The Application of Unmanned Aerial Vehicle to Precision Agriculture: Chlorophyll, Nitrogen, and Evapotranspiration Estimation

Manal Elarab

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ABSTRACT

The Application of Unmanned Aerial Vehicle to Precision Agriculture:
Chlorophyll, Nitrogen, and Evapotranspiration Estimation

by

Manal Elarab, Doctor of Philosophy
Utah State University, 2016

Major Professor: Dr. Mac McKee
Department: Civil and Environmental Engineering

Precision agriculture (PA) is an integration of a set of technologies aiming to improve productivity and profitability while sustaining the quality of the surrounding environment. It is a process that vastly relies on high-resolution information to enable greater precision in the management of inputs to production. This dissertation explored the usage of multispectral high resolution aerial imagery acquired by an unmanned aerial systems (UAS) platform to serve precision agriculture application. The UAS acquired imagery in the visual, near infrared and thermal infrared spectra with a resolution of less than a meter (15 - 60 cm). This research focused on developing two models to estimate cm-scale chlorophyll content and leaf nitrogen. To achieve the estimations a well-established machine learning algorithm (relevance vector machine) was used. The two models were trained on a dataset of in situ collected leaf chlorophyll and leaf nitrogen measurements, and the machine learning algorithm intelligently selected the most appropriate bands and indices for building regressions with the highest prediction accuracy. In addition, this research explored the usage of the high resolution imagery to
estimate crop evapotranspiration (ET) at 15 cm resolution. A comparison was also made between the high resolution ET and Landsat derived ET over two different crop cover (field crops and vineyards) to assess the advantages of UAS based high resolution ET. This research aimed to bridge the information embedded in the high resolution imagery with ground crop parameters to provide site specific information to assist farmers adopting precision agriculture. The framework of this dissertation consisted of three components that provide tools to support precision agriculture operational decisions. In general, the results for each of the methods developed were satisfactory, relevant, and encouraging.
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assess the advantages of UAS based high resolution ET. This research aims to bridge the information embedded in the high resolution imagery with ground crop parameters to provide site specific information to assist farmers adopting precision agriculture.

Manal Elarab
I dedicate this work to Mohammad, Fairouz, Nada and Ahmad.

Your unconditional love and support created the person I am today,
You made me believe in myself when I was in doubt.
I want to make you proud always.

... In the loving memory of Musa Nimah

Love you
Manal
ACKNOWLEDGMENTS

I am very grateful to my adviser and mentor, Dr. Mac McKee, for giving me this opportunity, providing me with such a great project and team to work with, and above all teaching me how to be a better researcher and person on daily basis. I would like to extend my gratitude to all my committee members. I would like to thank Dr. Alfonso Torres-Rua and Dr. Andres Ticlavilca for their guidance, help and support throughout my education at USU. I appreciate all those who helped me collect and process the data needed in my research (Roula Bachour, Shannon Syrstad, Mark Winkelaar, Alfonso Torres, Ian Gowing, etc.). Thank you to all the AggieAir team that helped in the Scipio project.

I also acknowledge all the members of AggieAir over the past few years who have contributed indirectly to this work. Most of all, I owe this work to my loving husband for his endless sacrifices and relentless support.
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CHAPTER 1

INTRODUCTION

Unmanned air systems (UAS) have been around for a century, and for a long time their sole application was in military practice. Then, UAS started branching into other applications like archeological site assessment and mineral exploration. In 2004, only approximately 2% of the UAS were operating merely in the civil market (Newcome, 2004). Since then, use has been increasing quickly. A report discussing the economic impact of UAS published by the Association for Unmanned Vehicle Systems International (2013) estimated an economic impact of $82 billion by 2025. Those estimates are rationalized by a large, emerging application for UAS: precision agriculture.

Precision agriculture (PA), the intelligent crop production system, is a scientific and modern approach to agriculture production in the 21st century. Building on traditional knowledge, this production farming system integrates new technologies. The three key technological components are (a) a remote sensing platform like UAS that collects data; (b) a geographic information system, where data analysis and visualization are performed using various techniques and tools; and (c) modern precision farming tools like the variable rate applicator that allows the implementation of site-specific recommendation. Site-specific in PA is a term that refers to the treatment of the smallest possible area as a single element. Precision agriculture is designed to increase long-term, site-specific production efficiency, productivity, and profitability while avoiding the
undesirable effects of excess chemical loading to the environment or productivity loss due to insufficient input application.

Precision agriculture requires remote sensing platforms with unique features that are not found in conventional platforms like satellites and airborne platforms. These features prevail in UAS and are the following: (a) cost-effectiveness, with a much lower operational cost compared to satellite and manned aircraft; (b) high spatial resolution that could reach centimeters; and (c) practicality, such that the UAS can be flown any time, under reasonable weather condition. In precision agriculture applications, UAS collects aerial imagery of agricultural fields to monitor the health of crops, estimate nutrient status, quantify crop water demand, and estimate yield and many other practices. All of these help the farmer to achieve the “three glory Ms”: maximize yield, minimize resource utilization, and minimize adverse environmental footprint.

The capability to increase the adoption of precision agriculture among farmers relies on five specific points, which need to be addressed by the research community:

1. Identify the management challenges that the producers encounter daily, including being agronomical, environmental, or economical.
2. Adopt cost-efficient, high spatial resolution platforms that can collect data to address the identified issues.
3. Enhance the data-processing procedures from automatic photogrammetric software, to instrument calibration and atmospheric correction.
4. Build algorithms that can extract and interpret the information in the processed data.
5. Communicate these findings by building decision-support tools that can support a better informed management decision to best management practices for operations.

This research is a step in this direction. This dissertation explores remotely sensed data acquired from a UAS to serve precision agriculture application. The UAS, named AggieAir, was developed in the Utah Water Research Laboratory. This battery-powered aircraft has onboard a payload computer that controls three sensors acquiring imagery in the visible, near-infrared and thermal infrared spectra. The three sensors are ideal because of their small size, light weight, and low cost. The imagery produced from AggieAir is of a spatial resolution of 5–60 cm. After processing these images, they are used to develop models that estimate crop chlorophyll content, plant leaf nitrogen content, and crop water use. Platform and sensor description, image processing, radiometric calibration, and estimation models are described in this research. The information generated by this research is directly beneficial to both small- and large-scale producers and indirectly to the environment.

Objectives

The chapters of this research each address specific objectives of this study. Chapter 2 was written to address the following objectives: (a) investigate the suitability of high spatial resolution data acquired by AggieAir to estimate chlorophyll concentration, (b) develop a model that can estimate chlorophyll concentration from remotely sensed crop surface reflectance, and (c) determine which bands in the reflectance spectrum are sensitive to estimation of leaf chlorophyll concentration. The
objectives of Chapter 3 were the following: (a) determine whether leaf nitrogen content could be predicted from reflectance data collected by AggieAir, and (b) develop a model that can estimate leaf nitrogen of oat crop with a 15 cm spatial resolution. The objectives of Chapter 4 were the following: (a) explore the applicability of AggieAir 15 cm resolution data collected in the visible, near-infrared, and thermal infrared spectra to estimate crop evapotranspiration (ET); (b) propose modification on existing model inputs to accommodate AggieAir data; (c) compare ET estimations derived from Landsat data to those from AggieAir; and (d) develop a 15 cm ET estimate with recommendations on farm manageable units.

Dissertation Organization

This dissertation’s objectives, outlined above, were met in a three-manuscript format. In Chapter 2, the retrieval of cm-scale chlorophyll content from thermal and multispectral optical imagery collected by a UAS is presented. A relevance vector machine is trained on a dataset of in situ collected leaf chlorophyll measurements, and the machine learning algorithm intelligently selects the most appropriate bands and indices for building regressions with the highest prediction accuracy. Chapter 3 applies the same methodology used in Chapter 2 to estimate leaf nitrogen content. The model recommends a set of inputs that are needed to estimate the spatial distribution of nitrogen at a 15 cm spatial resolution. Chapter 4 discusses the application of AggieAir data to map ET at a 15 cm spatial resolution. A detailed description of the pre- and post-processing procedure of the AggieAir data is presented in this chapter. Chapter 4 also suggests adjustments done on a surface energy balance algorithm with inputs to accommodate AggieAir imagery. A
comparison per the smallest manageable area is presented for better irrigation
management practices over the two study sites. Chapter 5 provides a summary of this
work, draws the major conclusions, and presents recommendations for further research.
The structure of this dissertation is based on the multiple-paper format. As a result, some
redundancies and repetition of parts of the material presented occur, especially the
description of the study area and the UAS platform. Additionally, each chapter is edited
in a stand-alone format, with acronym usage and references specific to each chapter.

**Contributions**

The findings of this dissertation contribute towards a greater understanding of
high spatial resolution data acquired by a UAS in precision agriculture application.
Specifically, this dissertation contributes the following:

- The research demonstrates the capability of a UAS system named AggieAir to
  successfully determine important agronomical parameters to be used in a
  precision agriculture farming system (Chapter 2, 3, 4).
- The research introduces Bayesian-based learning machine algorithms in precision
  agriculture research (Chapter 2, 3).
- The research identifies sensitive bands and indices for building regressions with
  the highest prediction accuracy that can estimate plant chlorophyll content and
  nitrogen leaf content (Chapter 2, 3).
- Whereas other documents may contain some of these steps, this is the first
  document to include a detailed description of the AggieAir platform (sensors,
thermal calibration, radiometric calibration, flight planning, and imagery orthorectification) (Chapter 4).

- The research demonstrates the potential of using data-mining learning machine algorithms to build regressions that relate spectral information and ground samples in a spatial context (Chapter 2, 3).

- Findings demonstrate that crop water demand estimates using UAS high-resolution data were comparable to the estimates generated from Landsat 8 data (Chapter 4).

- The research identifies the spectral difference of consumer-grade cameras and Landsat 8 sensors and applies an adequate correction procedure (Chapter 4).

- The paper presents a novel approach of comparing estimates that replaces the traditional pixel-by-pixel comparison with a unit based on the irrigation management system and design (Chapter 3, 4).

References


CHAPTER 2

ESTIMATING CHLOROPHYLL FROM THERMAL AND BROADBAND MULTISPECTRAL HIGH RESOLUTION IMAGERY FROM AN UNMANNED AERIAL SYSTEM USING RELEVANCE VECTOR MACHINES FOR PRECISION AGRICULTURE

Abstract

Precision agriculture requires high-resolution information to enable greater precision in the management of inputs to production. Actionable information about crop and field status must be acquired at high spatial resolution and at a temporal frequency appropriate for timely responses. In this study, high spatial resolution imagery was obtained through the use of a small, unmanned aerial system called AggieAir™. Simultaneously with the AggieAir flights, intensive ground sampling for plant chlorophyll was conducted at precisely determined locations. This study reports the development of a relevance vector machine (RVM) coupled with cross validation and backward elimination to a dataset composed of reflectance from high-resolution multispectral imagery (visible/near-infrared, or VIS-NIR), thermal infrared (TIR) imagery, and vegetative indices, in conjunction with in situ SPAD measurements from

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which chlorophyll concentrations were derived, to estimate chlorophyll concentration from remotely sensed data at 15 cm resolution. The results indicate that an RVM with a thin plate spline kernel type and kernel width of 5.4, having leaf area index (LAI), normalized difference vegetation index (NDVI), thermal and red bands as the selected set of inputs, can be used to spatially estimate chlorophyll concentration with a root mean-squared error (RMSE) of 5.31 μg.cm⁻², efficiency of 0.76, and 9 relevance vectors.

**Keywords:** Remote Sensing, High Spatial Resolution Imagery, Relevance Vector Machine, Precision Agriculture, Chlorophyll Concentration

**Introduction**

Increasing world population levels will bring increased demand for food, water, and agricultural inputs. Various agricultural farming strategies are being reevaluated to determine how to improve food production, minimize environmental impact, and reduce costs. Among many, precision agriculture has evolved as a viable system to improve profitability and productivity (Daberkow, McBride, Robert, Rust, & Larson, 2000; Lambert & Lowenberg-De Boer, 2000; Swinton & Lowenberg-DeBoer, 1998). Precision agriculture is a process of finely adjusting agricultural inputs (e.g., water, nutrients) and in-field practices (e.g., irrigation, fertilization), through the use of site-specific information and spatial imagery, to improve measures of agricultural productivity (e.g., yield, net farm income; Pierce & Nowak, 1999).

Use of spatial imagery in agriculture has been the focus of many studies for the past five decades (Bauer, 1985; Benedetti & Rossini, 1993; Franke & Menz, 2007; Idso, Jackson, & Reginato, 1977; MacDonald & Hall, 1980; Mathur & Foody, 2008; Shanahan
et al., 2001; Stone et al., 1996), requiring increased investments in relevant research and technologies (Schellberg, Hill, Gerhards, Rothmund, & Braun, 2008) that indicate remote sensing can be a valuable tool to enhance precision agriculture (Haboudane, Miller, Tremblay, Zarco-Tejada, & Dextraze, 2002; Lamb & Brown, 2001; Seelan, Laguette, Casady, & Seielstad, 2003). However, remote sensing has yet to reach its full capability in precision agriculture applications. Lack of fine spatial resolution and near real-time data, compounded by high costs, has hindered remote sensing applications at the field scale (Brisco, Brown, Hirose, McNairn, & Staenz, 1998; Kalluri, Gilruth, Bergman, & Plante, 2002; Liaghat & Balasundram, 2010; M. S. Moran, Inoue, & Barnes, 1997).

Thirty years ago, Jackson (1984) envisioned an autonomous remote sensing platform that could overcome most of the limitations; this is becoming a reality with the introduction of affordable unmanned aerial systems (UAS). UAS, a potential substitute for satellite-based remote sensing, are gaining attention and recognition in the scientific community as a potential technology that can generate high spatial resolution imagery (< 1 m) and at a temporal frequency appropriate for timely responses in the production of actionable information about crop and field status.

One such UAS, named AggieAir™, was developed by the Utah Water Research Laboratory at Utah State University. AggieAir is designed to carry camera payloads to acquire high-resolution, georeferenced aerial imagery to be used in various water, natural resources, and agricultural applications, including precision agriculture. AggieAir holds three sensors: Sensors 1 and 2 are consumer-grade cameras (personal point-and-click cameras) that capture imagery, depending on flight elevation above ground, of 6–25 cm
resolution in the VIS (red, green, blue spectrum) and NIR spectrum, respectively. Sensor 3 is a micro bolometer thermal camera that captures images of 30–150 cm resolution in the TIR spectrum. The three sensors are ideal because of their small size, light weight, low cost, and high resolution. The use of high-resolution imagery (< 1 m) can potentially improve the ability to evaluate the spatial dynamics of chlorophyll and detect its temporal variation. In this study, the use of multispectral VIS-NIR-thermal high-resolution imagery is investigated as a tool to estimate plant chlorophyll concentration to provide time-critical information for precision agriculture.

