in each flux tower include a net radiometer, copper constant thermocouple, a temperature and relative humidity probe, a soil heat flux plate, an infrared thermocouple sensor, a platinum resistance thermometer and a tipping bucket. Table 3 illustrates the variables measured by the flux towers and utilized in this research.
Table 7. Micrometeorological and Flux Data utilized in this Research

<table>
<thead>
<tr>
<th>Micrometeorological Data (From Flux Tower 30ft)</th>
<th>Flux Data (From Flux Towers 10 and 11)</th>
<th>Radiation/Temperature Data (From Flux Towers 10 and 11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Speed</td>
<td>Latent Heat Flux (LE)</td>
<td>Soil Heat Flux (G1)</td>
</tr>
<tr>
<td>Air Temperature</td>
<td>Sensible Heat Flux (H)</td>
<td>Soil Heat Flux (G2)</td>
</tr>
<tr>
<td>Incoming Solar Radiation</td>
<td>-</td>
<td>Net Radiation (Rn)</td>
</tr>
<tr>
<td>Relative Humidity</td>
<td>-</td>
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</tr>
</tbody>
</table>

Figure 18. Eddy Covariance Method

Source: https://stsh7809.files.wordpress.com/2014/05/irga.jpg
3.4 Data Pre-Processing

Section 3.3 Data Pre-Processing describes the methods and techniques utilized in this research for pre-processing imagery from multispectral and sensors and cameras and the flux data measured by the flux towers. Pre-process of imagery include the techniques and software used to geotag, mosaic, resample and georeference thermal and multispectral images, and the pre-processing of flux data include the correction for lack of closure. Furthermore, in this section, the radiometric calibration and atmospheric correction of thermal and multispectral imagery will be addressed.

3.4.1 Imagery Pre-Processing

Pre-processing thermal and multispectral images is an extensive and cumbersome process that involves a number of steps carried in multiple software and platforms. The workflow goes as follows: (1) imagery geotagging; (2) imagery mosaicking; (3) geometric correction and imagery resampling and (4) atmospheric correction – empirical line calibration. Considering that, the methods utilized for pre-processing thermal and multispectral images were about the same and carried with the same software and workflow, this section will describe them together.
Imagery Geotagging – eMotion Software

Raw imagery from thermoMAP, Cannon S110 and Sequoia are various in format, including .tiff and .CR2. These raw pictures do not have any sort of coordinates attached to it. The first pre-processing step is to geotag these pictures on eMotion software, proprietary of SenseFly, which capable of reading eBee flight log files that contains the coordinates of the UAS route and attach them to the pictures, attributing latitude and longitude for each one of the pictures. Thus, eMotion creates georeferenced images.

Imagery Mosaicking – Pix4D Software

Mosaicking multispectral and thermal images were carried once the raw pictures had been geotagged, using the photogrammetry software Pix4D that is capable of creating orthomosaics, point clouds and other photogrammetric products. The software accounts for imagery overlapping for extracting digital surface models and digital elevation models that are utilized for creating orthomosaics that are corrected for terrain distortions. Aside from creating orthomosaics, Pix4D can also retrieve indices such as NDVI and thermal maps in temperature units such as Fahrenheit and Celsius.

Some problems were identified when creating mosaics, such as fault lines, blurriness and replicated features, especially with the thermal data. It was noticed later in the field campaign that by increasing overlapping from 80 to 85% a considerable improvement is noticed in the texture and quality of the thermal mosaics. While unsure of
the reason to why Pix4D could not resolve some mosaics with the desired quality, it is suspected that most of the problems are related with the homogeneity of the study area, where soybean and corn canopies dominate the scene.

Geometric Correction and Imagery Resampling – ERDAS Imagine Software

All of the thermal and multispectral mosaics produced by Pix4D have a default georeferencing obtained from the coordinates registered by the IMU and GPS embedded on eBee Ag. Even still, a more accurate georeferencing was performed using ground control points surveyed with the Trimble GPS receiver described before in this section. The default ground control points were set to survey in the World Geodetic System, WGS 1984, thus all of the imagery were georeferenced to this same coordinate system.

Considering that SEBAL utilizes the thermal and multispectral mosaics for deriving energy fluxes and ET images, all of the mosaics have to overlap and have the same pixel size, thus the georeferencing and a further step of resampling the imagery pixel size had to be done in order to create a standardized dataset for the image processing and modelling with a same cell size.

 thermoMAP, NIR S110 and Sequoia have different focal lenses and field of view, thus their pixel size differ even if flying in the same height. The cubic convolution technique was applied considering its method for resolving a new cell value for the new raster image that obtains a smooth curve from the nearest 16 neighbor pixels, hence
indicated for continuous type of raster data (ArcGIS). Figure 19 illustrates the resampling technique and its effects in the output raster image.

*Figure 19. Image resample example*

Source:


All of the images were resampled to an output pixel size of 19 x 19cm, or approximately 7.5 x 7.5 inches, and this is the new spatial resolution for the entire raster dataset in this research.
3.4.2 Atmospheric Correction – Empirical Line Calibration

Remotely sensed data often contain errors or noise from the sensor or the environment, such as bad striping and atmospheric scattering and absorption of electromagnetic light. Therefore, atmospheric correction is a prerequisite in remote sensing when estimating biophysical properties of plants, evaluating land cover changes and change detection over space and time and cross comparing sensors, being the case in this research (Wang & Myint, 2015). The empirical line calibration (ELC) is a popular method for absolute atmospheric correction of multispectral data considering its effectiveness and relative ease of use.

This method was applied for correcting Cannon NIR S110 and the Sequoia sensor, on a band-by-band basis where only the red and near infrared band of each sensor were corrected with the proposed method. For the in-situ reflectance measurement, four targets were surveyed and marking flags were placed for guiding the fieldwork throughout the growing season. Two targets were placed in the corn field and other two in the soybean field. Measurements of the surface reflectance were obtained using a field spectroradiometer FieldSpec Pro 3, at the same time eBee was flown over the two crop fields. This method forces the remote sensing data to match with the ground measurements (Jensen, 2004), tying down with the observed at the surface level, as described on equation 2 (Smith & Hamilton, 1999):
\[ BV_K = \rho_K A_K + B_K \]  

where \( BV_K \) is the digital number (DN) for a pixel in band \( K \), \( \rho_K \) is the scaled reflectance or temperature of the material within the sensor field of view (FOV) at a specific wavelength \( \lambda \), \( A_K \) is a multiplicative factor affecting the DN (slope) and \( B_K \) is an additive factor (intercept) affecting the term (Jensen, 2004). This equation was originally developed for transforming digital numbers to reflectance from multispectral sensors, but in this research, it is being experimented for both thermal and multispectral sensors.

3.4.3 Flux Data Pre-Processing

Turbulent fluxes measured individually are susceptible to instrument biases, and often not consistent with the conservation of energy principle. To minimize these effects, turbulent fluxes can be forced to closure following a number of methods, such as the Bowen Ratio Energy Balance (BREB) and the Residual Method (RE). The residual method can be appealing due to its nature of assuming that \( R_n, G \) and \( H \) are correctly estimated by the eddy covariance method and LE estimates are ignored (Twine et al., 2000). However, in this research, the Bowen Ratio ended up overestimating the turbulent fluxes by about 40% for Flux Tower 10 and 34% for Flux Tower 11. Therefore, and with the knowledge of its limitations, the residual method was utilized for performing the forced closure of energy balance from the flux towers.
3.5 SEBAL Modelling

SEBAL is a remote-sensing energy balance model developed in the Netherlands to estimate ET as a residual of the energy budget equation (2). In this research, the model was applied to the images acquired by the UAS and written on Python. This section describes formulas and equations utilized by SEBAL to estimate the surface energy fluxes Net Radiation (Rn), Soil Heat Flux (G), Sensible Heat Flux (H) and Latent Heat Flux (LE) as well as instantaneous evapotranspiration (ET).