Chlorophyll concentration, measured in mass per unit leaf area (μg cm\(^{-2}\)), is an important biophysical parameters retrievable from reflectance data. Chlorophyll is a vital pigment primarily responsible for harvesting light energy used in photosynthesis (Evans, 1989; Niinemets & Tenhunen, 1997; Sims & Gamon, 2002) and is therefore an excellent indicator of a crop’s overall physiological status (Evans, 1989; Yoder & Pettigrew-Crosby, 1995), stress or disease (Chaerle & Van Der Straeten, 2000; Peñuelas & Filella, 1998; Zarco-Tejada Miller, Morales, Berjón, & Agüera, 2004), and yield predictions (Dawson, North, Plummer, & Curran, 2003; Gitelson et al., 2006). Chlorophyll can potentially provide an assessment of leaf nitrogen, an essential plant nutrient, due to the close relationship between leaf chlorophyll and leaf nitrogen (Daughtry, Walthall, Kim, De Colstoun, & McMurtrey, 2000; J. A. Moran, Mitchell, Goodmanson, & Stockburger, 2000; Wood, Tracy, Reeves, & Edmisten, 1992). Chlorophyll concentration varies with vegetation growth, thus estimating chlorophyll across the field at different growth stages could offer the farmer time- and location-specific critical information ideal for assisting
decision makers in monitoring their crops and managing farming activities to achieve maximum production.

Several leaf scale studies have focused on estimating chlorophyll concentration from VIS-NIR reflectance data. These studies indicated that the green and far-red regions of the visible spectrum are sensitive to variations in chlorophyll concentrations (Datt, 1999; Demarez & Gastellu-Etchegorry, 2000; Gitelson & Merzlyak, 1994; Kim, 1994; Zarco-Tejada Miller, Noland, Mohammed, & Sampson, 2001). Various successful indices have been formulated to estimate chlorophyll concentration (Broge & Leblanc, 2001; Haboudane et al., 2002; le Maire, François, & Dufrène, 2004). Some of these indices are ratios of reflectance in individual narrow visible wavebands (Blackburn, 1998; Carter & Spiering, 2002) or ratios of reflectance in VIS and NIR (Gitelson, Kaufman, & Merzlyak, 1996), whereas others are red-edge reflectance ratio indices (Gitelson & Merzlyak, 1994; Kim, Daughtry, Chappelle, McMurtrey, & Walthall, 1994; Zarco-Tejada & Miller, 1999) or first and second derivatives of reflectance spectra (Miller, Hare, & Wu, 1990). Composites of indices have been developed (Haboudane et al., 2002) in an attempt to correct for distortions in the reflectance data caused by soil background effect and canopy architecture.

Detailed discussions and thorough reviews concerning appropriate optimal wavelengths and various chlorophyll indices can be found in the literature (Broge & Leblanc, 2001; Haboudane, Miller, Pattey, Zarco-Tejada, & Strachan, 2004). However, most of the studies have had low spatial and coarse spectral resolution characteristics; therefore, the applicability of those indices to high spatial resolution airborne data cannot
be evaluated. Regarding thermal imagery, it is mainly explored when information on plant water status is in question, for example when screening drought-tolerance genotypes (Blum, Mayer, & Gozlan, 1982), detecting crop water stress levels (Berni, Zarco-Tejada, Suárez, & Ferereset, 2009), or estimating soil moisture and evapotranspiration (Hassan Esfahani, Torres-Rua, Jensen, & McKee, 2014a, 2014b; Jackson, Idso, Reginato, & Pinter, 1981; Wallace, Lucieer, Watson, & Turner, 2012). However, TIR data have not been investigated in estimating chlorophyll yet. Exploring thermal data in this study is rationalized by the close relationship between heat stress and the photosynthetic capacity of the leaves (Raison, Roberts, & Berry, 1982; Sharkey, 2005) and consequently the chlorophyll concentration. The mechanism by which moderate heat stress reduces photosynthetic capacity has been debated since the 1980s, when researchers attributed the photosynthesis inhibition to different factors such as the impairment of electron transport activity or the inactivation of Rubisco (Berry & Bjorkman, 1980; Murakami, Tsuyama, Kobayashi, Kodama, & Iba, 2000; Salvucci & Crafts-Brandner, 2004; Weis, 1981).

Estimating chlorophyll at a canopy level from optical remotely sensed data can generally be carried out by several methodologies. The simplest methodology that is widely accepted is the empirical method, such as those based on vegetation indices (Johnson, Hlavka, & Peterson, 1994). Nevertheless, indices generated in this context are inclined to unstable performance when applied to images that differ from the designed method (Verrelst, Schaepman, Malenovský, & Clevers, 2010). Physical behavior based methods are another approach to formulating estimates from remotely sensed data. This
method is based on physical laws that describe the transfer and interaction of radiation within the atmospheric column and canopy, such as radiative transfer models (Myneni et al., 1995). This approach has become more promising with advances in atmospheric radiative transfer modeling. The biggest drawback for such a model is that it requires site-specific information for proper model parameterization, which is not always available. As a result, methods based on vegetation indices or physical models may be either too simple or too complex to deliver accurate estimates (Baret & Buis, 2008).

Several books and published papers have reviewed these methodologies and highlighted the advantages and disadvantages associated with the complexity of the modeling approach selected, and the degree of general or local applicability of the methodology in remote sensing (Baret & Buis, 2008; Zarco-Tejada et al., 2001).

Considerable research has been carried out to explore advanced computational methods that are both accurate and robust. Machine learning regression algorithms present a potential approach for generating adaptive; robust; and, once trained, fast estimates (Hastie, Tibshirani, & Friedman, 2009; Knudby, LeDrew, & Brenning, 2010). Recent studies have demonstrated successful performance of a very well-known machine learning algorithm in estimating biophysical parameters using neural network models (Cipollini, Corsini, Diani, & Grasso, 2001; De Martino et al., 2002; González Vilas, Spyrakos, & Torres Palenzuela, 2011; Hassan Esfahani et al., 2014a; Verrelst, Alonso, Camps-Valls, Delegido, & Moreno, 2012). In recent studies, neural networks are being replaced by more advanced regression-based methods that are simpler to calibrate, like support vector machines (SVMs; Camps-Valls, Bruzzone, Rojo-Álvarez, & Melganiet,
SVMs have been widely used in various remote sensing applications; nevertheless, their large computational complexity is a major drawback. This complexity of SVM models is due to their liberal use of basis functions that typically grow linearly with the size of the training set (Tipping, 2001). Studies have shown that the behavior of RVMs is often superior to that of SVMs (Demir & Erturk, 2007). The results given by Tipping (2001) demonstrated that the RVM has a comparable generalization performance to the SVM, while requiring dramatically fewer kernel functions or model terms. RVM, in a statistical learning method proposed by Tipping, constitutes a Bayesian approximation for solving nonlinear regression models and is often used for classification and pattern recognition. RVMs offer excellent sparseness characteristics, are robust, and can produce probabilistic outputs that permit the capture of uncertainty in the predictions (Gómez-Chova, Muñoz-Mari, Laparra, Malo-López, & Camps-Valls, 2011; Thayananthan, Navaratnam, Stenger, Torr, & Cipolla, 2008).

The main purposes of this study were to (a) introduce AggieAir as a successful tool for use in precision agriculture; (b) explore the use of VIS, NIR, and TIR in estimating chlorophyll concentration, and (c) use RVM algorithms to formulate spatially distributed chlorophyll concentration estimates.

**Materials and Methods**

**RVMs**

This section presents a brief description of RVMs relevant to this study. Tipping introduced the RVM in 2001. The RVM was developed with a Bayesian framework to
find sparse solutions in classification and regression studies based on acquiring relevance vectors and weights by maximizing a marginal likelihood. In RVM regression models, the weight of each input is governed by a set of hyperparameters that describe posterior distribution of the weights and are estimated iteratively during the machine learning training step (Tipping, 2001). This paper adopts the RVM introduced by Tipping (2004), which resembles the 2001 model. The main feature in the 2004 model is that the inferred predictors are even sparser, with relatively few relevance vectors. This model also offers good generalization performance (Yuan, Wang, Yu, & Fang, 2007).

To build the model, input-output vector pairs $\{x_i, y_i\}_{i=1}^N$ are sampled from a data set of $N$ input vectors $\{X_n\}_{n=1}^N$ with corresponding $N$ output values $\{y_n\}_{n=1}^N$. From these vector paired data, we generate a training data subset from which the model learns the dependence between inputs and the output target, with the purpose of making accurate predictions of $y$ for previously unseen values of $x$ shown in Equation 1:

$$y = w\varphi(x) + \varepsilon$$

(1)

where $w$ is a vector of weight parameters, $\varphi(x) = [1, f(x, x_1, \ldots, f(x, x_N)]^T$ is a design matrix of $N + 1$ vectors of kernel basis functions $f$, $\varepsilon$ is the error that for algorithmic simplicity is assumed to be zero-mean Gaussian with variance $\sigma^2$.

The kernel or basis function is a method that detects embedded patterns in the data by transforming or extending linear algorithms into nonlinear ones. Kernel methods map the data into higher dimensional spaces to increase the computational power of the machine (Cristianini & Shawe-Taylor, 2000; Genton, 2001; Souza, 2010; Vapnik, 2000). Kernel functions could be linear, polynomial, and Gaussian kernel. However, choosing
the most appropriate one highly depends on the nature of the relationship between the inputs and outputs. Six kernel types, \( f \), were considered: Gauss, Laplace, spline, Cauchy, thin plate spline, and bubble (Bachour, Walker, Ticlavilca, McKee, & Maslova, 2014; Ticlavilca, McKee, & Walker, 2013; Torres, Walker, & McKee, 2011). The process of selecting the kernel type in this paper was conducted by trial and error.

The Gaussian likelihood of the data set can be written as in Equation 2:

\[
\int p(y \mid w, \sigma^2) = (2\pi)^{-N/2} \sigma^{-N} \exp \left\{ -\frac{\|y - w\Phi\|^2}{2\sigma^2} \right\}
\]

(2)

One of the classic approaches to estimating the parameters \( w \) and \( \sigma^2 \) in Equation 2 is using the method of maximum likelihood. However, with many parameters used as training observations, the maximum likelihood estimation would lead to severe overfitting (Tipping, 2004). To overcome this complexity, Tipping (2001) proposed adding a “prior” to constrain the selection of parameters by defining an explicit zero-mean Gaussian prior probability distribution over them as shown in Equation 3:

\[
p(w \mid \alpha) = (2\pi)^{-M/2} \prod_{m=1}^{M} \alpha_m^{-1/2} \exp \left\{ -\frac{\alpha_m w_m^2}{2} \right\}
\]

(3)

Where \( M \) is the number of independent hyperparameters \( \alpha = (\alpha_1, ..., \alpha_M)^T \). Each \( \alpha \) is associated independently with every weight to moderate the strength of the prior and provide the sparsity of the model (Tipping, 2001). How far each weight is allowed to deviate from zero is controlled by the hyperparameter vectors (Yuan et al., 2007). Consequently, using Bayes’s posterior inference, the posterior over \( W \) could be computed as shown in Equation 4:
\[
p(w|y,\alpha,\sigma^2) = \frac{p(y|w,\sigma^2)p(w|\alpha)}{p(y|\alpha,\sigma^2)} 
\]

(4)

Here, \( p(y|\alpha,\sigma^2) \) is the normalizing factor; \( p(y|w,\sigma^2) \) and \( p(w|\alpha) \) are both Gaussian priors, so the posterior is also Gaussian with \( p(w|y,\alpha,\sigma^2) \sim N(w|\mu,\Sigma) \). The posterior mean \( \mu \) and covariance \( \Sigma \) are defined as:

\[
\Sigma = (A + \sigma^2\Phi^T\Phi)^{-1} \quad \text{And} \quad \\
\mu = \sigma^2\Sigma\Phi^Ty,
\]

(5)

where \( A \) is \( \text{diag} \{ \alpha, \ldots, \alpha, \} \).

A fast marginal likelihood optimization algorithm is used to obtain the optimal set of hyperparameters, \( \alpha^{opt} \). This optimization algorithm uses an efficient sequential addition and deletion of candidate basis functions described by Tipping and Faul (2003).

Given an unseen input vector, \( x^* \), the predictive distribution for the corresponding target \( y^* \) can be computed. This search for optimal hyperparameters is learned using a type II maximum likelihood method coupled with iterative estimation (Tipping, 2001) as shown in Equation 7:

\[
p(y^*|\alpha^{opt},(\sigma^{opt})^2) = \int p(y^*|w,\sigma^{opt})p(w|\alpha^{opt},(\sigma^{opt})^2)dw 
\]

\[
=> p(y^*|\alpha^{opt},(\sigma^{opt})^2) = N(y^*|\mu^*(\sigma^*)^2) 
\]

(7)

Where \( \mu^* \) is the predictive mean of the output of the unseen data, \( x^* \) and the posterior mean weight of \( \mu, \mu^* = [\mu_1^*, \ldots, \mu_M^*]^T \); and \( (\sigma^*)^2 = [(\sigma_1^*)^2, \ldots, (\sigma_M^*)^2]^T \) is the predictive variance. This predictive variance is the sum of variances associated with both the noise of the data and the uncertainty in the prediction of the weight parameters (Tipping, 2004).
In this optimization process, the vectors from the training set associated with nonzero weights are called the relevance vectors. The theory behind RVM, mathematical formulation, likelihood maximization, and optimization procedure is discussed in detail in Tipping (2004) and Tipping and Faul (2003).

**Study Area**

The field study was carried out in the summer of 2013 on privately owned agricultural land in Scipio, Utah (39°14'N 112°6'W; see Figure 2.1). The plot, mainly composed of loamy clay soil, was equipped with a center pivot sprinkler for irrigating and fertilization oats (*Avena sativa*). The study area was restricted to the northwest quarter of the center pivot so that samples could be collected within a close time frame relative to the AggieAir flight. AggieAir aircraft were flown four times over the area, covering the entire growth cycle of oats. The flights on 05/16, 06/01, 06/09, and 06/17 reflected the four stages of growth: 10 days after planting, early growth, mid growth, and early flowering. Oats were harvested after the fourth flight to be used as forage.

*Figure 2.1.* The location of the study area in Utah (left), The quarter used in plant chlorophyll estimation model (right).
Instrumentation: Remote Sensing Platform AggieAir

AggieAir is a UAS designed to carry camera payloads to acquire aerial imagery for precision agriculture and other types of applications (Figure 2.2). The UAS aircraft is battery powered and equipped with a payload system (which includes three cameras and a computer), avionics, two inertial sensors (a GPS module and an inertial measurement unit), radio controller, and flight control. The aircraft is propelled using an electric, brushless motor. It does not require a runway and can be flown autonomously or manually. In autonomous mode, the aircraft follows a preprogrammed flight plan containing navigation waypoints defined by GPS and altitude. While operational, the payload computer instructs the three cameras to acquire imagery in the VIS, NIR, and thermal spectra and records the position and orientation of the aircraft when each image is taken. Table 2.1 illustrates the UAS specification in more detail.