In any given system on Earth’s surface, the energy budget is linked with the hydrologic cycle through evaporation (Brutsaert, 1982). For a simple system and neglecting lateral advection and the energy stored by vegetation in the process of photosynthesis, the energy budget can described as:

\[ Rn = LE + H + G \]  

(3)

where \( Rn \) is the net radiation (sum of all incoming and outgoing shortwave and longwave radiation at the surface); \( G \) is the soil heat flux stored into the ground, \( H \) is the sensible heat flux convected to the air and \( LE \) is the latent heat consumed by the evaporative process. Variables are expressed in Wm/2 (Allen, Tasumi & Trezza, 2007). Each term of equation 3 will be describe in this section as follows below.
3.5.1 Net Radiation (Rn)

The net radiation (Rn) represent the radiant energy at the surface, or the available energy at the surface. This energy is partitioned into H, G and LE. Net radiation is calculated by subtracting all outgoing radiant fluxes from all incoming radiant fluxes, including solar and thermal radiation (Allen et al., 2011):

\[
Rn = (1 - \alpha)R_s \downarrow + R_L \downarrow - R_L \uparrow - (1 - \varepsilon_o)R_L \downarrow
\]

where \(\alpha\) is the surface albedo; \(R_s \downarrow\) is the incoming shortwave radiation; \(R_L \downarrow\) is the incoming longwave radiation from the heated atmosphere; \(R_L \uparrow\) is the outgoing longwave radiation and \(\varepsilon_o\) is the surface thermal emissivity. All units are expressed in watts per square meter.

Surface Albedo (\(\alpha\))

Because SEBAL is a satellite-based model, the surface albedo, or broadband surface albedo, is calculated by integrating the surface reflectance of all multispectral satellite bands and applying a weighting coefficient that represents the fraction of the solar radiation occurring within the spectral range per band (Allen et al., 2002). Considering the spectral limitations of the multispectral devices utilized in this research, the method proposed by Iqbal (1983) for calculating ground surface albedo with a
spectroradiometer was experimented for estimating the net radiation described on equation 4.

This method involves measuring the integrated radiance (full shortwave spectrum) for the area of interest, and diving its radiant flux by the radiance measured from a white reference. Figures 29 and 30 illustrate the radiance measured from corn canopies and the white reference. The product of this division is the surface albedo, a dimensionless unit ranging from 0 to 1.0. Because this method does not account for albedo variations within the field, but only to the area where they were measured, multiple observations were done from each field and averaged as a single number per field.

Incoming Shortwave Radiation ($R_s \downarrow$)

Incoming broad-band short-wave radiation represents the main source of energy for ET (Allen, Tasumi & Trezza, 2007). This is the energy that triggers biological and physical process at the Earth’s surface, stored and dispersed in thermal, mechanical or chemical form (Monteith & Unsworth, 1990). SEBAL calculates the broad-band short-wave radiation as depicted in equation 5:

$$R_s \downarrow = G_{Sc} \times \cos \theta \times d_r \times \tau_{SW}$$

(5)
where G\textsubscript{SC} is the solar constant (1367 W/m\textsuperscript{2}); \cos{\theta} is the cosine of the solar incidence angle; d\textsubscript{r} is the inverse squared relative earth-sun distance; and \(\tau_{SW}\) is the atmospheric transmissivity.

For a flat area such as in the study area, the cosine of the solar incidence angle can be obtained as a trigonometric function described in equation 6:

\[
\cos{\theta} = \sin(\delta) \sin(\phi) + \cos(\delta) \cos(\phi) \cos(\omega)
\]  \hspace{1cm} (6)

where \(\delta\) is the declination of the Earth (positive in the summer in the northern hemisphere); \(\phi\) is the latitude of the pixel (positive for the northern hemisphere and negative for the southern hemisphere); and the \(\omega\) parameter is the hour angle, where \(\omega = 0\) at solar noon, negative in the morning and positive in the afternoon (Allen, Tasumi & Trezza, 2007).

Atmospheric transmissivity is calculated using a general equation formulated from ASCE-EWRI (2005):

\[
\tau_{SW} = 0.75 + 2 \times 10^{-5} \times z
\]  \hspace{1cm} (7)

where \(z\) is the elevation above the sea level (m)
Incoming Longwave Radiation ($R_L\downarrow$)

The incoming longwave radiation is simply the result of atmospheric absorption and scattering of heat energy and its emission. The intensity for each one of these processes depend upon the atmospheric vertical profile, including the moisture content, temperature and aerosol concentration (Liang et al., 2012). The term is usually calculated using the Stefan-Boltzmann equation:

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

(8)

where $\varepsilon_a$ is the atmospheric emissivity (dimensionless); $T_a$ the near-surface air temperature (K) and $\sigma$ the Stefan-Boltzmann constant ($5.67 \times 10^{-8} \, W \, m^{-2} \, K^{-4}$).

The atmospheric emissivity is calculated based on the equation developed by Bastiaanssen (1995) and modified by Allen et al. (2002), as shown below:

$$\varepsilon_a = 0.85(-ln\tau_{sw}) \times 0.09$$

(9)

where the term $\tau_{sw}$ is the atmospheric transmissivity obtained from equation 7.
Outgoing Long-Wave Radiation (R_L↑)

The outgoing long-wave radiation term, is the flux of long-wave radiation emitted by the surface as a function of the surface emissivity and surface temperature (Allen, Tasumi & Trezza, 2007). The outgoing long-wave radiation is driven by the heating of the surface by the incoming solar radiation, and it is also calculated using the Stefan-Boltzmann constant as seen in equation 10:

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

(10)

where $\varepsilon_o$ is the surface emissivity (dimensionless); $\sigma$ the Stefan-Boltzmann constant; and $T_s$ is the surface temperature (K).

Broadband Surface Emissivity

The broadband surface emissivity is obtained following the equation proposed by Tasumi (2003) based on soil and vegetative thermal spectral emissivities (Allen, Tasumi & Trezza, 2007):

$$ \varepsilon_o = 0.95 + 0.01 \times LAI \text{ for } LAI \leq 3 $$

(11)

and $\varepsilon_o = 0.98$ where $LAI > 3$. 

3.5.2 Soil Heat Flux (G)

Soil heat flux is defined as the amount of thermal energy that moves through an area of soil in a unit of time (Sauer & Horton, 2005). It is the smallest component of the surface energy budget, considering that most of the incident energy at the surface is either convected into the atmosphere, transported as thermal long-wave radiation or as latent heat when water molecules evaporate. The SEBAL method for estimating G (Bastiaanssen, 2000), is based on the ratio Rn/G:

\[
\frac{G}{Rn} = (Ts - 273.15)(0.0038 + 0.0074\alpha)(1 - 0.98NDVI^4)
\]  

(12)

Where Ts is the surface temperature (K), \(\alpha\) is the surface albedo and NDVI is the normalized difference vegetation index. G is then calculated by multiplying the ratio G/Rn from equation 12 by Rn calculated in (4)

NDVI is a spectral index developed in the 1970’s by Rouse, Haas, Schell & Deering (1974) to extract and model vegetation biophysical variables using remote sensing data (Jensen, 2004). NDVI is derived as a ratio of the reflected and absorbed red and near infrared light from a surface, and it is sensitive the chlorophyll concentration on a plant canopy. NDVI can be obtained such as:
where $\rho_{NIR}$ is the reflected light from a surface in the near infrared spectrum (dimensionless); and $\rho_{RED}$ is the reflected light from a surface in the red portion of the electromagnetic spectrum (dimensionless).

### 3.5.3 Sensible Heat Flux ($H$)

Sensible heat flux ($H$) is a major component of the energy balance at the Earth’s surface, and it represents the flow of heat energy that is transferred from the surface to the atmosphere by conduction and convection, due to temperature difference (Allen et al., 2002). This temperature difference between the surface and the atmosphere is triggered by surface heating due to incoming solar radiation.

SEBAL estimates $H$ as a function of the near surface-air temperature difference ($dT$) and the aerodynamic resistance to heat transport ($rah$), as seen on equation 14:

$$H = \rho C_{p} \rho \times \frac{dT}{rah}$$  

(14)

where $\rho$ is the air density (kg m$^{-3}$), $C_p \rho$ is the specific heat of air at constant pressure (J kg$^{-1}$ K$^{-1}$), and the $rah$ is the aerodynamic resistance to heat transfer (s m$^{-1}$) between two
heights, z1 and z2 (generally 0.1 and 2m), computed as a function of estimated aerodynamic roughness of the particular pixel (Allen, Tasumi & Trezza, 2007).

Calculating the sensible heat flux is the most difficult and extensive term to be calculated, as it is affected by a variables such as wind speed, temperature difference between surface and atmosphere, surface roughness, aside from the internalized calibration process that represents one of the pillars of this model. All terms and equations for deriving H are detailed in this section. The first term to be calculated is the aerodynamic resistance to heat transfer (rah), as seen on equation 15:

\[ r_{ah} = \frac{\ln \left( \frac{z_2}{z_1} \right)}{u_* \times k} \]  

(15)

where z1 and z2 are heights in meters above the zero plane displacement (d) of the vegetation (usually 0.1m and 2.0m respectively); \( u_* \) is the friction velocity (m/s), a term that quantifies the turbulent velocity fluctuations in the air; and k is the von Kerman’s constant (0.41).

Friction velocity is first calculated at the weather station as illustrated in equation 15. The terms in the equation must come from instruments located within the study area, in this case from flux towers Flux 10 and 11, therefore two friction velocities are obtained per flight.
where $k$ is the van Karman constant; $u_x$ is the wind speed (m/s); and $z_{om}$ is the momentum roughness length (m), at times called surface roughness. This term is a measure of the form drag and skin fraction for the layer of air that interacts with the surface (Allen et al., 2002).

SEBAL incorporates the empirical equation from Brutsaert (1982) to estimate $z_{om}$:

$$z_{om} = 0.12h$$  \hspace{1cm} (17)

where $h$ is the vegetation height (m). $z_{om}$ calculated in 17 represents the surface roughness in the surroundings of the weather station, as of the friction velocity calculated in equation 15.

SEBAL requires the computation of the wind speed at a height above the weather station, at an altitude where the surface roughness plays no effect. This height is called the “blending height”, and 200 meters is used (Allen, Tasumi & Trezza, 2007). It is calculated as illustrated in equation 18:
where $u_*$ is the friction velocity at the weather station (equation 16).

Once the wind speed at blending height is calculated for a given weather station (flux 10 or 11 in this research), friction velocity and aerodynamic resistance to heat transfer can be obtained on for the study area on a pixel basis as rasters. Equation 19 depicts the estimation of friction velocity for each pixel in the study area.

\[
    u_* = \frac{k u_{200} \ln\left(\frac{200}{z_{om}}\right)}{k}
\]

where $z_{om}$ is the surface roughness length for each pixel in the study area.

In agricultural areas, surface roughness can be estimated as a function of LAI (Allen et al., 2002).

\[
    z_{om} = 0.018 \times LAI
\]

where LAI is the leaf area index image obtained as a function of NDVI.
With friction velocity now estimated for each pixel, equation 14 can be calculated and the aerodynamic resistance to heat transfer estimated per pixel. The second term, dT can now be calculated as SEBAL utilizes an image-based internalized calibration method.

The near surface-air temperature difference (dT) is a difficult term to be obtained because of the difficulties in estimating accurate surface temperature Ts from the remote sensing sensor, due to atmospheric attenuation and sensor calibration (Allen, Tasumi & Trezza, 2007). Bastiaanssen (1995) found that that dT can be approximated as a linear function of Ts as written equation 21:

\[
dT = a + b T_s
\]

where a and b are the linear regression coefficients valid for one particular moment and landscape (Bastiaanssen, 1995), and \(T_s\) the thermal mosaic in degrees kelvin. This linear relationship between dT and Ts is a major assumption of SEBAL and METRIC, and however, research done by Bastiaanssen (1995, 2000), Bastiaanssen, Menenti et al. (1998) and scientists at the University of Idaho at Moscow (Allen et al., 2002) found that this assumption is fit for a large range of conditions, landscapes and climate.

To solve dT and the \(a\) and \(b\) coefficients, SEBAL requires the choice of two anchor pixels, representing the extreme conditions of temperature and humidity at the image. These pixels are the hot and cold pixels, and represent two extreme scenarios: a dry bare agricultural field where \(\lambda ET\) is assumed to be 0, and a well irrigated crop surface, where the surface temperature \(T_s\) close to the air temperature \(T_a\) and \(H\) is assumed to be
Liou and Kar (2014) and Kaplan et al. (2014) pointed out that the cold or wet pixels are frequently spotted at a location of well-watered areas or over a relatively large, calm water surface, where ET is assumed to be at its maximum.

The first step to calculate \( dT \) is to find its value for the anchor pixels. \( dT \) in the cold pixel is calculated according to equation 22:

\[
dT_{cold} = H_{cold} \times r_{ah\ cold} / (\rho_{cold} \times c_p)
\]  

(22)

where \( H_{cold} \) is the flux of sensible at the cold anchor pixel (W/m²); and \( r_{ah\ cold} \) is the aerodynamic resistance to heat transfer at the cold pixel (m/s⁻¹). SEBAL assumes that \( H_{cold} \) is to be 0 in the cold edge, considering that all of the energy is being consumed by LE to evaporate water. Therefore, \( dT_{cold} = 0 \).

For the hot pixel, \( dT \) is calculated as follows:

\[
dT_{hot} = H_{hot} \times r_{ah\ hot} / (\rho_{hot} \times c_p)
\]  

(23)

where \( H_{cold} \) is the flux of sensible at the hot anchor pixel (W/m²); and \( r_{ah\ hot} \) is the aerodynamic resistance to heat transfer at the hot pixel (m/s⁻¹).

In SEBAL, the flux of sensible heat in the hot pixel is calculated according to equation 24:
\[ H_{hot} = (Rn_{hot} - G_{hot}) - LE_{hot} \]  

where \( Rn_{hot} \) and \( G_{hot} \) are the energy fluxes for the hot pixel (W/m²); and \( LE_{hot} \) is assumed to be 0. Therefore, the sensible heat flux for the hot pixel is the product of \( Rn - G \), and this represents that all of the energy is being dissipated as convection through the movement of rising warm air.

The relationship between hot and cold pixels can now be solved and fitted into a line, by regressing the near-surface temperature difference (dT) in the anchor pixels to the land surface temperature also in the anchor pixels, as seen on Figure 20.

\[ y = 0.1497x - 44.642 \]

\( dT_{cold} vs. T_{cold} \) and \( dT_{hot} vs. T_{ho} \)
With the regression coefficients a and b obtained from graph 11, equation 20 can be run and dT obtained for the entire scene on a pixel basis. With dT and \( r_{ah} \) now estimated for the entire, H can be estimated for every pixel as depicted in equation 13. In order to account for atmospheric instability and improve the accuracy of H estimates, SEBAL utilizes an iterative process based on the Monin-Obukhov theory (Silva Oliveira & Moreira, 2016). This process is thoroughly described by Allen, Tasumi & Trezza (2007).

3.5.4 Latent Heat Flux (\( \lambda LE \))

Latent Heat Flux is the rate of which energy is loss due to evapotranspiration. ET represents the major consumer of latent heat at the Earth’s surface. LE is obtained as the residual of the energy budget equation (3), as seen on equation 25:

\[
\lambda LE = Rn - G - H
\]  

(25)

where \( \lambda LE \) represents the instantaneous flux of latent heat loss to ET for the time of the UAS overpass (W/m2) (Allen, Tasumi & Trezza, 2007).
3.5.5 Instantaneous Evapotranspiration ($ET_{inst}$)

To convert the amount $\lambda LE$ into ET, the evaporation depth is calculated such as:

$$ET_{inst} = 3600 \frac{\lambda LE}{\lambda}$$

where $ET_{inst}$ is the instantaneous ET (mm/hr); 3600 is the time conversion from seconds to hours, and $\lambda$ is the latent heat of vaporization (J/kg), or the heat absorbed when a gram of water evaporates (Campbell, 1977). $\lambda$ can be calculated according to equation 27:

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

where $T_s$ is the surface temperature in degrees kelvin (from thermoMAP).