Figure 2.2. AggieAir airframe layout.
Table 2.1

*AggieAir Unmanned Aerial System Specifications*

<table>
<thead>
<tr>
<th>Specification</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight duration</td>
<td>45–60 min</td>
</tr>
<tr>
<td>Flight altitudes</td>
<td>200–1000 m</td>
</tr>
<tr>
<td>Maximum takeoff weight</td>
<td>6.35 kg</td>
</tr>
<tr>
<td>Visible/near-infrared resolution</td>
<td>6–25 cm</td>
</tr>
<tr>
<td>Thermal resolution</td>
<td>30–150 cm</td>
</tr>
<tr>
<td>Wing span</td>
<td>2.5 m</td>
</tr>
</tbody>
</table>

The VIS camera used in AggieAir is a Canon S-95, with a 10-megapixel charge-coupled device (CCD) sensor and an ISO range of 80 to 3200. The radiometric resolution of the Canon S-95 is 8-bit color, which means that the digital measurement for a particular pixel in a given spectral band ranges from 0 to 255. The NIR camera is an identical Canon S-95, modified by replacing the manufacturer’s optical filter with a Wratten 87 NIR filter that allows NIR wavelengths of 750 nm. The relative spectral responses of the VIS-NIR cameras were not provided by the manufacturers but were obtained using the algorithm provided by Jiang, Liu, Gu, and Susstrunk (2013). The camera VIS-NIR spectral response is shown in the left portion of Figure 2.3. AggieAir also carries a small, low-power, microbolometer thermal camera from Infrared Cameras, Inc. (2014). The relative spectral response of the thermal camera is shown in the right portion of Figure 2.3.
Figure 2.3. Relative spectral response of the VIS-NIR (left) and thermal camera (right). VIS-NIR = visible/near-infrared; ICI = Infrared Cameras, Inc.

Following VIS and NIR image acquisition, a two-step processing phase occurs. The first step is image mosaicking and orthorectification. This technique, achieved with EnsoMOSAIC software (MosaicMill, 2009), combines all of the images into one large mosaic and rectifies it into a ground coordinate system. The software generates hundreds of tie-points between overlapping images by using photogrammetric principles in conjunction with image GPS log file data and exterior orientation information from the on-board cameras to refine the estimate of the position and orientation of individual images. The resulting image is an orthorectified digital number mosaic. The second step involves radiometric calibration: the conversion of the digital pixels into a measure of reflectance. This conversion is based on methods adapted from the research (Crowther, 1992; Miura & Huete, 2009; Neale & Crowther, 1994). The major steps involved in this
methodology are the reference panel calibration and solar zenith angle calculations. This method converts raw airborne multispectral data by calculating the ratio of linearly interpolated reference values from the pre- and post-flight reference panel readings, as discussed in detail by Zaman, Jensen, Clemens, and McKee (2014) and by Clemens (2012). After completing the two-step process, images are geometrically rectified and radiometrically corrected to obtain a four-layer (red, green, blue, NIR) canopy surface reflectance in a single image (Figure 2.4).

Figure 2.4. Raw natural color images from the unmanned aerial system (left), accurate orthorectified mosaic image from EnsoMOSAIC (center), and radiometric calibration of visible spectrum image (right).

Thermal imagery processing also requires an initial step of mosaicking and orthorectification similar to the VIS and NIR images. However, the resulting thermal mosaic is composed of brightness temperature in degrees Celsius (± 0.1 degrees) instead of digital numbers. Compensating for external disturbance and geometric calibration are also unique challenges associated with the thermal camera. Jensen (2014) thoroughly explained the methodology of processing thermal maps adopted by the authors.
**Data Collection**

The collection of the ground and remotely sensed data occurred under similar weather conditions in a 1- to 2-hour window.

**Multispectral image acquisition.** Four multispectral mosaics were acquired by AggieAir during summer 2013. Acquisition dates were planned to coincide with different development stages and with overflights of Landsat. Images were collected, following the Landsat image acquisition protocol, close to solar noon (between 12 a.m. and 1 p.m.). The flight time (beginning to end) ranged from 30–40 min. All four missions were successfully performed, providing image data covering the earliest, middle, and latest periods of the oat growth. The spatial resolution is 0.15 m for VIS and NIR images and 0.6m for the TIR images.

**Ground data acquisition.** Intensive ground truth sampling of plant chlorophyll was conducted simultaneously with the AggieAir flights at precise GPS locations. The GPS data were collected using an rtkGPS with < 1 mm precision in a 1 Hz bandwidth (Trimble® R8, Global Navigation Satellite System, Dayton, Ohio). A SPAD-502 chlorophyll meter (Minolta Corporation, New Jersey) was used for *in vivo* measurement of the ratio of light transmittance through the leaf at wavelengths of 650 and 940 nm. Instrument readings have been shown to correlate well to laboratory measurements of chlorophyll concentration in several species (Yadawa, 1986). On each sampling campaign, 40 SPAD measurements were collected on average. The chlorophyll meter readings were taken midway on the fully expanded top-of-canopy leaves. Each measurement was characterized by the mean of six replicate measurements. The
chlorophyll meter measures an area of 2 x 3 mm with an accuracy of ± 1.0 SPAD unit (at room temperature). However, the SPAD-502 meter displays the chlorophyll readings in arbitrary units (SPAD unit) rather than the actual amounts of chlorophyll in mass per leaf area; thus, further conversions were needed. The SPAD units were transformed to a chlorophyll concentration index (CCI) unit using Equation 8 and then to chlorophyll in mass per leaf area using Equation 9 (Parry, Blonquist, & Bugbee, 2014). Equation 9 was developed for barley crops; however, literature has shown that monocots have a similar optical/absolute chlorophyll concentration relationship.

\[
\text{CCI} = 1 + 0.00119 \times SPAD^{2.67} \\
\text{Chlorophyll (\(\mu\text{mol.m}^{-2}\))} = -132 + 146(CCI^{0.43})
\]  

(8)  
(9)

**Linking on-ground measurements to airborne imagery.** Ground coordinates of sampled chlorophyll coincided precisely with the location of the plants in the geo-rectified imagery. Ground coordinates of the samples were overlaid onto the geo-rectified imagery, and, using the ArcGIS spatial analyst tool (Extract Multi Values to Points), an automated process was developed to extract the pixel value representing the center of each sampled area.

**Model Potential Inputs and Performance**

Three of the four flights (early growth, mid growth, and early flowering), excluding the flight 10 days after planting, were used in the dataset to train and test the model. The dataset contains coincident in situ SPAD measurements used to derive chlorophyll concentration and remote sensing reflectance measurements. All the data were collected from inside the center pivot quarter (within field data); the zeros found in
the data set represent the areas of no vegetation (center pivot wheels trajectory). A statistical description of the dataset is presented in Table 2.2. Each pair of data consists of a target, which is the chlorophyll concentration, and a set of 8 potential inputs tabulated in Table 2.2. The potential inputs are composed of data retrieved form the UAS imagery (VIS, NIR, TIR); vegetative indices (green model and NDVI) that were reported to be sensitive in estimating chlorophyll (Gitelson, Vina, Ciganda, Rundquist, & Arkebauer, 2005; Shanahan et al., 2003); and LAI, a well-known and widely used vegetation index related to crop growth. Table 2.3 shows the indices formulations.

Table 2.2

<table>
<thead>
<tr>
<th>Input</th>
<th>Range</th>
<th>M ± SD</th>
<th>Range</th>
<th>M ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Potential inputs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AggieAir inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blue</td>
<td>0.11–0.36</td>
<td>0.15 ± 0.04</td>
<td>NIR</td>
<td>0.51–0.61</td>
</tr>
<tr>
<td>Green</td>
<td>0.20–0.49</td>
<td>0.26 ± 0.05</td>
<td>Thermal (°C)</td>
<td>23.11–36.16</td>
</tr>
<tr>
<td>Red</td>
<td>0.15–0.51</td>
<td>0.22 ± 0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indices inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>0.00–0.78</td>
<td>0.44 ± 0.12</td>
<td>LAI (m²/m²)</td>
<td>0.00–4.23</td>
</tr>
<tr>
<td>GM</td>
<td>0.17–1.74</td>
<td>1.17 ± 0.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Target/output</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chlorophyll (μg.cm⁻²)</td>
<td>0.00–61.64</td>
<td>47.01 ± 11.26</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* GM = green meter; LAI = leaf area index; NDVI = normalized difference vegetation index; NIR = near-infrared.

These potential predictors, exert to a certain degree correlation between each other. This is because they are derived from the same AggieAir reflectance bands
(statistical correlation). While in customary statistics (e.g., linear regression) using these predictors would raise issues, the Bayesian regression machine applied in this study can deal with this problem. The kernel or basis function projects these potential inputs into a higher dimensional space. The way these inputs are projected in the new dimensional space, as well as the sparse representation of the observations in the final model, help the model deal with collinearity issues.

Table 2.3

*Vegetative Indices Formulation Used for Plant Chlorophyll Estimation*

<table>
<thead>
<tr>
<th>Indices</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green model</td>
<td>$\frac{R_{\text{NIR}}}{R_{\text{Green}}} - 1$</td>
<td>Gitelson et al., 2005</td>
</tr>
<tr>
<td>NDVI</td>
<td>$(R_{\text{NIR}} - R_{\text{red}}) / (R_{\text{NIR}} + R_{\text{Red}})$</td>
<td>Rouse, Haas, Schell, Deering, &amp; Harlan, 1974</td>
</tr>
<tr>
<td>LAI*</td>
<td>$\ln \left(\frac{(NDVI - NDVI_{\text{max}})}{(NDVI_{\text{min}} - NDVI_{\text{max}})}\right) / -0.54$</td>
<td>Duchemin et al., 2006; Smith, Bourgeois, Teillet, Freemantle, &amp; Nadeau, 2008</td>
</tr>
</tbody>
</table>

*Note.* LAI = leaf area index; NDVI = normalized difference vegetation index.

*LAI was calculated empirically and not validated by field measurements.

In preliminary runs different potential inputs were explored. For example, one set composed of only single bands, and another set composed of the ratio of the single bands. In addition, the authors tried vegetative indices sensitive to chlorophyll estimations (transformed chlorophyll absorption reflectance index, modified chlorophyll absorption ratio index, and modified triangular vegetation index) that were modified to adapt to the spectral response of AggieAir sensors (e.g., replacing the required red edge by the NIR band). However, details on these preliminary runs are not reported in this study because of their low statistical performance.
The RVM is a well-established statistical learning algorithm that adopts a full probabilistic framework. Its key feature is that it can yield a solution function that depends on only a very small number of training samples (called relevance vectors). In the RVM framework, the model is built on the few training examples whose associated hyperparameters do not go to infinity during the training process, leading to a sparse solution. The implemented RVM is based on the MATLAB code provided via Michael E. Tipping’s website. The RVM model in this research was first trained and tested using K-fold cross validation (K = 5); the cross validation technique is utilized to generalize an independent training data set (Kohavi, 1995). In this procedure, the training set is partitioned into K disjoint sets. The model is trained, for a chosen kernel, on all the subsets except for one, which is left for testing. The procedure is repeated for a total of K trials, each time using a different subset for testing. After the selection of the kernel function and its width, the whole data set is trained using RVM based regression. The advantage of this method over a random selection of training samples is that all observations are used for either training (K times) or evaluation (once).

The model was developed with an input selection process (Guyon & Elisseeff, 2003) in an attempt to explain the data in the simplest way possible. Potential inputs were examined to see which were most relevant to the target function and thus avoid degrading the performance of a learning algorithm due to the presence of irrelevant input variables. In each iteration, the input with the minimum efficiency was eliminated.

The RVM model was tested using six kernel types: Gauss, Laplace, spline, Cauchy, thin plate spline, and bubble. The performance of the model was evaluated by
comparing the RMSE and the Nash-Sutcliffe efficiency (E); these two parameters have been widely used to evaluate the performance of RVM models. The larger the value of E and the smaller the value of RMSE, the greater the precision and accuracy of the model to predict chlorophyll. The RMSE and E are computed as shown in Equations 10 and 11, respectively:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (\hat{y}_t - y_t)^2}
\]  

(10)

\[
E = 1 - \frac{\sum_{t=1}^{N} (y_t - \hat{y})^2}{\sum_{t=1}^{N} (y_t - \bar{y})^2}
\]

(11)

where \(\hat{y}_t\) = predicted chlorophyll concentration; \(y_t\) = measured chlorophyll concentration; \(\bar{y}\) = mean of the observed chlorophyll concentration; \(\bar{\hat{y}}\) = mean of the estimated chlorophyll concentration; and \(N\) = total number of observations.

**Result and Discussion**

Each of the six kernel types was tested over a wide range of kernel widths \((10^{-5}-10^5)\), and RMSE and E were calculated for all of the resulting models to assess their predictive capabilities. An embedded loop in the coding model was developed to represent the backward elimination tool. For each type of kernel and its corresponding width, the RVM was first run using all of the 8 inputs, consequently generating all of the needed statistical model performance estimates to assess the model. A set of defined iterations then eliminated, in order, the input with the minimum efficiency, thus removing
the input least relevant to the target function. After numerous computational runs, four options presented themselves as potential “best model” scenarios (Table 2.4). All four of these potential best model scenarios had an RMSE < 6 μg.cm$^{-2}$ and an $E > 0.7$. In 94% of all runs conducted across the six kernel types, the thermal band was the last input to be dropped, suggesting that thermal imagery is an important input, at least in the case of study area, possessing the most relevant information for estimating chlorophyll concentration. Thermal data allowed the models to differentiate between the bare soil and the different level of vegetation per pixel resulting in a more accurate chlorophyll estimates. A preliminary interpretation could be the fact that oat leaves are very thin, with minimal heat capacity, and as a result, leaves exposed to full sunlight can warm up substantially above air temperature. This elevated temperature can help identify greener leaves and as a result those with higher chlorophyll values. Nevertheless, additional experiments that explore thermal imagery and its effect on chlorophyll estimations need to be conducted.