3.6 Flux Footprint Modelling

A flux footprint can be said as the observed area by the instrumentation at the tower site, or in other words, the field of view – FOV of that tower. This footprint represents the area or the spatial content on which the eddy covariance method estimates micrometeorological processes based on the motion of eddies and turbulent mixing (Schmid, 2002). There is a variety of models that can be utilized to estimate the footprint,
including analytical, stochastic or numerical approaches in Eulerian or Lagrangian frameworks (Kljun, Calanca, Rotach & Schmid, 2004).

In this research, we incorporate the Flux Footprint Prediction (FFP) model to estimate the spatial context for Flux Towers 10 and 11. FFP is based on a previous method developed by Kljun and its associates (2004), with the addition of providing the shape of the footprint besides the extent of it (Kljun, Calanca, Rotach & Schmid, 2015). The footprint modeled here is the spatial context on which the raster-energy fluxes estimated with the UAS platform were validated. The validation process is thoroughly described on Chapter 4.

We utilized the FFP for automatically calculate the footprints, based on the methods proposed by the author. All equations and a thorough description of the method can be found in the paper “A two-dimensional parameterization for Flux Footprint Prediction (FFP)” by Kljun et al. (2015).

3.7 Conclusions

This chapter covered information about the methods and material that were utilized in this research to estimate and map ET and surface energy fluxes from the soybean and corn fields within the study area. Among the methods and material discussed, the study area, instrumentation utilized and the office work done to preprocess and process all of the data were described per section. Chapter 4 is linked with Chapter 3
in which the results from the methods are analyzed, evaluated and validated with ground truth data.
CHAPTER 4

RESULTS

4.1 Introduction

Chapter 4 describes the results obtained from field work, including the dataset obtained from the flight campaign, auxiliary data obtained in-situ, the forced closure for energy balance on towers 10 and 11, and the footprints calculated after the Kljun FFP model. Statistical findings are shown and discussed as follows (1) Net Radiation; (2) Soil Heat Flux; (3) Sensible Heat Flux and (4) Latent Heat Flux. An analysis of the estimated fluxes and the temporal dynamics of their variation is shown in a series of maps created to display their variability within each farm field.

4.1.1 Remote Sensing Imagery

Tables 8 and 9 depict the data collected using eBee UAS with thermal and multispectral cameras. The pixel size resent the dataset before being resampled to 19x19 cm, as in its original format from the flight campaign.
Table 8. *Thermal Imagery collected from Flight Campaign – thermoMAP*

<table>
<thead>
<tr>
<th>Date</th>
<th>Flight Height (meters)</th>
<th>Overlap</th>
<th>Pixel Size (cm)</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-May</td>
<td>94</td>
<td>75%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>27-Jun</td>
<td>94</td>
<td>75%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>15-Jul</td>
<td>94</td>
<td>75%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>3-Aug</td>
<td>94</td>
<td>75%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>18-Aug</td>
<td>118.3</td>
<td>80%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>1-Sep</td>
<td>118.3</td>
<td>80%</td>
<td>17.9</td>
<td>~10:45 and ~11:45</td>
</tr>
</tbody>
</table>

Table 9. *Multispectral Imagery collected from Flight Campaign - Cannon S110 and Sequoia*

<table>
<thead>
<tr>
<th>Date</th>
<th>Flight Height (meters)</th>
<th>Overlap</th>
<th>Pixel Size (cm)</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-May</td>
<td>123.44</td>
<td>75%</td>
<td>0.04</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>27-Jun</td>
<td>123.44</td>
<td>75%</td>
<td>0.04</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>15-Jul</td>
<td>110</td>
<td>75%</td>
<td>0.11</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>3-Aug</td>
<td>110</td>
<td>75%</td>
<td>0.11</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>18-Aug</td>
<td>110</td>
<td>75%</td>
<td>0.11</td>
<td>~10:45 and ~11:45</td>
</tr>
<tr>
<td>1-Sep</td>
<td>110</td>
<td>75%</td>
<td>0.11</td>
<td>~10:45 and ~11:45</td>
</tr>
</tbody>
</table>
Raw imagery contained a number of problems, including blurriness, fault lines, replicated features, saturation (multispectral images only), amongst others.

*Figure 21.* thermoMAP Temperature Mosaic and Replicated Features, on July 15
Figure 22. Sequoia Surface Reflectance Mosaic, fault lines and mosaicking issues, on August 18

4.2 Atmospheric Correction

This section describes the outputs and results obtained from the atmospheric correction performed on both thermal and multispectral imagery. The following graphs describe the regression model built from the empirical line calibration described on equation (2). For the following graphs, the values shown in the Y-axis represent the reflectance and temperature values obtained from the field of view of each camera, and the values shown in the X-axis represent the reflectance and temperature values obtained at-the-surface as described in the methods section. The Y-axis were regressed to the X...
values, that represent a more accurate reading for surface reflectance and surface temperature. The surface reflectance was collected using the spectroradiometer FieldSpec Pro 3, from soybeans and corn canopies, and the temperature data at-the-surface was obtained from the calibration boards showing on section three.

From the empirical line method described on section 3.3.2, all multispectral and thermal images were corrected for ground truth measurements. The regression models created from this step are seen below. Figures 23 and 24 illustrate empirical line created for the red and near infrared bands for the modified Cannon S110 NIR camera and Sequoia sensor.

\[ y = -0.3726x + 0.1308 \]

Figure 23. Cannon S110 NIR - Red Band Empirical Line Calibration
Figure 24. Cannon S110 NIR - NIR Band Empirical Line Calibration

The Cannon S110 camera was only used twice, on May 18 and June 27, being replaced by the enhanced Sequoia sensor. For this reason, the number of observations made by the camera and regressed to the in-situ measurements are limited. On top of that, on May 18 the atmospheric conditions were unstable, with clouds rolling and affecting the quality of the multispectral images. The three observations seen in graphs 2 and 3 where values are close to zero, represent one of the flights were the clouds were casting shadow over the study area, hence the low reflective values.

The sequoia sensor was utilized in the other four dates, July 15, August 3, August 18 and September 1. The atmospheric conditions were more stable in every one of these dates, and a much better empirical line was constructed where FOV observations from
the sensor were regressed to in-situ measurements. Figures 25 and 26 depict the empirical line created for this sensor for the red and near infrared bands.

*Figure 25. Sequoia Sensor - Red Band Empirical Line Calibration*
Correcting thermal remote sensing data for atmospheric attenuation is usually a robust and complex process that involves a large number of routines and data. In this research, the calibration method proposed by Smith and Milton and applied to atmospherically correct the multispectral dataset was implemented and experimented to radiometrically correct the thermal imagery from thermoMAP. This method was applied considering the retrieval of surface temperature by thermoMAP on Pix4D, where a proprietary algorithm by SenseFly is used to convert brightness values to temperature.

The infrared temperature measured with the handheld thermometer from the calibration boards was utilized as input for the X-axis in the empirical line built as seen on Figure 27. The data plotted on the Y-axis is the calibration board temperature seen from the sensor FOV.
4.3 Surface Albedo and Coefficient of Absorption

For the development of this research and the calculation of net radiation and soil heat flux, surface albedo measurements were obtained for the six dates of fieldwork and incorporated to SEBAL. Figures 29 and 30 illustrate the computation for surface albedo on June 27 for the corn field, where measurements for the corn canopy were averaged by sampling multiple canopies across the field and diving its value for the obtained radiance values for the white reference. This method follows the guidelines from Iqbal (1983) and described in the methods section. The same process executed for computing the surface
albedo for both fields and throughout the growing season. Figure 28 illustrates the measurement of reflected light from soybeans canopies on August 3.

Figure 28. Measurement of Reflected Light from Soybeans Canopy on August 3rd
**Figure 29.** White Reference Radiance on June 27

**Figure 30.** Corn Canopy Radiance on June 27
Tables 10 and 11 illustrate the surface albedo calculated for the corn and soybean fields in the six dates of data collection, and the coefficient of absorption, respectively. Figure 31 illustrates the temporal changes for the surface albedo measured for the corn and soybean fields.

Table 10. *Integrated Surface Albedo per Field - May through September*

<table>
<thead>
<tr>
<th>Day</th>
<th>Corn Field</th>
<th>Soybean Field</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-May</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>27-Jun</td>
<td>0.17</td>
<td>0.25</td>
</tr>
<tr>
<td>15-Jul</td>
<td>0.25</td>
<td>0.41</td>
</tr>
<tr>
<td>3-Aug</td>
<td>0.22</td>
<td>0.2</td>
</tr>
<tr>
<td>18-Aug</td>
<td>0.19</td>
<td>0.16</td>
</tr>
<tr>
<td>1-Sep</td>
<td>0.24</td>
<td>0.22</td>
</tr>
</tbody>
</table>
Table 11. *Coefficient of Absorption per Field - May through September*

<table>
<thead>
<tr>
<th>Day</th>
<th>Corn Field</th>
<th>Soybean Field</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-May</td>
<td>0.77</td>
<td>0.77</td>
</tr>
<tr>
<td>27-Jun</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td>15-Jul</td>
<td>0.75</td>
<td>0.59</td>
</tr>
<tr>
<td>3-Aug</td>
<td>0.78</td>
<td>0.8</td>
</tr>
<tr>
<td>18-Aug</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td>1-Sep</td>
<td>0.76</td>
<td>0.78</td>
</tr>
</tbody>
</table>

*Figure 31. Surface Albedo per plot from May 18 to September 1*
4.4 Forced Energy Balance Closure – Residual Method

Closing the energy balance at the surface has been proved impossible since the 1980’s. Experiments done by Foken and Oncley (1995) have found that in most of times the available energy at the surface (sum of net radiation and soil heat flux) was larger than the sum of the turbulent fluxes (latent and sensible heat fluxes), i.e. the balance does not close (Foken, 2008). In this research, the energy balance closure had been tested and a poor closure was found for flux towers 10 and 11, as seen on Figures 32 and 33, where the sum of the turbulent fluxes correspond to only about 63% of the available energy for flux 10 and 58% for flux 11.

Figure 32. Flux Tower 10 Energy Balance Before Closure
From the lack of closure found from regression models seen Figures 32 and 33 the residual method (RE) was applied and the forced closure executed for correcting latent heat flux (LE) observations.

4.5 Flux Footprint Modelling

A total of 24 footprints were estimated for all six dates where images were obtained from the study area. These footprints are essential for the validation of the estimates computed with SEBAL, as they represent the area of observation, the FOV for every tower at the time the UAS was flown over them. Figures 34, 35, 36 and 37
illustrate their spatial extent for flights 1 and 2, on May 18, June 27, July 15, August 3, August 18 and September 1.
Figure 34. Sensible Heat Flux - Flux Footprint Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 35. Sensible Heat Flux - Flux Footprint Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
Figure 36. Latent Heat Flux - Flux Footprint Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 37. Latent Heat Flux - Flux Footprint Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
4.6 SEBAL Validation and Interpretation

Statistical methods for validating the estimated energy fluxes include linear regression models, residual plots, the evaluation of the root mean squared error (RMSE) and the absolute mean error (MAE). This process involved the averaging of all pixels in each raster-energy flux from within each flux footprint seen on Figures 35, 35, 36 and 37. These averaged values were then compared with the observed values from the flux towers. The regression models seen in this chapter are designed such as the values on the X-axis represents the independent variable, the observed fluxes from the flux towers processed for lack of closure. The Y-axis represents the energy fluxes estimated with SEBAL and the UAS imagery.

4.6.1 Net Radiation (Rn)

The net radiant flux of energy (Rn) predicted by SEBAL was underestimated by approximately 19% in comparison with the observed with the flux towers at the surface, with a coefficient of determination of $R^2 = 0.71$. It was especially difficult to estimate Rn on May 18, considering that SEBAL utilizes the land surface temperature to derive outgoing longwave radiation. SEBAL estimated about 625.25 watts per square meter (W/m$^2$) for both towers on this date, and however the measured with the net radiometers at the surface was approximately 95 W/m$^2$. That is most likely due to the presence of
clouds at the time eBee was flown over the fields. The net radiation estimates averaged from 427.24 W/m² to 688.759 W/m² in all six dates from May through September.

The root mean squared error (RMSE) for the net radiation was of 6.09 W/m². Figures 38 and 39 illustrate the linear regression and residual plots for this surface energy flux when compared with the observed data measured in each flux tower using the eddy covariance method. The random distribution of residuals on Figure 39 indicate that the linear model fits the data appropriate for the data. The temporal changes from the net radiant flux in the two fields for flights 1 and 2 in May, June, July, August and September are depicted on Figures 40 and 41.

*Figure 38. Net Radiation (Rn) Regression Model: Observed vs. Estimated*

\[ y = 0.8129x + 101.63 \]
\[ R^2 = 0.7194 \]
Figure 39. Net Radiation (Rn) Residual Plot
Figure 40. Net Radiation Temporal Evolution for the First Flight at Approximately 10:15 A.M.
Figure 41. Net Radiation Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
4.6.2 Soil Heat Flux (G)

Soil heat flux was the most challenging energy flux to be estimated with SEBAL and the eBee imagery. The energy fluxes estimated with SEBAL were compared with the two-soil heat flux plates present in each field, and its statistical findings are presented below on Figures 42, 43, 44 and 45.

The deviation between observed and estimated G in both plates for both towers was found to be randomly distributed all along the growing season, however, for plate 2, the deviation increased as the crop canopy developed.

SEBAL estimates the soil heat flux using empirical equations based on the ratio of the soil heat flux and the net radiation, G/Rn, and relies on surface properties such as albedo, vegetation indices and temperature, as these are related with soil moisture, surface heating and intercepted solar radiation (Bastiaanssen, 2000). In both towers, the rate of energy stored into the ground was considerably underestimated, with an RMSE of 11.23 W/m² when compared with plate 1 and 31.02 W/m² when compared with plate 2.

In addition, a poor correlation coefficient was found, of R² = 0.17 for plate 1 and R² = 0.22 for plate 0.22. Estimating soil heat flux faces the most difficult challenges when validating with ground truth data (Silva Oliveira, 2014). There are a couple of errors involved in the estimation of these energy flux, especially once the canopy grown fully covering the soil surface, considering that the ratio G/Rn is proportionally related with the surface temperature. The accuracy of the soil heat flux by plates dug into the
ground itself contain errors of heat energy ratio due to soil depth and type (Gentine, Entekhabi & Heusinkveld, 2012).

Figure 42. Soil Heat Flux (G) - Plate 1 - Regression Model: Observed vs. Estimated
Figure 43. Soil Heat Flux (G) Plate 1: Residual Plot

Figure 44. Soil Heat Flux (G) Plate 2 - Regression Model: Observed vs. Estimated
Figure 45. Soil Heat Flux (G) Plate 2 - Residual Plot
Figure 46. Soil Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 47. Soil Heat Flux Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
As seen from maps on Figures 46 and 47, the rate of heat energy stored into the ground shifts from June 27 on, where on that date the soil heat flux for the soybean fields was higher than in the corn field. For the remaining days, SEBAL estimated $G$ higher for the corn field. The canopy cover on June 27 was completely formed in the soybean field (V8), whereas in the corn field the leaves were much more developed and covering a bigger area, absorbing the incoming solar radiation and intercepting it before reaching the ground. As the corn plants develop, it reduces its leaf area as it dries up and builds up dry matter. The growth of soybeans have a similar pattern, but considering the planting dates – April 20 for corn and May 7 for the soybeans, the trend in leaf area for the soybean were also behind the corn field. Figure 48 illustrates leaf area index with respect to stage of crop development for the corn and soybean fields.
Figure 48. Leaf Area Index for the Growing Season - Corn and Soybean

The effects of the leaf area intercepting the solar radiation can be seen on Figures 49 and 50, from plates 1 and 2 respectively. These graphs show the daily rates of soil heat flux in the dates of fieldwork. Similarly, to the estimated fluxes with SEBAL, the soil heat flux plates also observed a change in heat rate flow as the canopy developed through the growing season.
Figure 49. Soil Heat Flux Rates from May through September (Plate1)

Figure 50. Soil Heat Flux Rates from May through September (Plate2)
The estimated values for $G$ range from -14.57 W/m² to 119.76 W/m², the latter one observed on May 18 when the fields were mainly bare ground, thus intercepting almost all of the solar radiation and using it for heat storage down the soil layers. It is also seen from the maps on Figures 46 and 47 that the soil heat flux was estimated for the two fields with nearly the same rate through their land. That might be questioned due to the soil composition and elevation change through the scene and their effects in the rate of heat storage down the ground. However, and considering the nature of SEBAL as an image-based energy balance model, all the energy fluxes are imaged based, and therefore difficult to estimate the flow of energy down the ground that is hidden by the canopy.