Table 2.4

<table>
<thead>
<tr>
<th>Model</th>
<th>Kernel type</th>
<th># of inputs</th>
<th>Inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gaussian</td>
<td>4</td>
<td>LAI, NDVI, thermal, green</td>
</tr>
<tr>
<td>2</td>
<td>Gaussian</td>
<td>3</td>
<td>Thermal, green, LAI</td>
</tr>
<tr>
<td>3</td>
<td>Laplace</td>
<td>4</td>
<td>NDVI, red, green, thermal</td>
</tr>
<tr>
<td>4</td>
<td>Thin plate spline</td>
<td>4</td>
<td>LAI, NDVI, thermal, red</td>
</tr>
</tbody>
</table>

*Note.* LAI = leaf area index; NDVI = normalized difference vegetation index.
When plotting the 1-1 plot for the four best scenario candidates, the plots looked almost identical. Since the statistical performance does not reveal an absolute best model, visual comparison was made of the chlorophyll estimation maps of the four models, on one hand, and the NDVI, LAI, and true-color maps, on the other hand. The chlorophyll estimates for the early growth, mid growth, and early flowering images were developed considering the unique characteristic of each of the four best models (kernel type, width, and set of inputs). Models 1 and 2 showed clear overfitting when plotted over the entire map: In each case, the resulting map was one solid color, with no variation in estimated chlorophyll between bare soil and fully grown oat plants. Model 3 showed more variation within the field; nevertheless, visual comparisons with Model 4 indicated that Model 4 was superior. Model 4 showed an RSME of 5.31 μg.cm⁻², an E of 0.76, and 9 relevance vectors. Figure 2.5 illustrates the measured chlorophyll concentration versus estimated values with a one standard error confidence interval. The three flights are separated by the yellow line in the graph. Some differences can be observed between the different dates; the estimates for the first and third flights are more precise than the second flight. This could be due to the stage of the crop growth or the homogeneity of the vegetation cover.

Figure 2.6 represents regression diagnostic plots of Model 4 that address model assumptions like linearity and equality of variances. The 1:1 plot confirms the adequacy of the model proposed for most of the chlorophyll values lying within the boundaries of ± 1.0 SPAD unit (sensor accuracy), which corresponds to 14 μg.cm⁻². The chlorophyll maps generated from Model 4, along with NDVI and LAI, are presented in Figure 2.7.
Figure 2.5. Measured versus predicted chlorophyll concentration in the three flights for Model 4. Vertical yellow lines separate the three flight dates.

Figure 2.6. Model 4: Residual plot of the three flights (left) and one-by-one plot excluding the bare soil–zero chlorophyll points and reflecting the chlorophyll meter accuracy (right).
As shown in Figure 2.7, the predicted chlorophyll concentration maps show a visual good agreement with the LAI and NDVI maps. In the early growth image, the field exterior had weeds growing in it, which explains the predicted chlorophyll concentration values. This area was not irrigated during the growing cycle, leaving the weeds to dry and senescence, thus a near-zero chlorophyll concentration value was assigned by the model in the following two images. Also, the wheel tracks and the access road that are located around the center pivot had no vegetation cover, and the model successfully assigned a near-zero chlorophyll concentration to these features.

Figure 2.7. True-color maps, normalized difference vegetation index (NDVI) maps, leaf area index (LAI) maps, and the estimated chlorophyll concentration (μg.cm⁻²) map for the three different dates representing early growth, mid growth, and early flowering.
Another common pattern was the two thick horizontal and vertical lines that protrude in the images. These were past ditch lines that had been used in flood irrigation activities prior to the conversion of the field to a center pivot system. The greater water content in those areas caused the plants growing along those two lines to be very vigorous. This is reflected in the high chlorophyll concentration values given to the plants in this area.

Chlorophyll concentration varies widely within the growing season, and therefore any recommended analytical technique must perform well under unseen data. To explore the model with unseen data, the May 16 flight was used. Now that the model was established with a defined set of features (inputs, kernel type, kernel width), data from the May 16 flight (10 days after planting of the oats) were entered in the model to explore the model’s performance when subjected to totally unseen data. The predicted chlorophyll concentration map is shown in Figure 2.8.

Figure 2.8. True-color image of flight zero (left), leaf area index (LAI) map (middle), and estimated chlorophyll concentration map (μg.cm$^{-2}$, right).
Again, the predicted chlorophyll concentration map for the fourth flight showed good association with the NDVI map. Areas of vigorous growth, bare soil, and low vegetation were similar in the three maps and represented similar growth patterns. This test reported an RSME of 8.52 μg.cm\(^{-2}\) and E of 0.71 for this flight. This result showed that the model successfully performed when given unseen data.

Despite the complexity of the statistical model included in this paper, it is anticipated that the lucid output (chlorophyll concentration maps) will help agricultural decision makers quantify field chlorophyll and address its variability and as a result improve input efficiency, environmental sustainability, and yield. Adoption of precision agriculture is likely to continue into the foreseeable future. However, studies that explore high-resolution sensors (<1 m) with adequate frequent coverage, combined with techniques capable of extracting information from imagery to provide near real-time information, will be a determining factor in the adoption rate of precision agriculture.

**Conclusion**

This paper presented the application of imagery from AggieAir, a remote sensing platform, combined with machine learning algorithms (RVM) to estimate chlorophyll concentration as an important biophysical parameter to be used in precision agriculture. The RVM modeling technique, coupled with cross validation and backward elimination, was applied to a data set composed of reflectance from high-resolution multispectral imagery (VIS-NIR), TIR imagery, and vegetative indices, in conjunction with *in situ* chlorophyll concentrations derived from SPAD measurements. Six kernel types were tested over a wide range of kernel widths. Model performance was evaluated by
comparing the RMSE and E of various models and later by visual comparison.

Chlorophyll concentration estimation was best achieved with Model 4 (kernel type: thin plate spline; kernel width: 5.4; selected inputs: LAI, NDVI, thermal, and red band; RSME: 5.31 μg.cm\(^{-2}\); E: 0.76; and 9 relevance vectors) for the three flights. Of all the inputs, thermal band was retained last in 94% of the models, proving the significance of thermal imagery as an input possessing the most relevant information in estimating chlorophyll concentration.

Converting these chlorophyll estimate maps into actionable information to benefit the end user now shows promise. Other research that estimates soil moisture, actual evapotranspiration, and soil nutrient content using the same high-resolution aerial platforms allows for wider adoption of precision agriculture by future farmers. Although the results presented in this section are arguably not yet actionable, maps like these could be used to quantify plant health, predict yield, and indicate where and how much fertilizer to apply.

AggieAir imagery, combined with appropriate analytic tools, allows spatial estimation of chlorophyll content. These estimates, made at such fine resolutions in space and time, can aid farmers in assessing the heterogeneity of their fields and subsequently implement needed actions accordingly. The high-resolution spatial information generated from AggieAir imagery could enable far greater precision in the application of nitrogen fertilizers and water through a center pivot irrigation system.
Acknowledgment

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References


CHAPTER 3

USE OF HIGH RESOLUTION MULTISPECTRAL IMAGERY TO ESTIMATE PLANT NITROGEN IN OATS (AVENA SATIVA).

Abstract

Remote sensing applications for precision agriculture depend on acquiring actionable information at high spatial resolution and at a temporal frequency appropriate for timely responses. This study was conducted to determine if high resolution canopy reflectance could be used to evaluate leaf Nitrogen (N) status in oats (Avena sativa) for precision agriculture. An unmanned aerial system platform named AggieAir™, was used to acquire high-resolution imagery in the visual, near infrared, and thermal infrared spectra. This study reports the development of a relevance vector machine (RVM) coupled with forward input selection process to a dataset composed of reflectance from high-resolution multispectral imagery (visible, near-infrared, thermal infrared imagery), and vegetative indices, in conjunction with in situ leaf N sampled and analyzed in the laboratory, to estimate leaf N content from remotely sensed data at 15 cm resolution. The results indicate that an RVM with a Gaussian kernel type and kernel width of 0.28, having Near-infrared, green ratio vegetation index, red/green ratio index, and simple ratio as the selected set of inputs, can be used to spatially estimate Leaf Nitrogen with a root mean-squared error (RMSE) of 0.48 mg/100 mg dry tissue (DT), efficiency of 0.76, and 6 relevance vectors.
Introduction

Monitoring crops and assessing their nutrient status throughout the vegetation growth is a fundamental practice in precision agriculture. An essential nutrient for plant growth is nitrogen (N), and when absent a significant decrease in both the photosynthetic and CO₂ assimilation capacity in crops is reported (Prsa, Stampar, Vodnik, & Veberic, 2007; Tracy, Hefner, Wood, & Edmisten, 1992). Farmers must balance the competing goals of supplying enough N to their crops to reach their production goals while minimizing the loss of N to the environment (Daughtry et al., 2000). When applied in excess, N represents a threat to water quality because it can increase the chance of nitrate contamination of surface and groundwater (Errebhi, Rosen, Gupta, & Birong, 1998; Ju, Kou, Zhang, & Christie, 2006). Over-application of N fertilizer can also be an economic loss to a farmer. Precise plant N evaluation has the potential to aid farmers in creating this balance, by early detection of N stress and matching N supply with crop N requirement at the correct rate, place, and time.

Traditionally, many methods have been utilized for determining crop N status, including tissue analysis performed on leaves sampled from the field (Roth, Fox, & Marshall, 1989). This method is known to be destructive, sample intensive, expensive, and time consuming, with a significant lag between collecting the samples, performing the laboratory analysis, and generating the final recommendation. This delay can result in
a missed opportunity in providing the crop with the needed nutrient in a timely fashion and consequently influence the crop productivity. Recently, portable optical instruments like chlorophyll meters are used to assess N status in crops (Filella, Serrano, Peñuelas, 1995; Han, Hedrickson, & Ni, 2001). These meters are less invasive, nondestructive, and relatively faster in providing results (Gianquinto, Sambo, & Pimpini, 2003; Schepers, Francis, Vigil, & Below, 1992; Turner & Jund, 1991). However, they are only practical at leaf level and limited to evaluating plant status in small areas. This technique measures the transmittance of radiation through a leaf in two wavelength bands centered near 650 nm and 940 nm (Peterson, Blackmer, Francis, & Schepers, 1993). The meter is actually measuring leaf chlorophyll, and since the majority of leaf N is contained in chlorophyll molecules, N content is deducted indirectly from those readings. However, some researchers challenged the general polynomial equation commonly used to relate N to measured chlorophyll and proposed an exponential equation that forces a more appropriate fit (Markwell, Osterman, & Mitchell, 1995). Others commented that at high N levels, N could be found in the NO₃⁻ N form and not only in chlorophyll molecules; thus, the relationship between leaf chlorophyll and leaf N concentration may be nonlinear (Wood, Reeves, & Himelrick, 1993). The successful usage of these meters when assessing N content is also affected by the crop type, growth stages, measurement positions on leaves, and environmental conditions (Chapman & Barreto, 1997; Ramesh et al., 2002; Schepers et al., 1992; Turner & Jund, 1991). Both of these methods can potentially lead to over- or underassessment of N status in the crops and as a result inaccurate recommendations.
The importance and interest in leaf N and its spatial variation suggest a need to analyze it in a spatially explicit and extensive manner. For instance, a leaf N content map displaying spatial variations at canopy level could facilitate diagnosis of nutrient availability and limitation and help to eliminate the need for intensive field sampling or nutrient addition. Obtaining such data for spatial representation could be achieved using remote sensing platforms. Remote sensing provides rapid, quantitative information about crops and, above all, does so nondestructively for diagnosing the spatial variability of crop field properties. Remotely sensed data infer canopy leaf N status based on leaf reflectance and transmittance measurements.

An early study by Thomas and Oerther (1972) found that reflectance in the green and red regions of the electromagnetic spectrum were highly correlated to leaf N content determined using the Kjeldahl method. Additional research reported by Martin, Shenk, and Barton (1989) established the relationship between crop N content and canopy reflectance at the visible (VIS, 400–700 nm) and near-infrared (NIR, 700–1100 nm) regions. In addition, light reflectance at wavelengths near 550 nm from individual leaves was found to be a good indicator of N stress in corn crops (Blackmer & Schepers, 1995). Researchers also developed various combinations of bands known as vegetative indices that are linearly related to N concentration, such as the Red-edge Index, \( R_{740}/R_{720} \) (Mokhele & Ahmed, 2010). Canopy reflectance in the red and NIR regions have reported success at determining crop N content, due to the ability to detect changes associated with chlorophyll content (Guyot, 1991). Researches have studied leaf N reflectance response on corn (Blackmer, Schepers, & Varvel, 1994: Lee, Searey, & Kataoka, 1999),
sweet pepper (Thomas & Oerther, 1972), sugarcane (Miphokasap, Honda, Vaiphasa, Souris, & Nagai, 2012), rice (Stroppiana, Boschetti, Brivio, & Bocchi, 2009; Yi, Huang, Wang, Wang, & Liu, 2007; Zhu, Zhou, Yao, Tian, & Cao, 2007), and many others.

With airborne and satellite multispectral sensors as the providers of remotely sensed data, various shortcomings emerged (Merlin et al., 2010; Mulla, 2013). The ability to deliver information for N management at high spatial resolution as dictated by precision farming practices was the biggest limitation. In addition, the high cost of images from aircraft, the infrequency of satellite overpasses, the interference of the weather conditions with the imagery, and delays between image capture and availability of usable data were major concerns for farmers. To implement precision N management successfully, efficient technologies to diagnose crop N status are needed to determine in-season, site-specific crop N requirements (Li et al., 2010). Unmanned aerial systems (UAS) have been proposed for precision agriculture applications (Berni, Zarco-Tejada, Suarez, & Fereres, 2009; Kooistra et al., 2013; Zhang & Kovacs, 2012). UAS can provide imagery with a higher spatial resolution, allow for more flexible acquisition times, and can be flown more frequently compared to satellite imagery (Zhang & Kovacs, 2012).

The current research explores the high spatial resolution imagery collected by a UAS system to estimate leaf N content. The imagery acquires reflectance information from the VIS, NIR, and thermal infrared (TIR) spectra with a spatial resolution of 15–60 cm. The estimated leaf N content developed by the proposed model was validated against the ground truthing data collected. The generated high-resolution leaf N map could help
farmers in customizing their fertilization practices to suit the variability and needs of the crop.

Our objective was to use canopy reflectance collected by AggieAir for estimating the crop N status within fields. Moreover, this research also would identify which inputs (e.g., individual reflectance, vegetative indices) are most sensitive for detection of crop N status differences. In conducting the work, we evaluated a relatively inexpensive UAS application in precision agriculture.

**Material and Methods**

**Study Area**

The study area is on a privately owned agricultural land in Scipio, Utah (39°14’N 112°6’W; see Figure 3.1). The field is equipped with a modern center pivot irrigation sprinkler system to supply water for oat crops. The study reported here was carried out in the summer of 2013. Four flights were flown over the study site. The flights on May 16, June 1, June 9, and June 17 reflected the four stages of growth: 10 days after planting, early growth, midgrowth, and early flowering. The study area was restricted to the northwest quarter of the center pivot so that samples could be collected within a close time frame relative to the AggieAir flight.
Figure 3.1. The location of the study area in Utah (left), The quarter used in leaf Nitrogen estimation model (right).