The overall results for $G$ were proved not to be good in this research. Although this energy flux has been historically difficult to estimate with remote sensing platforms, the results and statistical coefficients here found are below average. A number of reasons might be affecting the estimated variable, including quality of multispectral imagery, spatial distribution of surface albedo – in this research, we are considering a single value for albedo for the entire field, and the thermal temperature of the fields.

4.6.3 Sensible Heat Flux ($H$)

Estimating sensible heat flux with SEBAL involves a large number of equations and relies on the internalize calibration process described in the methods section. This internalized calibration process pioneered by Bastiaanssen (1995) requires the estimation
of near-surface temperature difference (dT) for two extreme conditions, cold and hot. These two conditions are represented as pixels within the image, and for this process SEBAL requires the cold pixel to be selected over a water body, where the latent heat flux is assumed to be at its maximum, consuming all of the available energy (Rn – G), and therefore sensible heat flux is inexistent. The first challenge on this research for estimating accurately H is the absence of a water body.

Attempts of artificially creating a water body for the cold pixel selection were made by placing an evaporative pan provided by the USDA office in Ames. This evaporative pan was placed just outside the corn field, as seen on Figure 51. The major problems in using the evaporative pan for estimating dT is related with the pan material, that differs from a natural water body. The surface albedo and coefficient of absorption (1 – α) for the evaporative pan have a greater value when compared with a river or a lake, affecting the calculation of net radiation and soil heat flux, as the intercepted solar radiation for these surface changes considerably. For these reasons, the anchor pixels selection for the cold pixel was carried by selecting the coldest pixel within each farm field. This method automatically creates a bias in the estimated values, considering that even the most watered, moist part of the field will not have the same LE rates for evaporating water as a water body.
A linear regression model comparing the observed and estimated values is shown on Figure 52. A correlation coefficient of $R^2 = 0.50$ shows that the estimated fluxes by SEBAL were not entirely in agreement with the estimated by the flux towers above the canopy, and the overall RMSE for $H$ is 8.84 watts per square meter. A slope of 1.05 indicates that the model overestimated the observed fluxes by 5%. $H$ values range from -299.76 and 979.61, and these large numbers represent the presence of non-natural materials areas such as the calibration boards, GCP boards and the flux towers itself. However, most of the sensible heat flux values for within the fields is much lower, averaging 91.84 W/m² for all of the dates and all of the flights from May through September. Figures 52 and 53 illustrate the regression model and the residual plot for the
sensible heat flux estimates. Figures 53 and 54 depict the temporal variation for the sensible heat flux for the corn and soybean plots.

Figure 52. Sensible Heat Flux Regression Model: Estimated vs. Observed
Figure 53. Sensible Heat Flux Residual Plot
Figure 54. Sensible Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 55. Sensible Heat Flux Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
4.6.4 Latent Heat Flux (LE)

Latent heat flux had the best correlation coefficient, $R^2 = 0.82$ and a root mean squared error of 2.67 W/m$^2$. The residual plot Figure (56) indicates random distribution of the residuals, a good indicator that the regression model fits the data. Latent heat flux varied as the crop developed, as well as the available energy at the surface, with a maximum value of 810.53 W/m on September 1 at 10:45 A.M. and a minimum of -556.607 on July 15. It is important to notice that both values were estimated in the outskirts and edges of the images, and it represents overestimated values due to a photogrammetric issue due to lack of overlapping that causes overestimation of reflectance and surface temperature in the raw data utilized to estimate LE.

A better way to evaluate the distribution of LE throughout the fields in all of the six dates analyzed is to look the mean maximum and minimum values, where the maximum mean is 564.90 W/m$^2$ and the minimum mean is 256.22 W/m$^2$. It is noticed from Figures 56 and 57 that the latent heat flux consumed by the surface and the canopies shifted from June 27 on, where in that date the transpiration rates were higher than in the soybean field. From July 15 on the LE rates increased in the soybean field and decreased for the corn field.

A decrease in the latent heat flux for sugar cane in the maturing and ripening stages of development were observed for a rural landscape in southeastern Brazil, and related with the decrease in transpiration rates for that crop type (Silva Oliveira, 2014). The same pattern seems to occur with corn in this research, where in June 27 the crop
was lush green and the LE rates are higher than every other surface. From July 15 on it was observed that the crop started to dry out, a process carried out during the reproductive stage (VR) and creating dry matter.

Figure 56. Latent Heat Flux Regression Model: Observed vs. Estimated
Figure 57. Latent Heat Flux Residual Plot
Figure 58. Latent Heat Flux Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 59. Latent Heat Flux Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
The following tables show statistical coefficients obtained from the correlation between the observed (X) vs the estimated (Y) energy fluxes. The root mean squared error (RMSE), mean absolute error (MAE) and confidence coefficient ($R^2$) are shown in Tables 12, 13 and 14 below. The estimations were compared per field and the overall is presented in the following tables.

Table 12. *Root Mean Squared Error (RMSE) per Energy Flux for the Corn and Soybean Fields*

<table>
<thead>
<tr>
<th></th>
<th>RMSE (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rn</td>
</tr>
<tr>
<td>Corn Field</td>
<td>14.86</td>
</tr>
<tr>
<td>Soybean Field</td>
<td>12.73</td>
</tr>
<tr>
<td>Overall</td>
<td>6.24</td>
</tr>
</tbody>
</table>

Table 13. *Mean Absolute Error (MAE) per Energy Flux for the Corn and Soybean Fields*

<table>
<thead>
<tr>
<th></th>
<th>MAE (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rn</td>
</tr>
<tr>
<td>Corn Field</td>
<td>37.69</td>
</tr>
<tr>
<td>Soybean Field</td>
<td>33.44</td>
</tr>
<tr>
<td>Overall</td>
<td>32.20</td>
</tr>
</tbody>
</table>
Table 14. *Confidence Coefficient R Squared per Energy Flux for the Corn and Soybean Fields.*

<table>
<thead>
<tr>
<th></th>
<th>Rn</th>
<th>G1</th>
<th>G2</th>
<th>H</th>
<th>LE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn Field</td>
<td>0.62</td>
<td>0.61</td>
<td>0.19</td>
<td>0.25</td>
<td>0.79</td>
</tr>
<tr>
<td>Soybean Field</td>
<td>0.80</td>
<td>0.50</td>
<td>0.82</td>
<td>0.80</td>
<td>0.87</td>
</tr>
<tr>
<td>Overall</td>
<td>0.71</td>
<td>0.17</td>
<td>0.22</td>
<td>0.50</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Evaporative rates for each plot were averaged and are seen below on Figures 59 and 60. The averages were obtained by adding the overall pixels within each field and dividing by (n) number of pixels. These values represent the averaged water vapor exhaled from plant canopies at the same the UAS was flown, and are repented in (mm/h). The evaporative rates are related not only to the weather conditions and the atmospheric demands, but also to the phonologic stage of each crop type. A discussion about the evaporative rates in relationship with the stage of crop development for corn and soybeans is discussed on Chapter 5.
Figure 60. SEBAL ET Rates per Field (mm/h) – Flight 1 at ~10:45 A.M.