Instrumentation: Remote Sensing Platform AggieAir

AggieAir is a UAS designed to carry a payload to acquire aerial imagery in the VIS, NIR, and TIR spectra. The unmanned aerial vehicle (UAV) navigates over an area of interest according to a preprogrammed flight plan. While operational, the payload computer instructs the three cameras to acquire imagery and records the position and orientation of the aircraft when each image is taken. The UAS aircraft is battery powered with a wingspan of 2.5 m and weight of 6.35 kg. AggieAir can fly in the air for up to 60 minutes and within elevation of 200–1000 m.

The VIS camera used in AggieAir is a Canon S-95, with a 10-megapixel CCD sensor and an ISO range of 80 to 3200. The NIR camera is an identical Canon S-95, modified by replacing the manufacturer’s optical filter with a Wratten 87 NIR filter that allows NIR wavelengths of 750 nm. AggieAir also carries a small, low-power, microbolometer thermal camera from Infrared Cameras, Inc. (2014). The VIS-NIR imagery is of a spatial resolution of 0.15 m; the TIR imagery is of 0.6 m spatial resolution. The relative spectral responses of the VIS-NIR cameras were not provided by
the manufacturers but were obtained using the algorithm provided by Jiang, Liu, Gu, and Susstrunk (2013). The wavelength range peaks around 420, 500, 600, and 800 nm, respectively, for blue, green, red, and NIR sensors. Please refer to Chapters 2 and 4 of this dissertation for more details about the UAV and the sensors.

**AggieAir Data Processing**

Following image acquisition, the imagery is imported into EnsoMOSAIC (MosaicMill, 2012). EnsoMOSAIC is a photogrammetry software for aerial image processing. The software generates hundreds of tie-points between overlapping images by using photogrammetric principles in conjunction with image GPS log file data and exterior orientation information from the on-board cameras to refine the estimate of the position and orientation of individual images. The resulting image is an orthorectified mosaic in 8-bit digital format. This mosaic is later converted to a mosaic of reflectance values by applying a modified reflectance mode method (Clemens, 2012; Zaman, Jensen, Clemens, & McKee, 2014). This radiometric normalization is the ratio of the digital number from the mosaic to the digital number from a spectralon white reflectance panel with known reflectance coefficients, multiplied by the reflectance factor, which accounts for the zenith angle of the sun at the time, date, and location of the photos. The end product is a four-layered image (blue, green, red, NIR) that is geometrically rectified and radiometrically corrected. As for the TIR imagery processing, the collected imagery is also processed in EnsoMOSAIC, and the resulting thermal mosaic is composed of brightness temperature in degrees Celsius. These mosaics are later converted to radiometric temperatures following the procedure of Jensen (2014).
Ground Data Acquisition

Intensive ground sampling of plant N was conducted simultaneously with the AggieAir flights at precise GPS locations. The GPS data were collected using an rtkGPS with < 1 mm precision in a 1 Hz bandwidth (Trimble R8, Global Navigation Satellite System, Dayton, Ohio). Leaves from the fully expanded top-of-canopy area were collected. The samples were placed in paper bags inside an iced cooler and taken for laboratory analysis. In the laboratory, plant samples were analyzed for leaf N content (percent). Each plant sample was dried in an oven at 70°C, dry weights measured and converted into dry biomass (kg/m²), and analyzed for N content.

Relevance Vector Machine (RVM)

The RVM was first introduced in 2000 and comprehensively detailed by Tipping (2001). The RVM is a sparse Bayesian learning algorithm that relies on probabilistic Bayesian principles to produce accurate predictions with a good generalization performance (Tipping, 2001). The original learning algorithm was improved by Tipping and Faul (2003), providing faster learning.

The RVM is based on a linear model where a prediction, y, is given as a weighted sum of x basis functions. The model “learns” the dependence between input and output target with the purpose of making accurate predictions of the target vector y for previously unseen values of x as shown in Equation 1:

\[ y = w^T \Phi(x) + \varepsilon \]  

(1)

Where \( w \) a vector of weight parameters is, \( \Phi(x) = [1, f(x, x_1), ..., f(x, x_N)]^T \) is a design matrix of \( N + 1 \) vectors of kernel basis functions \( f \), and \( \varepsilon \) is the error that for
algorithmic simplicity is assumed to be zero-mean Gaussian with variance $\sigma^2$.

Through training of the RVM, the optimal weights are determined. The few nonzero weights correspond to the so-called relevance vectors that are the sparse core of the RVM model (Tipping & Faul 2003). The optimal parameters are then used to obtain the optimal weight matrix with optimal covariance and mean. Model complexity, overfitting, and computational expenses are controlled by setting weights to zero to induce sparsity (Bachour, Walker, Ticlavilca, McKee, & Maslova, 2014). The mathematical formulation, likelihood maximization, and optimization procedure of the RVM are discussed in detail in Chapter 2. For further reading please refer to Tipping (2001); Tipping and Faul (2003); and Thayananthan, Navaratnam, Stenger, Torr, and Cipolla (2008).

**Generating the Model Inputs and Targets**

Three of the four flights (10 days after planting May 16, early growth June 1, and midgrowth June 9), were used to generate the model training input data. The dataset contains coincident in situ leaf N content and remote sensing reflectance measurements. Each GPSed location where leaves were collected and tested for N content was paired by its corresponding reflectance value. This was achieved by using the ArcGIS 10.2 ArcMap software spatial analyst tool (Extract Multi Values to Points). In addition to the reflectance in the VIS-NIR spectra, additional vegetative indices were generated. The vegetative indices selected for this study were reported to be sensitive in estimating N (Gitelson, Viña, Ciganda, Rundquist, & Arkebauer, 2005; Shanahan et al., 2003). Table 3.1 shows the indices formulations. In preliminary runs, different potential inputs were
explored. However, details on these preliminary runs are not reported in this study because of their low statistical performance. A statistical description of the dataset is presented in Table 3.2.

Table 3.1

**Vegetative Indices Formulation Used for Leaf Nitrogen Estimation**

<table>
<thead>
<tr>
<th>Index</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized difference</td>
<td>( \frac{R_{NIR} - R_{red}}{R_{NIR} + R_{red}} )</td>
<td>Rouse, Haas, Schell, Deering, &amp; Harlan, 1974</td>
</tr>
<tr>
<td>vegetation index (NDVI)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leaf area index(^a)</td>
<td>( \ln \left[ \frac{(NDVI - NDVI_{max})}{(NDVI_{min} - NDVI_{max})} \right] / -0.54 )</td>
<td>Duchemin et al., 2006; Smith, Bourgeois, Teillet, Freemantle, &amp; Nadeau, 2008</td>
</tr>
<tr>
<td>Green NDVI</td>
<td>( \frac{R_{NIR} - R_{green}}{R_{NIR} + R_{green}} )</td>
<td>Buschmann &amp; Nagel, 1993</td>
</tr>
<tr>
<td>Ratio vegetation index</td>
<td>\text{NIR/red}</td>
<td>Jordan, 1969</td>
</tr>
<tr>
<td>Green ratio vegetation index</td>
<td>\text{NIR/green}</td>
<td>Sripada, Heiniger, White, &amp; Meijer, 2006</td>
</tr>
<tr>
<td>(GRVI)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Red/green ratio index (RGRI)</td>
<td>\text{Red/green}</td>
<td>Yang, Willis, &amp; Mueller, 2008</td>
</tr>
<tr>
<td>Simple ratios (SR)</td>
<td>\text{Blue/green}</td>
<td>Birth &amp; McVey, 1968</td>
</tr>
</tbody>
</table>

\(^a\) LAI was calculated empirically and not validated by field measurements.
Table 3.2

Statistical Description of the Dataset Used for Leaf Nitrogen Estimation

<table>
<thead>
<tr>
<th>Index</th>
<th>Range</th>
<th>Mean ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Potential inputs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AggieAir inputs</td>
<td></td>
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</tr>
<tr>
<td>Blue</td>
<td>0.11–0.36</td>
<td>0.15 ± 0.04</td>
</tr>
<tr>
<td>Green</td>
<td>0.20–0.49</td>
<td>0.26 ± 0.05</td>
</tr>
<tr>
<td>Red</td>
<td>0.15–0.51</td>
<td>0.22 ± 0.07</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>0.51–0.61</td>
<td>0.57 ± 0.02</td>
</tr>
<tr>
<td>Thermal (°C)</td>
<td>23.11–36.16</td>
<td>29.88 ± 4.13</td>
</tr>
<tr>
<td>Indices inputs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green NDVI</td>
<td>0.00–0.46</td>
<td>0.35 ± 0.10</td>
</tr>
<tr>
<td>Ratio vegetation index</td>
<td>1.03–3.78</td>
<td>2.70 ± 0.60</td>
</tr>
<tr>
<td>Green ratio vegetation index (GRVI)</td>
<td>1.17–2.74</td>
<td>2.16 ± 0.33</td>
</tr>
<tr>
<td>Red/green ratio index (RGRI)</td>
<td>0.72–1.13</td>
<td>0.81 ± 0.08</td>
</tr>
<tr>
<td>Normalized difference vegetation index (NDVI)</td>
<td>0.00–0.78</td>
<td>0.44 ± 0.12</td>
</tr>
<tr>
<td>Simple ratio (SR)</td>
<td>0.47–0.73</td>
<td>0.56 ± 0.03</td>
</tr>
<tr>
<td>Leaf area index (m²/m²)</td>
<td>0.00–4.23</td>
<td>2.41 ± 0.90</td>
</tr>
<tr>
<td><strong>Target output</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leaf nitrogen (mg/100 mg DT)</td>
<td>0.00–5.36</td>
<td>3.905 ± 0.91</td>
</tr>
</tbody>
</table>

Model Configuration and Performance

Three of the images collected over the study area were used to build the model (May 16, June 1, June 9). The remaining imagery (June 17) was later used to test the model as unseen data scenarios. The RVM code used in this study is based on the MATLAB code provided via Michael E. Tipping’s website. A key feature of this statistical learning algorithm is that it can yield a solution function that depends on only a
very small number of training samples. These are called relevance vectors and are those samples from the training set that have nonzero weights. In the RVM regression model, the weight of each input is governed by a set of hyperparameters that describe the posterior distribution of these weights. They are estimated iteratively during the machine learning training step. The model “learns” the dependence between input and output target with the purpose of making accurate predictions of the target vector, which was the leaf N content in this study.

The model was developed with forward input selection process, in an attempt to only include the input variables of most significance (Guyon & Elisseeff, 2003). In each iteration, inputs with the best statistical performance were added to the set of inputs until no new predictors could be added. The RVM model was tested using six kernel types: Gauss, Laplace, spline, Cauchy, thin plate spline, and bubble. The performance of the model was evaluated by comparing the root mean squared error (RMSE) and the Nash-Sutcliffe efficiency (E); these two parameters have been widely used to evaluate the performance of RVM models. The larger the value of E and the smaller the value of RMSE, the greater the precision and accuracy of the model to predict leaf N. The optimal values of these parameters were selected by trial and error procedure to obtain the best RMSE and E values. The RMSE and E are computed as shown in Equations 2 and 3, respectively:

\[
RMSE = \sqrt{\frac{\sum_{t=1}^{N} (\hat{y}_t - y_t)^2}{N}}
\] (2)
\[ E = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \]  

(3)

where, \( \hat{y}_t \) = predicted nitrogen content; \( y_t \) = measured nitrogen content; \( \bar{y} \) = mean of the observed nitrogen content; \( \bar{\hat{y}} \) = mean of the estimated nitrogen content; and \( N \) = total number of observations.

### Results and Discussion

Each of the six kernel types was tested over a wide range of kernel widths (\(10^5–10^5\)), and RMSE and E were calculated for all of the resulting models to assess their predictive capabilities. An embedded loop in the coding model was developed to represent the forward selection tool. For each type of kernel and its corresponding width, the RVM was first run using all of the 8 inputs, consequently generating all of the needed statistical model performance estimates to assess the model. A set of defined iterations then added, in order, the input with the second best set of statistics, thus including the input the most relevant to the target function. After numerous computational runs, the model with the highest prediction accuracy was selected. The optimal kernel width, kernel type, selected inputs, and statistical performance are presented in Table 3.3.

Of all runs conducted across the six kernel types, the NIR band followed by the GRVI band were the two inputs selected first and second. This finding suggested these two bands in the sensor used possess the most relevant information for estimating leaf N. Canopy reflectance in the NIR regions have reported success at determining crop N
content, due to the ability to detect changes associated with chlorophyll content and decreasing cell layers (Guyot, 1991; Thomas & Oerther, 1977).

Table 3.3

**Selected Model Characteristics**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kernel type</td>
<td>Gaussian</td>
</tr>
<tr>
<td>Kernel width</td>
<td>0.28</td>
</tr>
<tr>
<td>Inputs</td>
<td>Near-infrared (NIR), green ratio vegetation index (GRVI), red/green ratio index (RGRI), simple ratio (SR)</td>
</tr>
<tr>
<td>Root mean square error (RMSE)</td>
<td>0.48 mg/100 mg DT</td>
</tr>
<tr>
<td>Nash-Sutcliffe efficiency (E)</td>
<td>0.76</td>
</tr>
<tr>
<td>Relevance vectors</td>
<td>6</td>
</tr>
</tbody>
</table>

Reflectance in the NIR spectrum has been reported to be sensitive to N estimate over potato (Fava et al., 2009). In addition, when N total biomass is measured in the laboratory by a spectroscopy an NIR band is used for its detection.

As for the GRVI index, a study that was monitoring leaf nitrogen status in rice with canopy spectral reflectance (Xue et al., 2004) reported that the GRVI index (NIR/green ratio) was especially linearly related to total leaf N, independent of N level and growth stage. The study recommended the index to be adopted for nondestructive monitoring of N status in rice plants. As for the RGRI index, Gamon and Surfus (as cited in Gitelson, Gritz, & Merzlyak, 2003) stated that this index is particularly influential in the separation of nonvegetation pixels from vegetation pixels, allowing for easy discrimination between soil (larger red/green ratio) and vegetation (smaller red/green
ratio). To the best knowledge of the authors, the SR index (blue/green) has not been reported to be influential in any attempts of N estimation from canopy reflectance.

The leaf N estimates for the two images used to build the model was developed based the unique characteristic (kernel type, width, and set of inputs) of the selected model. Figure 3.2 illustrates the measured leaf N versus estimated values with a one standard error confidence interval and the residual plot. It is evident from Figure 3.2 that the measured and RVM predicted leaf nitrogen values are in agreement, where most of the values lie within the 95% confidence interval. It is important to mention that zero leaf nitrogen values representing bare soil pixels were successfully assigned a zero value by the RVM predicted model.

The lower plot in Figure 3.2 presents the residual error over the value from the three flights. It is noticeable that the residual errors of the first flight (May 16) are higher than the other two flights (June 1st and 9th). This could be explained by the drastic variation in the percentage of crop cover in the first flight compared to the second and third. In flight one, vegetation was scares and bare soil was more prominent in the imagery. The predictive RVM model performance is superior in full crop cover compared to less homogenous covers.