Figure 61. SEBAL ET Rates per Field (mm/h) – Flight 2 at ~11:45 A.M.
From equation (26) instantaneous ET maps (ET$_{\text{inst}}$) were obtained on a spatially distributed context, for both fields and throughout the growing season. These maps represent the spatial distribution of ET through the fields on a pixel basis, and it is the product of converting latent heat flux to evaporative rates by multiplying LE by the latent heat of vaporization as described in the methods section.
Figure 62. ET Temporal Evolution for the First Flight at Approximately 10:45 A.M.
Figure 63. ET Temporal Evolution for the Second Flight at Approximately 11:45 A.M.
4.7 Conclusion

Chapter 4 covered the discussion about the results found in this research. The chapter includes a discussion about the validation of the model in estimating surface energy fluxes and ET as a residual of energy balance equation, including regression models, the distribution of residuals from residual plots, the overall statistical results and coefficients from root mean squared error (RMSE), mean absolute error (MAE) and the r squared. On top of that, a water consumption analysis by evaluating the ET rates estimated by SEBAL over the fields provide useful information for decision making on farming and agricultural management. The water consumption per plot was provided by means of graphs, evaluating the water consumption per stage of crop development. The relationship between NDVI and ET was also evaluated and the findings presented, where a poor relationship between them emphasized the need for more investigation on the usage of vegetation indexes for directly predicting ET in the study area.
CHAPTER 5
DISCUSSION

5.1 Introduction

Chapter 5 discusses the findings and results obtained from the fieldwork and methods proposed in this research. The first part discusses the main findings, including an analysis from ET maps at the study area and evaluates the statistical coefficients and findings elaborated from comparing estimated with observed values in-situ. An assessment per day of flight campaign about the ET rates and their distribution across the soybean and corn fields is detailed in depth. The second part addresses the correlation between NDVI and ET, and whether the vegetation index is a good predictor for estimating ET using near visible and near infrared optical bands only. Also, the challenges. The last part of this chapter is related with the future directions and what can be improved in further research involving a similar theme.

5.2 Discussion

The averaged water consumption per plot was calculated by averaging all the ET pixels per image and per plot. Figures 59 and 60 illustrated the averaged water consumption per plot in the six dates and represent the ET rates for different stages of
crop development, wherein for flights 1 and 2 that the ET rates for the corn field is higher up until July 15, which is related to the stages of crop development from vegetative up until VT. After the tassel is out and the plants start its reproductive stages, the leaf area starts do decrease, and so as the evaporative rates. This stage of development is critical for the yield production, as droughts and water shortage can drastically affect the crop production. On top of that, the VT stage represents the stage of maximum crop development and growth (Magalhaes & Duraes, 2006). Because most of physiological aspects of the plants do happen within its leaves, including photosynthesis and the production of dry matter, the exchange of water vapor and carbon dioxide also occur on a leaf scale. Thus, the ET rates are reduced as the leaf area decreases.

However, in between flights one and two, there has been little change in the amounts of ET happening per plot. However, it is not possible to predict this pattern for the completely growing season, considering that the ET values predicted by SEBAL depend on the weather conditions at the time the UAS was flown over the fields. The images retrieved by the cameras and sensors and utilized by the model to predict water consumption are instantaneous, i.e. they represent the reality on that instance on those conditions, of solar radiation, wind speed and air humidity. Figures 34 and 35 illustrate the temporal evolution for the evapotranspiration over the corn and soybean fields on flights and one and two from May 18 to September 1.

Aside from the averaged water consumption per field, the spatial distribution of ET provides great insight on the water consumption in very fine scale. From Figures 61 and 62 corresponding to the ET variations between hours ~10:45 and ~11:45. The distribution
of ET on May 18 correspond to the same flight, considering the second thermal flight failed on the mosaicking processing. Below are some considerations of the distribution of the water consumption per field in every one of the dates imaged.

- May 18: ET rates are averaging 0.30 mm/h for most of the fields, with some patches of well-watered areas in the southernmost portions of the corn field and on the edges of the soybean field.

- June 27: For flights 1 and 2, the ET rates for the corn field indicate a well-watered and almost homogenous condition through its canopies. For the soybean field, the conditions changes, where a couple hotspots of low evaporative rates are visible, including in the northwest portion of the field and near the drainage tile.

- July 15: Corn field presenting lower values of ET in comparison with previous dates and in comparison with the soybean field. As previously discussed, the lowering of ET rates for this crop type is related with its stage of crop development, which by July 15 had a tassel out and it started is reproductive stage for in most plants. In the soybean field, there are two ET patterns, divided in the southern and northern halves of this field. The northern most portion of the field has a well-watered hot spot in the first flight, and for the second flight, the ET rates are even higher, taking most of the field.

- August 3: For the first flight on August 3, the ET patterns persist in which the soybean field is evaporating more than the corn field. Both ET mosaics show a fuzzy pattern of the ET distribution, because of the nature of the thermal data
utilized to derive this map. Some striped areas in the southern portion of the fields indicate a bias pattern that is most likely to be originated from the data itself.

- **August 18:** For the corn field on flights and one and two it is possible to see the progression of the water consumption the one hour separating these two observations. The first flight shows less ET values, especially in the margins and edges of the field. The soybean field is considerably releasing more water vapor than the corn field. As with the corn field, with the increasing solar radiation between 10:45 and 11:50, ET rates also increased for all of that field.

- **September 1:** The ET maps for this day are considerably better presented than the other dates, possibly due to an increase in the overlapping of the thermal data, therefore improving the quality of the thermal data. The corn field shows a regular distribution of the ET values, for the first flight, whereas in the second flight some low ET hot-spots are identifiable in the southern part of the field, as well as in the northeast area of that field. The ET values for the soybean field seem to follow the rule of thumb where low ET values are found near the drainage tile. Some patches of low evaporative rates are also found in the central/western part of the area, of damaged soybeans as seen on the ET mosaic of June 27.

The ET mosaics provide a useful insight of the water consumption distribution within each field. More than calculating the amount of water per pixel and per field, this
research intended to estimate the spatially distribute ET throughout the growing season, that can be used to pinpoint water-stressed areas.

Figures 61 and 62 summarize the purpose of this research and the importance of estimating ET using a UAS versus the measured with an eddy covariance flux tower. The estimates from eBee provide an understanding of the variations in-situ, on a pixel basis, whereas the eddy covariance flux towers provide its measure as a single value averaged from the mixture of blowing eddy through its sensors. The ET and energy fluxes map can be used to assess water consumption and ensure maximum yield production.

5.3 NDVI as an ET Predictor

NDVI has been used to predict ET and a crop coefficient (Kc) in several areas around the world (Kerr et al., 1989; Seevers & Ottman, 1994; Singh et al., 2005), considering the relationship between the amount of vegetation per unit area as NDVI relates the amount of light reflected in the red and near infrared spectrum with the amount of vegetation and chlorophyll content at the surface. It is assumed that there is a linear relationship between the amount of vegetation and ET rates. However, Allen,
Walter et al. (2005) found that the soil wetting might affect the Kc and therefore the predicting of ET.

The NDVI values were obtained for both fields as described on equation 13. The values were obtained for each pixel and compared with the ET values for the same pixel. Figures 63 and 64 illustrate the relationship between NDVI and ET from the corn and soybean fields respectively, considering all stages of crop development from vegetative on, in all of the imaged dates.

*Figure 64. NDVI – ET Correlation: Corn Field*
In both fields, the relationship between NDVI and ET does not satisfy statistical coefficients for a direct prediction of ET by using the vegetation index. In the soybean field, the correlation appears to be stronger, in cases such as in June 27 where a correlation coefficient of 0.51 indicates similar patterns in between the two variables. In most of other dates, the R Squared is considerably low, as well as in the corn field. However, the usage of two different multispectral devices in this research may cause some bias in the overall agreement between ET and NDVI, even though atmospheric correction had been applied to both datasets. With the above result, it is not
recommended to utilize NDVI measures to derive ET rates. Further and deeper analysis of the relationship between these two variables is needed in order to establish a viable and realistic model for deriving ET from vegetation indexes. Aside from vegetation indexes, further analysis taking in consideration surface slope, soil composition, elevation and aspect is indicated to better understand the distribution of ET rates over both fields. Appendix A illustrates soil composition and elevation in the study area.