The leaf N estimate maps for May 16, June 1, and June 9 generated from the model, along with the corresponding true color image, are presented in Figure 3.3.
Figure 3.2. Measured versus RVM predicted leaf nitrogen in the two flights used to build the model (above) and residual plot of the selected mode (below).

As shown in Figure 3.3, the predicted leaf N maps show a visual good agreement with the true-color maps. Two visual comments can be drawn from the imagery in Figure 3.3:

1. The wheel tracks and the access road that are located around the center pivot had no vegetation cover, and the model successfully assigned a near-zero N content to these features.
2. Two high vegetation horizontal and vertical lines protrude in the images. Those were past ditch lines that had been used in flood irrigation activities prior to the conversion of the field to a center pivot system.

Figure 3.3. True-color maps (left), the estimated plant leaf nitrogen estimate map (right).

The greater water content in those areas caused the plants growing along those two lines to be very vigorous. The model estimated higher leaf N content values given to the
plants in these areas.

To explore the behavior of the model with previously unseen data, the June 17 flight was used. Now that the model was established with a defined set of features (inputs, kernel type, kernel width), June 17 data (early flowering stage) were entered in the model to explore the model’s performance when subjected to totally unseen data. The predicted leaf N map is shown in Figure 3.4.

![Figure 3.4. June 17 image in false color (left), and estimated leaf nitrogen map (right).](image)

Again, the predicted leaf N map for the fourth flight showed good association with the 4:2:3 map. Areas of vigorous growth, bare soil, and low vegetation were similar in the maps and represented similar growth patterns. This test reported an RSME of 0.68 mg/100 mg DT and E of 0.61 for this flight. This result showed that the model successfully performed when given unseen data.

This quarter of the field is irrigated by a modern center pivot sprinkler irrigation system with a capacity of 610 GPM. A local upstream reservoir feeds this pivot regularly.
The pivot is automated to spray water every 15 degrees of rotation, creating six distinct manageable areas in this quarter as shown in Figure 3.5.

![Diagram of pivot areas](image)

*Figure 3.5. The six individually manageable areas as defined in this study.*

The estimated leaf N is averaged over the six sectors for the four flown flights. Figure 3.6 is showing the average change in each sector over the course of the cropping season. The highest leaf N are seen in the last imagery (June 17\textsuperscript{th}) coinciding with the early flowering stage in oats. The lowest Leaf N per sector were prominent in the first flight (May 16\textsuperscript{th}) where sparse vegetation was present in sectors three to six.

The information presented in the bar graph in Figure 3.6 aids the farmer in quantifying the leaf nitrogen content among the different sectors during the growing season. This data would be helpful when compared with the fertilization application schedule to assess its efficiency within the different sectors.
Averaging estimates over manageable areas allows the decision maker to consider applying different amounts of fertilizer per sector to better accommodate for the need and specification of the sector. Formatting the output in a form that the farmer can use is another beneficial step in this new field. Providing site-specific, practical recommendations to farmers is the next step in increasing the adoption rate of precision agriculture.

**Conclusion**

This paper presented the application of imagery from AggieAir, a remote sensing platform, combined with machine learning algorithms (RVM) to estimate leaf N content concentration as an important biophysical parameter to be used in precision agriculture. The RVM modeling technique, coupled with forward input selection, was applied to a data set composed of reflectance from high-resolution multispectral imagery (VIS-NIR),
TIR imagery, and vegetative indices, in conjunction with *in situ* leaf N measurements.

Six kernel types were tested over a wide range of kernel widths. Model performance was evaluated by comparing the RMSE and E of various models and later by visual comparison. Leaf N estimation was best achieved with a model of kernel type: Gaussian kernel width: 0.28; selected inputs: NIR, GRVI, RGRI, SR; RSME: 0.48 mg/100 mg DT; E: 0.76; and six relevance vectors. Across all of the model scenarios the NIR band followed by the GRVI band were the two inputs selected, agreeing with the literature. These two bands possess the most relevant information for estimating leaf N. While the model developed was trained and built to estimate leaf N in oats, a similar methodology can be applied to train a predictive model of a different crop type. With the foreseeable high availability and fast development occurring in the high resolution imagery platforms, these estimation models could become more common and further embedded in farmer management tools.

**References**


CHAPTER 4

ASSESSMENT ON THE USE OF AGGIEAIR UNMANNED AERIAL SYSTEM REMOTE SENSING CAPABILITIES TO ESTIMATE CROP EVAPOTRANSPIRATION AT HIGH SPATIAL RESOLUTION

Abstract

Estimation of spatial distribution of evapotranspiration (ET) based on remotely sensed imagery has become of critical importance for managing water in irrigated agriculture at fine spatial scales. Currently, data acquired by conventional satellites (Landsat, Advanced Space borne Thermal Emission and Reflection Radiometer [ASTER], etc.) lack the needed spatial resolution to capture within-farm variability to support crop water-consumption estimates. Newly available remote-sensing technologies, called unmanned aerial systems (UAS), are proving to be able to deliver time-flexible, cost-effective, tailored spatial information for decision-making purposes. In this study, a UAS called AggieAir™ was used to acquire high-resolution imagery in the visible (VIS), near-infrared (NIR, 0.15 m resolution), and thermal infrared (TIR) spectra (0.6 m resolution) for estimation of crop water use or actual ET. AggieAir flew over two study sites in Central Utah and the California Central Valley. The imageries were used as input to an extensively used surface energy balance model designed for Landsat called Mapping Evapotranspiration With Internalized Calibration (METRIC™), and results at AggieAir and Landsat scales were compared. The discussion highlights the difference in ET estimates and the implications of high-resolution ET map availability.
Keywords: Evapotranspiration, Remote Sensing, Unmanned Aerial Systems, High Resolution Imagery, Precision Agriculture, METRIC

**Introduction**

Water scarcity is becoming a major concern in agriculture, and the fear that future water availability might be threatened has been a driving force to improve existing crop water demand assessments. Failing to meet crop water requirements negatively affects vegetative growth, yield, and various product-quality attributes. Water requirements are typically described by the term evapotranspiration (ET). ET is the largest outgoing water flux from agricultural surfaces and the most difficult to measure directly.

ET is the combination of two processes that occur simultaneously: evaporation and transpiration, whereby water is lost to the atmosphere from soil and vegetation respectively. The ET rate is expressed in depth (e.g., mm, inches) per unit time (hour, day). Estimated ET has been widely used in research related to crop water use (Penman, 1948; Thevs, Peng, Rozi, Zerbe, & Abdusalih, 2015), soil water availability prediction (Oki & Kanae, 2006), flood and drought forecasting (Bouilloud et al., 2010; Sheffield & Wood, 2008), and desertification (Zhou, Zhu, & Sun, 2002). Above all, the calculation of the ET rate has become vital in the planning and management of irrigation practices. In agriculture, key water-management decisions focus on knowing when to begin irrigation for the growing season, how often to irrigate, and how much water to apply. In precision agriculture particularly, these critical decisions are often complicated not only by micro weather and climate variability, but also by intrafield variations in soil texture, terrain, and soil fertility. Precision irrigation, a common practice of precision agriculture, has
developed in the last few years practices to assess intra- and interfield spatial variability and to implement site-specific management systems (Arnó, Martínez Casanovas, Ribes Dasi, & Rosell, 2009; Barnes et al., 2000; Bramley, 2010; Sadler, Evans, Stone, & Camp, 2005). These management practices are designed to supply the crop with the needed amount of water at the smallest manageable scale to obtain optimum response. However, ET estimates obtained by various current methodologies are incapable of supporting precision irrigation decisions due to the limitations discussed below.

Traditionally, ET is measured at the either point or farm scale (e.g., lysimeter–point level, and eddy covariance system–farm level). These measurements are problematic because they are average or single values, time consuming, expensive, only applicable to small homogenous surfaces, and incapable of accounting for the dynamic nature of fluxes when dealing with large spatial scales (Kaheil, Rosero, Gill, McKee, & Bastidas, 2008). Therefore, extrapolating ET rates from a single value to a large area decreases the accuracy of the estimation (Mauser & Schädlich, 1998; Petropoulos, Carlson, Wooster, & Islam, 2009). For operational applications, many water managers adopted the methodology of measuring ET published in the Guidelines for Computing Crop Water Requirements (Allen, Pereira, Raes, & Smith, 1998). This method consists of estimating crop ET and land-surface fluxes for a crop canopy using a weather station reference ET and a crop coefficient (Kc), where reference ET is retrieved using the Penman-Monteith method. The Penman-Monteith equation used in this methodology calculates the reference ET over grass, assuming optimum soil moisture conditions and a constant value of surface canopy resistance (Allen et al., 1998). In reality, soil moisture
conditions or surface canopy resistance is neither optimal nor constant. Therefore, it is fundamental to have a spatial distribution of the land-surface fluxes to achieve more accurate ET estimates.

In 1973 Brown and Rosenberg (as cited in Nouri, Beecham, Kazemi, Hassanli, & Anderson, 2013) first used TIR remotely sensed temperature for predicting evapotranspiration; since then, quantitative estimation of ET based on remotely sensed data has evolved rapidly. Imagery collected from different platforms over various temporal and spatial scales in conjunction with meteorological data from ground stations became the most efficient and economic technology in ET estimation (Nouri et al., 2013). Remote sensing technology collects spatially distributed observations of the land-surface fluxes as radiances and temperatures. Radiances and temperatures measured are converted into land-surface characteristics such as albedo, leaf area index (LAI), vegetation indices, surface emissivity and surface temperature. Better estimating these inputs individually results in more reliable ET estimates. All remote sensing based ET estimates make use of the information collected in the TIR, VIS bands (blue, green, and red [BGR]), and NIR spectrum. The TIR band is the most important variable in ET estimates because it plays a crucial role in sensible heat flux, ground heat flux, and the balance of long-wave radiation.

Using remotely sensed satellite imagery (e.g., Landsat, moderate resolution imaging spectroradiometer [MODIS], geostationary operational environmental satellite [GOES], ASTER), algorithms have been developed to estimate ET with various inputs and model-structure complexity. The literature is rich with review papers that categorize,
explain, compare, and discuss the advantages and shortcomings of the different remote sensing based ET estimate methods (Allen, Pereira, Howell, & Jensen, 2011a; Calcagno, Mendicino, Monacelli, Senatore, & Versace, 2007; Contreras, Jobbagy, Villagra, Nosetto, & Puiddefabregas, 2011; Courault, Seguin, & Olioso, 2005; Kustas & Norman, 1996; Li et al., 2009; Liou & Kar, 2014; Van Der Tol & Parodi, 2012). Many of the remotely sensed data techniques are based on the surface energy balance and have been considered the most accurate methods for estimating ET over spatially varying areas. Of the energy balance methods, the Surface Energy Balance Algorithms for Land (Bastiaanssen, Menenti, Feddes, & Holtslag, 1998) and METRIC (Allen, Tasumi, & Trezza, 2002, 2007) have been extensively used and tested for operational accuracy in the western United States and other areas in the world (Allen, Tasumi, Morse, et al., 2007; Allen, Tasumi, & Trezza, 2007; Bastiaanssen et al, 2005). METRIC, developed by Allen et al. (2002), is an image processing model for mapping ET as a residual of the energy balance. METRIC uses a self-calibration procedure that involves ground-based hourly reference ET measurements and the selection of extreme (hot and cold) pixels within agricultural surfaces (Gowda et al., 2007). Performance of the METRIC model has been tested by Gowda et al. (2007); Santos, Lorite, Tasumi, Allen, and Ferreres (2008); and Tasumi, Trezza, Allen, and Wright (2005). These studies showed that ET estimates derived from METRIC were comparable with data derived from soil moisture budget and lysimeter.

Despite the advantages of using remote sensing techniques to measure ET, several disadvantages have been reported (Allen, Pereira, Howell, & Jensen, 2011a, 2011b;
Challenges are common for researchers using various remote sensing platforms like Landsat (Allen et al., 2002; Moran, Jackson, Raymond, Gay, & Slater, 1989), MODIS (Zhang & Wegehenkel, 2006), and aircraft-based remote sensing (Chávez, Neale, Hipps, Prueger, & Kustas, 2005; Gómez, Olioso, Sobrino, & Jacob, 2005; Jacob et al., 2002a; Neale, Jayanthi, & Wright, 2003). These limitations include (a) dealing with heterogeneous pixels, which leads to uncertainties of land-surface variables; (b) the recurrence of satellite passage, which results in missed opportunities for addressing plant needs in a timely fashion; (c) and the high costs associated with obtaining high-resolution images, particularly airborne images (Allen et al., 2011b; Boegh et al., 2009; Chen et al., 2005; Courault et al., 2005; Jiang et al., 2009; McCabe & Wood, 2006; Min & Lin, 2006; Mutiga et al., 2010; Rana & Katerji, 2000; Stisen, Sandholt, Nørgaard, Fensholt, & Jensen, 2008; Wu, Cheng, Lo, & Chen, 2010). These limitations are most significant when the estimates are intended for use in precision agriculture.

A potential remote sensing platform that could overcome some of these limitations is the unmanned aerial vehicle (UAV) system capable of acquiring high-resolution imagery in the VIS, NIR and TIR bands. Some of the most attractive features of UAVs include high spatial resolution and lower operating costs (Berni et al., 2009). These characteristics make this platform particularly suitable for agricultural application, where multitemporal flights are required for management applications and high resolution is crucial for recognizing the inherent spatial variability associated with crops.
UAV use is currently increasing due to the advantages mentioned (Baluja et al., 2012; Chiabrando, Lingua, & Piras, 2013) and because it has been successfully used to research other agricultural topics (Berni, Zarco-Tejada, Suárez, González-Dugo, & Fereres, 2009; Demarez, Duthoit, Baret, Weiss, & Dedieu, 2008; Johnson et al., 2003; Pinter et al., 2003; Zarco-Tejada, Berni, Suárez, & Fereres, 2008). Other studies (Jacob et al., 2002a; Kustas et al., 2003; Kustas, Jackson, Prueger, MacPherson, & Wolde, 2004; McCabe & Wood, 2006) evaluated the scale influences on the estimation using remotely sensed data using conventional satellite platforms (e.g., Landsat 7, MODIS, ASTER, airborne), Nevertheless, remotely sensed data acquired by UAVs has yet to be explored in ET estimation applications.

The main objective of this study was to investigate the compatibility of using high-resolution data (15 cm) acquired by a UAV system called AggieAir in conjunction with a modified version of METRIC. The developed ET estimate was compared to the Landsat 8 derived ET. The paper describes the UAV platform as well as the processing chain from designing the flight plan to orthorectification and lastly radiometric calibration.