5.4 Challenges and Limitations

This research presents a number challenges and limitations that affected the overall results. These are presented below as follows:

Anchor Pixels Selection

SEBAL nature in resolving ET as a residual of the energy budget equation relies on an internalized calibration, which is based on a pixel selection, the so-called anchor pixels, that represent to extreme conditions within a study area. These two extremes are a cold/wet and hot/dry surface. Originally, SEBAL requires the presence of a water body for the selection of the cold pixel, as it is assumed ET rates to be at a maximum and H to be at a minimum. The absence of a water body forced the pixel selection for the cold pixel to be found within the agricultural fields, looking for the coldest spot within the
soybean and corn canopies. On top of that, both fields are not irrigated, thus limiting even further the selection of the anchor pixels, considering the reliance upon natural irrigation, thus being almost impossible to locate a pixel with maximum ET and inexistent flow of sensible heat.

Soil Heat Flux (G) Estimates

Estimating soil heat flux was especially difficult in this research. The problematic may rely on two events: the accuracy and precision of the estimates retrieved by the soil heat flux plates dug in the study area, and the application of the algorithm for the study site. SEBAL estimates G as the function of surface albedo, presence of vegetation and surface temperature, and rely on the empirical equation formulated by Bastiaanssen (1995). This equation was originally developed for Mediterranean regions, thus a different climate and conditions than the Midwest.

Surface Albedo Estimates

The calculation of the net radiation (Rn), the available energy at the surface, relies on accurate estimates of the surface albedo. Because of the multispectral coverage from Sequoia and the modified Cannon S110 NIR, that has a limited number of bands and lack on wavelengths in the short-wave infrared, the estimation of surface albedo was carried using a FieldSpec Pro 3 that averaged the surface albedo for the corn and the soybean
fields as one single value. That represents a limitation for the estimation of Rn, once it
does not account for variations within the field.

Atmospheric Correction and Empirical Line Calibration

For the radiometric calibration of the Cannon S110 NIR, a limited number of
measurements were made for the estimation of a reliable regression model. On top of
that, the weather conditions in both dates where this camera was utilized was unstable.
That means that the measurement of the reflectance targets with the FieldSpec Pro 3 and
the calibration with its data carry biases from illumination changes. These can greatly
affect the regression line and the final calibrated products.

Saturation of Multispectral Data

Even though Sequoia accounts for the Sunshine sensor, saturation issues were
found present in multiple images in various dates. Saturated values compromise the
quality of the data and the retrieval of required indexes such as NDVI and LAI, required
for the estimation of G and H. The top-of-atmosphere reflectance values were regressed
to surface reflectance with the atmospheric correction procedure described in this thesis,
returning to the natural reflectance scale of 0.0 to 1.0. The illumination conditions due to
the presence of clouds is believed to have influenced this saturation issues, even though
Sunshine is supposed to correct reflectance for real-time conditions.
Quality of Thermal Images

Other problems were found in the thermal imagery from thermoMAP. Replicated features and a windy-shaped pattern on July 15, August 3 and August 18 are to be questioned and the impacts on the accuracy of the real land surface temperature is unknown. The correlation between the measured IR temperature from calibration boards and the estimates by thermoMAP were found to be acceptable, with an R squared of 0.87 but with a slope of 0.55, indicating the thermoMAP under predicted the ground values measured with the IR thermometer by 45%. The land surface temperature is the most important type of the data for SEBAL and the estimation of surface energy fluxes, thus its accuracy is indispensable for a reliable computation of ET.

5.5 Future Directions

First of all, and more important, it is highly recommended that for further studies involving the use of thermoMAP an increased overlap to be set. Thermal mosaics retrieved with an overlap of 75% on July 15, August 3 and August 18 presented a poor visual quality, with replicated features. With the increasing of overlapping by 5%, most of the fuzziness and replicated problems were eliminated.

Aside from the overlapping problem, it is recommended that in every UAS application, whether using thermal or multispectral cameras, to be carried out under
cloud-free conditions and clear-sky conditions. The impacts of illumination changes can greatly influence the signal obtained by sensors such as Cannon S110 NIR and Sequoia.

For further analysis on the water consumption, the soil composition is thought to be of great value for the interpretation of the findings. Different soil composition, soil conductance and mineral composition would affect the transport of water and moisture from the soil to the plant canopy, thus directly related with ET rates.

5.6 Conclusions

Chapter 5 discussed the more important findings and the results obtained from the methods designed to achieve this research goals and objectives. In the first part, an analysis detailing the ET maps and the statistical findings from correlating measured and estimated turbulent fluxes is addressed, followed by an assessment of ET rates per day and under different stages of crop development per field. On top of that, the correlation between NDVI and ET, and whether the vegetation index is a good predictor for estimating ET using near visible and near infrared optical bands only was presented. Finally, the challenges and limitations and the future directions for related work had been discussed.
CHAPTER 6

CONCLUSIONS

6.1 Introduction

This chapter covers the conclusions obtained in this research, including main remarks, statistical findings, flux footprint modeling and the validation with flux footprints, the analysis of the water consumption per field and the creation of a workflow for the data collection and image processing and analysis. In addition, the main challenges and limitations and the future directions for similar research in the UAS field and application of remote sensing energy balance models (RSEB) is presented.

6.2 Conclusions

This research goal was to integrate traditional remote sensing methods and techniques such as estimating surface energy fluxes and ET in different stages of crop development for a corn and soybean field in central Iowa. The SEBAL algorithm developed in the Netherlands and applied throughout the world for a wide range of applications was applied to the thermal and multispectral images retrieved by thermoMAP, Sequoia and
Cannon S110 NIR cameras, and its estimates were validated with ground truth eddy covariance flux data.

A set of statistical methods utilized to evaluate the model performance indicated a good correlation between the estimated by SEBAL and the measured by the flux towers, for the net radiation (Rn) and Latent Heat Flux (LE), with an R squared of .71 for Rn and .82 for LE. The same cannot be said for the estimates of soil heat flux (G) and sensible heat flux (H). When compared with the observed G from plates 1 and 2 that are at the study site, a poor R squared of .17 for plate 1 and .22 for plate 2 were obtained as a residual of the cross-comparison. The correlation coefficients found from the regression, MAE and RMSE indicate that SEBAL better estimated ET as a residual of the surface energy budget with the given material.

Flux footprints were estimated using the Kljun model (2015), and plotted on a GIS environment considering the crosswind, width and length of the total estimated flux fetch. The validation occurred by averaging the total amount of pixel values within each footprint, for every modeled energy flux.

The water consumption, i.e. ET, was modeled on a pixel-basis for the corn and soybean fields, for all the six dates of data acquisition, May 18, June 27, July 15, August 3 and August 18. As previously discussed, the ET rates seem to follow the LAI trends and the stages of crop development, as a result of gas exchange and photosynthesis happening in the canopy leaves.

A workflow was developed for the data acquisition, pre-processing and modeling. This workflow can be utilized for a similar study site and materials, but some suggestions
for further work are given next in this chapter. The relationship between NDVI and ET was also evaluated, taking into consideration that attempts had been made to estimate water consumption straight from vegetation indices. However, considering the findings in this research, it is advised that further research and experiments be done in order to better correlate these two products.

In conclusion, the partition of the surface energy budget to estimate ET using the SenseFly eBee UAS platform yielded satisfactory results. A good statistical agreement in between the observed and estimated values of net radiation, sensible heat flux and latent heat flux, with exception for the soil heat flux, wherein the estimated values were found to be poorly correlated with the ground truth data obtained by the soil heat flux plates.

This can be of great value for farmers across the world, where the management of natural resources and the sustainable use of water resources is becoming of great importance as climatic shifts can pose severe threats to the farming yield. More than that, the method proposed in this research can be used for decision-making when real-time information on the crop conditions are in demand. UAS platforms are generally easy to use and fast to deploy, which make them a resourceful platform for imaging over a farming field. The algorithms proposed by the SEBAL model and utilized in this research were automated on Python, facilitating the processing of big data to retrieve ET and water consumption information of each plant in a field in real-time.
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APPENDIX A

MAPS

Figure A1. Elevation Map
Figure A2. Soils Map