Data Collection

Site Description

The study was conducted in the summer of 2013 over Site S and the summer of 2014 over Site G (see Figure 4.1). Site S is 80 hectares of privately owned agricultural land in Scipio, Utah (39°14'N 112°6'W at 1628 m). The plot, mainly composed of loamy clay soil, is equipped with a center pivot sprinkler for irrigating and planted with oats.
(Avena sativa) and alfalfa (Medicago Sativa). Site G is a 70-hectare commercial vineyard located in Lodi, California (43°38'N, 116W at 40 m) in a wine-producing region, under Mediterranean–continental climate. Site G is planted with pinot noir (Vitis vinifera) vines, grafted on 110R rootstock, and trained to the Geneva Double Curtain trellis. Vine spacing was 2 m between rows and 1.5 m in the row. Irrigation was applied during the growing season through drip irrigation. Standard management practices were applied in this vineyard. Global radiation, wind speed, air temperature, and humidity were acquired by a meteorological station located on each site.

Figure 4.1. The location of the study areas in Scipio, Utah, and Lodi, California.

UAV Description

AggieAir is a UAS designed to carry camera payloads to acquire aerial imagery. The UAS aircraft is battery powered and equipped with a payload system (which includes three cameras and a computer), avionics, two inertial sensors (a GPS module and an inertial measurement unit), radio controller, and flight control (see Figure 4.2). The aircraft is propelled using an electric, brushless motor. It does not require a runway and
can be flown autonomously or manually. In autonomous mode, the aircraft follows a
preprogrammed flight plan containing navigation waypoints defined by GPS and altitude.
While operational, the payload computer instructs the three cameras to acquire imagery
in the VIS, NIR, and TIR spectra and records the position and orientation of the aircraft
when each image is taken. See Table 4.1 for specifications.

Figure 4.2. Details of AggieAir airframe.

Table 4.1

<table>
<thead>
<tr>
<th>Specification</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight duration</td>
<td>45–60 min</td>
</tr>
<tr>
<td>Flight altitudes</td>
<td>200–1000 m</td>
</tr>
<tr>
<td>Maximum takeoff weight</td>
<td>6.35 kg</td>
</tr>
<tr>
<td>Visible/near-infrared spectrum resolution</td>
<td>6–25 cm</td>
</tr>
<tr>
<td>Thermal resolution</td>
<td>30–150 cm</td>
</tr>
<tr>
<td>Wing span</td>
<td>2.5 m</td>
</tr>
</tbody>
</table>
Sensors Description

The VIS camera used in AggieAir is a Canon S-95, with a 10-megapixel CCD sensor and an ISO range of 80 to 3200. The NIR camera is an identical Canon S-95, modified by replacing the manufacturer’s optical filter with a Wratten 87 NIR filter that allows NIR wavelengths of 750 nm. AggieAir also carries a small, low-power, microbolometer thermal camera from Infrared Cameras, Inc. (2014). The corresponding relative spectral responses is shown in Figure 4.3.

![Relative Spectral Response](image)

*Figure 4.3. Relative quantum response of the VIS-NIR (left) and thermal camera (right). VIS-NIR = visible/near-infrared; ICI = Infrared Cameras, Inc.*

Flight Details

On June 9, 2013 and August 9, 2014 Site S and G, respectively, were flown by AggieAir. Flights occurred following the Landsat image acquisition protocol, close to
solar noon (between 11 a.m. and 1 p.m.). The flight time (beginning to end) ranged from 30–40 minutes. Sensors used were Canon S95 cameras and an ICI 9000 TIR camera.

Images were collected in the VIS-NIR spectrum at a spatial resolution of 0.15 cm and at 0.60 cm for the TIR. The UAV was flown at an altitude of 450 m acquiring a total of 165 images from Site S and 240 images from Site G.

**Processing Chain of AggieAir**

The process chain in AggieAir mapping consists of the following steps: mission planning, image processing and orthorectification, reflectance calibration, and thermal data calibration. Each is described in detail.

**Mission Planning**

The two flight missions were planned with AggieAir Mission Complete, a tool built by the AggieAir team that uses the open source World Wind SDK from NASA software. The flight routes were designed over the two sites by accounting for three major parameters: flight area (site dimension), camera specifications (focal length), and the desired overlap in the imagery. A longitudinal overlap of 70% and a lateral overlap of 60% have been adopted while flying at 450 m altitude. Once all this information and the flight altitude were introduced in the module, it automatically generated the flight route and estimated the flight duration according to the total number of images planned. The route file is exported to a memory card embedded in the UAV via a standard serial link.
**Image Processing and Orthorectification**

Following image acquisition, all images are imported into AggieAir Mission Complete for further cleaning of the flight lines. In this process all the images collected outside the area of interest, captured before reaching the desired altitude, or captured in an oblique manner are deleted. The remaining images are stretched and made ready to be combined into a single image. The process of stitching the imagery and geometrically correcting it to align with geospatial coordinates is called orthorectification. A photogrammetric software named Agisoft PhotoScan was employed for this task. In Agisoft, the software generates hundreds of tie-points between overlapping images by using photogrammetric principles in conjunction with image GPS log file data to automatically align and orthorectify the imagery. To further refine the estimate of the image position and orientation of individual-image ground control points (GCPs), control points located within the area of interest were surveyed with an RTK GPS and added to the image for further accuracy in the geo-referencing procedure. The outputs from Agisoft are a four-band (BGR, NIR) orthorectified mosaic with digital numbers, a TIR orthorectified mosaic with brightness temperature, a digital terrain model derived by creating a mesh from a simplified and filtered version of the point cloud, digital surface model, a high-density point cloud that makes details easily recognizable, and a detailed summary report. An example of the summary report is shown in Figure 4.4, which demonstrates camera positioning and overlapping in addition to other details related to the software processing algorithm.
Figure 4.4. An example of the summary report, the number of overlapped images range from 1 to 9 per frame. The black dots represent the center of the frame collected over the four flight lines.

**Radiometric Calibration**

Radiometric calibration is a process of converting digital numbers into a measure of reflectance. The radiometric quality of the images is critical in order to enable the application of quantitative remote sensing methodologies for a successful estimation of biophysical parameters from remote sensing imagery (Berni et al., 2009). AggieAir follows the reflectance mode method conversion, which is based on methods adapted from the research (Crowther, 1992; Miura & Huete, 2009; Neale & Crowther, 1994) and discussed in detail by Clemens (2012). In this method the ratio of digital number mosaic
to the digital number from a Spectralon white reflectance panel is multiplied by the panel reflectance factor, as shown in Equation 1. After learning that the new Labsphere is a perfect Lambertian surface that does not need to account for sun angles or time of day, weighted averages over the range of each band in the sensor were calculated using Labsphere’s reflectance factor report. An updated reflectance factor was calculated, and the product of this method was an orthorectified mosaic in reflectance values.

\[ R_r = \frac{D N_T(t)}{D N_R(t)} R_R \]  

(1)

where: \( D N_T(t) \): digital numbers in mosaic at the time \( t \); \( D N_R(t) \): digital number from panel at the time \( t \); \( R_R \) is the reflectance factor of the reference panel with respect to a Lambertian surface of unit reflectance.

**Thermal Calibration**

TIR data are measured as brightness temperature by the sensor embedded on the AggieAir payload. After data collecting the imagery, these measurements are corrected and calibrated to account for various errors. Errors are introduced in the measurement from the convection across the lens during the course of the flight. To develop the correction equation, GCPs were collected simultaneously with the flights over the two sites. The field data collection procedure was designed to acquire three GCP temperature measurements over various sampling surfaces (e.g., high vegetative crops, inter-row crops, bare soil, top of the vines canopy, etc.). For every GCP frame (a) TIR imagery is collected by AggieAir at an elevation of 450 m on average, (b) TIR imagery is collected by an identical sensor mounted on a moving vehicle from an elevation of 3 m, and (c) an
ambient absolute temperature is measured by a Blackbody instrument placed on the GCP.

Figure 4.5 is an example of two measurements collected.

![Figure 4.5](image)

*Figure 4.5.* An example of a ground control point (GCP), high vegetation, needed for calibration of thermal infrared (TIR) data. A picture of the GCP is captured right, a TIR imagery from a 3 m elevation in the middle, and the Blackbody reading on the left.

Since the Blackbody emissivity is 0.95 and not 1.0 like the TIR sensors, adjustment to the Blackbody reading was necessary. Equation 2 describes the correction done on the Blackbody readings.

\[
T_{bb\_corr} = T_{bb} \cdot \left(\frac{1}{BB\_emissivity}\right)^{1/4}
\]

Where: \(T_{bb\_corr}\) = corrected temperature of the blackbody; \(T_{bb}\) = reading of the blackbody; \(BB\_emissivity\) = Blackbody emissivity. The collected data were used to develop a correction equation used to produce radiometric temperature.

**Models: METRIC and METRIC High Resolution (METRIC-HR)**

METRIC was selected as the base model to investigate the capability of AggieAir data in estimating ET because it has been tested with operational applications in Idaho, California, and Colorado and because of the researcher’s knowledge and expertise in this model. A brief description of the original METRIC algorithm and the modified version
called METRIC-HR is provided below. A more detailed description of METRIC can be found in the applications manual (Allen, Tasumi, Trezza, & Kjaersgaard, 2010). The version of METRIC used in this study is METRIC v 2.0.8 (developed March 2012).

METRIC

METRIC algorithm is a satellite image processing model whose approach is based on the rationale that ET is a change of the state of water using available energy in the environment for vaporization (Su, McCabe, Wood, Su, & Prueger, 2005). This energy is partitioned into net incoming radiation, ground heat flux, sensible heat flux, and latent heat flux. METRIC estimates spatially distributed values of actual ET as the residual of the energy balance (Allen et al., 2007):

\[ LE = R_n - G - H \]  \hspace{1cm} (3)

where

- \( LE \) = heat flux density (W m\(^{-2}\));
- \( R_n \) = incoming radiation flux density (W m\(^{-2}\)) and is calculated by solving the radiation balance as described by (Allen, Tasumi, & Trezza, 2002)
- \( G \) = soil heat flux density (W m\(^{-2}\)) and is estimated as a function of sensible heat flux \( H \), net incoming radiation \( R_n \), surface temperature, and the normalized difference vegetation index (NDVI) and LAI.
- \( H \) = sensible heat flux density (W m\(^{-2}\)) and is estimated as a function of air density (kg m\(^{-3}\)); air specific heat (J kg\(^{-1}\) K\(^{-1}\)); temperature difference between two heights; the aerodynamic resistance to heat transport (s m\(^{-1}\)); and
temperature gradient between two near-surface air temperatures (K), generally approximated at 0.1 m and 2 m above the canopy (Bastiaanssen et al., 1998).

The sensible heat flux is considered to be the most difficult term in the energy balance equation to calculate using remote sensing; thus, computing $H$ might require multiple iterations. A strong linear relationship exists between $dT$ and the radiometric surface temperature (Allen, Tasumi, & Trezza, 2007; Bastiaannssen et al., 1998, 2005; Jacob et al., 2002a). The relationship can be expressed in Equation 4:

$$dT = a + bT_s$$  \hspace{2cm} (4)

where $a$ and $b$ are empirically derived parameters based on two extreme conditions pixels, termed *hot* and *cold* pixels. These anchor pixels define the upper and lower bounds of the sensible heat flux in the study area and thus the gradient. The cold pixels should represent well-watered and fully vegetated areas of the image, where no water stress is present such that $H$ is assumed to be minimal and ET maximum or near maximum. As for the hot pixel, it should be located in a dry and bare agricultural field where the evaporative flux is almost zero, thus $H$ dominating the turbulent fluxes. Once surface temperature, $T_s$, and $dT$ are calculated corresponding to hot and cold conditions, the linear relationship as indicated in Equation 4 is defined. To effectively select reasonable cold and hot anchor pixels, the user must be skillful and understand the principles associated with the energy balance. For further details, refer to (Allen, Tasumi, Trezza, & Kjaersgaard, 2010).
METRIC-HR

Since METRIC is designed to use Landsat 8 imagery as inputs, a few adjustments were made to accommodate the high-resolution AggieAir input data. These modifications are described below.

**Digital elevation model (DEM) and DEM high resolution (DEM-HR).** To account for the various topography of a site, METRIC incorporated a DEM. This DEM is used to adjust surface temperatures for lapse effects caused by elevation variation as well as in estimating solar radiation on slopes. The 30 m resolution DEM used in the original METRIC is downloadable from the U.S. Geological Survey website. In METRIC-HR a DEM-HR of 15 cm replaced the original coarse DEM. The DEM-HR was generated with Agisoft software extension tool. Note that the two versions of the models use DEM term to refer to the digital terrain model.

**National Land Cover Database (NLCD) and NLCD high resolution.** Another basic input file needed to run METRIC is land use maps. The NLCD maps hold land cover information. Those maps are also used to support the estimation of aerodynamic roughness and soil heat flux during METRIC processing. In METRIC-HR a high-resolution NLCD of 15 cm replaced the original coarse NLCD. A supervised classification was performed on the NDVI maps to identify vegetation, roads, urban infrastructure, and other features present in the high-resolution imagery. The obtained classes were used to develop the NLCD high-resolution maps.

**Shortwave infrared (SWIR) bands.** METRIC requires the usage of the SWIR band acquired by Landsat 8. SWIR is used to calculate the normalized difference water
index primarily to identify water, for it tends to give values less than zero for water and snow and is therefore a more reliable water indicator than NDVI. However, water and snow do not exist in either study site, and therefore the absence of SWIR has no effect on the processed model. To ensure the model ran smoothly a pseudo null band replaced the SWIR in METRIC-HR. In addition, METRIC incorporated the SWIR bands in the albedo estimations; this was neglected by METRIC-HR, for albedo was estimated solely over the available four bands: BGR and NIR.

**Thermal band resampling.** The thermal band acquired by AggieAir is of 60 cm spatial resolution. METRIC requires all bands used in the model to have identical resolution; therefore, resampling the TIR data was necessary. The resampling was performed using the nearest neighbor resampling method in ESRI’s ArcGIS 10.2 ArcMap software. Nearest neighbor resampling is a technique of raster data resampling where each cell in an output raster is computed using the values of the nearest pixel in the input image. This particular approach was selected as it does not alter the original pixel’s value (Duggin & Robinove, 1990; Lillesand & Kiefer, 2000).

**High-resolution VIS data.** Landsat 8 shortwave radiance imagery (BGR) is replaced by high-resolution shortwave in METRIC-HR. However, AggieAir sensor acquires the BGR reflectance’s with a consumer-grade sensor whose spectral relative response is different from Landsat 8, as shown in Figure 4.6.

Comparing the AggieAir and Landsat reflectances in the BGR spectrum revealed that AggieAir reflectances were relatively higher than Landsat’s with a consistent trend in both imagery of Site S and Site G. Therefore, a correction to the AggieAir reflectance in
the BGR spectrum was developed as described below. This process included two steps: (a) upscaling AggieAir BGR using Landsat 8 point spread function (PSF) and (b) developing the individual correction equations.

Figure 4.6. Landsat 8 and AggieAir relative spectral response.

**Upscaling AggieAir BGR using Landsat 8 PSF.** Several studies noted that upscaling using the PSF produces reliable upscale data (Goforth, 1998); hence, this methodology was adopted. The PSF of an imaging system is a measure of the amount of blurring that occurs due to all of the components that comprise the imaging system (Wenny et al., 2015). In other words, PSF assumes that the spectral information in a pixel does not originate solely from within its footprint; a substantial portion comes from surrounding areas (Forster & Best, 1994; Huang, Townshend, Liang, Kalluri, & DeFries, 2002; Townshend & Tucker, 1981). PSF is computed as the square modulus of the field.
amplitude on the focal plane; the amplitude function, in turn, is built through the
diffraction integral, derived from the wave description of electromagnetic radiation (Gai
& Cancelliere, 2007). Landsat 8 PSF was developed by the team at U.S. Geographical
Survey Earth Resources Observation Systems Data Center and NASA Goddard Space
Flight Center. Using the data they provided, Figure 4.7 represents the PSF of the three
bands (BGR).

![Figure 4.7. Landsat 8 point spread function (PSF) along the blue, green, and red (BGR)
bands (left); Landsat 2D PSF representation on the right.](image)

A squared matrix of 210 x 210 m slides over the AggieAir imagery every 30 m,
multiplying each pixel by its corresponding weight according to the PSF. The upscaling
equation is described in Equation 5.

$$\rho_{30m} = \sum_{PSF} \rho_{0.15m}$$

After upscaling the BGR bands to 30 m, a linear equation was identified that
depicts the linear relationship between the 30 m upscale AggieAir and Landsat 8. Table
4.2 presents individual equations used to correct the 30 m upscale AggieAir. Note that the correction was performed on the VIS (BGR) bands and not on the NIR band. Given the nature of the long pass filter on the NIR band, no correction was performed or required.

Table 4.2

The Developed Correction Equations for Each Band

<table>
<thead>
<tr>
<th>Band</th>
<th>Site G</th>
<th>Site S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>$y = 0.62x - 0.06 \ (r^2 = 0.95)$</td>
<td>$y = 0.58x - 0.04 \ (r^2 = 0.99)$</td>
</tr>
<tr>
<td>Green</td>
<td>$y = 0.51x - 0.01 \ (r^2 = 0.89)$</td>
<td>$y = 0.47x + 0.01 \ (r^2 = 0.92)$</td>
</tr>
<tr>
<td>Red</td>
<td>$y = 0.39x + 0.02 \ (r^2 = 0.90)$</td>
<td>$y = 0.42x + 0.02 \ (r^2 = 0.94)$</td>
</tr>
</tbody>
</table>

Albedo

Surface albedo is defined as the fraction of incident solar energy (diffuse and direct components) reflected both in all directions above the surface and over the whole solar spectrum (Jacob & Olioso, 2002; Jacob et al., 2002b; Pinty & Verstraete, 1992). The in situ albedo is calculated as the ratio of reflected to incoming solar radiation measurements; however, such data were not collected from either site to calculate albedo. Estimating albedo from remote sensing imagery has its challenges, bidirectional reflectance distribution function being one of them. This phenomenon may result in over- or underestimating of albedo. An overestimate of albedo by 20% occurs when the sun and sensor angles match, thus resulting in higher canopy reflectance (Liu et al., 2009). Conversely, when solar angle is substantially different from the sensor view angle, albedo can be less than hemispherical albedo (Allen et al., 2011b). The bidirectional reflectance
distribution function is corrected for MODIS-based albedo retrievals but not for Landsat (Salomon, Schaaf, Strahler, Gao, & Jin, 2006). Acknowledging this phenomenon, METRIC determines the albedo as a weighted average of the shortwave bands based on the percentage of total at-surface radiation occurring with each band (Tasumi, Allen, & Trezza, 2008). METRIC weighting coefficients proposed are for low-haze atmospheric conditions and are optimized for Landsat images. Equation 6 represents the weighting coefficients associated with the Landsat bands for calculating albedo (Tasumi et al., 2008).

\[ \alpha_{\text{short}} = 0.254\alpha_1 + 0.149\alpha_2 + 0.147\alpha_3 + 0.311\alpha_4 + 0.103\alpha_5 + 0.036\alpha_6 \] (6)

where \( \alpha_{\text{short}} \) is the albedo and \( \alpha_n \) is the at-surface reflectance calculated for each Landsat shortwave band.

Knowing the importance of the albedo values in selecting the extreme pixels needed to properly run the model, customized albedo coefficients were developed. A linear relationship between Landsat albedo and AggieAir reflectances was established as shown in Equation 7.

\[ \alpha_{\text{short}} = 0.716\alpha_{\text{blue}} - 0.744\alpha_{\text{green}} + 0.538\alpha_{\text{red}} + 0.6555\alpha_{\text{NIR}} \] (7)

Equation 7 was developed using the total number of 30 m pixels in the imagery from both sites. These pixels included vines, vegetation, dry soil, and wet soil pixels. The linear regression showed a residual error of root mean square error of 0.007 and an \( R^2 \) of 0.88. Figure 4.8 shows a 1:1 plot of the albedos from Landsat and AggieAir over the two sites. Note that the graph has two clusters visually; the lower left cluster of pixels form Site S, and the upper right cluster are the pixels from Site G.
In theory the sum of coefficients should have a value close to 1, and coefficients should be positive. However, when comparing the derived coefficients with Landsat

Figure 4.8. 1:1 Plot of the albedo from AggieAir and Landsat.

coefficients in the green band, a change of sign was noticed. Nevertheless, a similar negative response in the green band was also reported in the study by Jacob and Olioso (2002) that derived albedo coefficient from airborne platforms.

Results and Discussion

Hot and Cold Pixel Selection

Identifying the hot and cold pixels requires expertise and time to select a reliable representation of the anchor pixels. Various sensitivity analyses reported that selecting different hot and cold pixels leads to large deviations in final ET estimates (Wang et al., 2009). The researchers properly select the hot and cold pixels that satisfy the assumptions
made in METRIC, such that the linear correlation between the near surface temperature difference and remotely sensed surface temperature holds true.

METRIC recommends for the cold pixel to be located in a homogenous well-watered, full-cover crop in the image with an NDVI range of 0.76–0.84 and a surface albedo range of 0.18–0.24. As for the hot pixel, METRIC recommends that the hot anchor pixel should be selected in homogenous bare and dry or nearly dry agricultural soil with little or no vegetation, with an NDVI range no higher than 0.2 and a surface albedo range of 0.17–0.23. Further details on the selection of the two pixels are described by Allen, Tasumi, Morese, et al. (2007) and Allen (2008).

All four anchor points were selected from the perimeters of a common overlapping area. The values of the NDVI, albedo, LAI, surface temperature, and the coefficients for Equation 4 are reported in Table 4.3. Note that the sensitivity of the selection of the hot/cold pixels in this study wasn’t performed.

The hot pixel in Site S, planted with alfalfa mainly, was selected from the clear, bare soil area inside the northern center pivot. As for the cold pixel, more than one candidate pixel were considered, for the crop was homogenous with full land cover in various locations in the imagery. The cold pixel was selected from the northern part of the southern center pivot. Both anchor pixels lay in the METRIC recommended ranges of NDVI and albedos.

However, Site G, dominated with vineyard canopies, presented different challenges in the selection process. Challenges were closely linked to the specific geometrical canopy structure and the radiation balance pattern. The vineyard’s unique
characteristics are standing grape canopy, variable shaded areas, wide spacing between
rows, discontinuous soil cover, and various vertical leaf thickness.

Table 4.3
Details on the Selected Hot and Cold Pixels from the AggieAir and Landsat Imagery

<table>
<thead>
<tr>
<th>Source</th>
<th>Albedo</th>
<th>NDVI</th>
<th>LAI</th>
<th>$T_s$</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site S</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AggieAir</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot pixel</td>
<td>0.264</td>
<td>0.254</td>
<td>0.149</td>
<td>319.983</td>
<td>0.14270</td>
<td>-39.7412</td>
</tr>
<tr>
<td>Cold pixel</td>
<td>0.233</td>
<td>0.869</td>
<td>5.345</td>
<td>308.406</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot pixel</td>
<td>0.177</td>
<td>0.277</td>
<td>0.824</td>
<td>327.481</td>
<td>0.1176</td>
<td>-31.9722</td>
</tr>
<tr>
<td>Cold pixel</td>
<td>0.229</td>
<td>0.868</td>
<td>6.000</td>
<td>308.489</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Site G</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AggieAir</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot pixel</td>
<td>0.320</td>
<td>0.370</td>
<td>0.444</td>
<td>332.395</td>
<td>0.19919</td>
<td>-63.3236</td>
</tr>
<tr>
<td>Cold pixel</td>
<td>0.238</td>
<td>0.910</td>
<td>6.000</td>
<td>300.355</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hot pixel</td>
<td>0.164</td>
<td>0.174</td>
<td>0.038</td>
<td>322.885</td>
<td>0.25852</td>
<td>-78.2922</td>
</tr>
<tr>
<td>Cold pixel</td>
<td>0.226</td>
<td>0.838</td>
<td>5.338</td>
<td>305.076</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. LAI = leaf area index; NDVI = normalized difference vegetation index.

All these variables create complex dynamics that generate a spatial heterogeneity
in the horizontal distribution of energy at the soil surface; thus, finding a homogenous area
that fulfills the METRIC recommendation was a challenge to the end user. The albedo and
NDVI for the hot pixel exceeded the recommendations, possibly due to the lack of a
prominent bare soil area within the vineyard. The hot pixel was chosen from the northwest
side of the vineyard, which was distinguishable by the leafless vines, part of a separate
yield study.
METRIC Results

Landsat 8 cloud-free satellite images were obtained from the U.S. Geological Survey Earth Explorer site (http://earthexplorer.usgs.gov) for June 9, 2013 and August 9, 2014. The images were processed using the ERDAS Imagine 2014 software. METRIC was applied on the corresponding Landsat imagery of Site G and Site S to obtain instantaneous and daily reference ET fraction (ETrf) maps. Maps of reflectance of shortwave radiation, vegetation indices (NDVI and LAI), surface temperature, net radiation, and soil heat flux were generated as intermediate products during METRIC processing. The final outputs from the METRIC energy balance model were images showing instantaneous ETrf (fraction of alfalfa-based reference ET) at the satellite overpass time. Instantaneous ETrf produced after running METRIC over Site G and Site S are shown in Figures 4.9 and 4.10, respectively.
Figure 4.9. Site S: Landsat reflectance in false color (left), Mapping Evapotranspiration with Internalized Calibration (METRIC) reference evapotranspiration fraction (EtrF) output (right).
Figure 4.10. Site G: Landsat reflectance bands in true color (left), Mapping Evapotranspiration with Internalized Calibration (METRIC) reference evapotranspiration fraction (ETrf) output (right).

METRIC-HR Results

METRIC-HR was run with the AggieAir derived inputs including corrected reflectance (BGR, NIR), TIR band, DEM-HR, NLCD high resolution, albedo, and NDVI. The resulting instantaneous ETrf images are shown in Figures 4.11 and 4.12.
In figure 4.11 it is clear that the “crop coefficient” $K_c$, also known as “reference ET fraction” $ET_{rf}$, follows a similar spatial pattern as its corresponding false color and TIR imagery. The values of the crop coefficient ranged between 0 and 1.15, with patterns of ET linked to canopy temperature and cover. Lower values of $K_c$ corresponded to hotter areas where bare soil is mainly found, particularly in the outer surroundings of the two center pivots and in the unplanted quarters in the northern center pivot. Higher values of $K_c$ are prominent in wet areas (one can see the pivot arm in the northern plot). Areas of cooler temperatures where crops are homogenous and crop cover is dense have higher $K_c$ values.
Figure 4.12. Site G: AggieAir reflectance bands in true color (left). Mapping Evapotranspiration with Internalized Calibration (METRIC) reference evapotranspiration fraction (ETrf) output (center) TIR (Celsius) map (right).

Figure 4.12 represents the Ke estimates from site G derived from the AggieAir imagery. Considering that the vines planted in site G are all of the same type (Pinot noir), similar growth stage and irrigated in a similar fashion (drip irrigation), there still exist a variation in crop water demand within the field. This variation could be explained by the different soil types present in the vineyard.
Comparison in Site S

Site S is irrigated by two modern, center-pivot sprinkler irrigation systems with a capacity of 610 GPM each. A local upstream reservoir feed these two pivots regularly. The pivots are automated to spray water every 15 degrees of rotation, creating 24 distinct manageable areas in each center pivot as shown in Figure 4.13. The arcs are labeled from 1–48 covering the two center pivots.

*Figure 4.13. Site S: Mapping Evapotranspiration With Internalized Calibration high resolution (METRIC-HR) reference evapotranspiration fraction (ETrf) on left, METRIC ETrf on right, both showing the 48 manageable arcs as defined in this study.*
ETrf estimates were averaged over each sector. The obtained measurements from the northern center pivot are shown in Figure 4.14.

Figure 4.14. Northern center pivot reference evapotranspiration fraction (ETrf) estimates from Landsat and AggieAir inputs.

METRIC-HR resulted in a higher ETtrf estimated, except for Sectors 20 and 21. This could be partly explained by the presence of pixels of multiple vegetation growth with significant differences in cover (2 m and 15 cm alfalfa crops); a variation of surface roughness is most prominent in these two sectors. However, identical results were obtained from Sectors 1 and 13. These two sectors are the wettest sectors in the northern center pivot, where the spraying arm could be seen in the high-resolution imagery.
Sectors 1 and 13 are also surrounded with vegetation outside the center pivot, resulting in an extended homogenous land cover. The maximum difference in estimates occurs in sector 7 (20% difference).

A similar analysis was performed on the southern center pivot. The averaged ETrf over the sectors were plotted from the two tested models, as shown in Figure 4.15.

![Southern Center Pivot](image)

**Figure 4.15.** Southern center pivot reference evapotranspiration fraction (ETrf) estimates from Landsat and AggieAir inputs.

In the southern center pivot a more homogenous crop cover was observed. ETrf data derived from AggieAir imagery estimated higher ETrf across all sectors of the center
pivot. This could be explained by the surrounding dry landscape of the center pivot; these peripheral mixed pixels lowered the average ET estimates in the sectors. The averaging in each sector included the field edges where pixel contamination can cause METRIC ET estimates to deviate from the field average (Allen, Tasumi, & Trezza, 2007).

A comparison between $E_{Trf}$ estimates derived from Landsat and AggieAir data is presented in Figure 4.16. These values were close and had a 0.90 coefficient of correlation.

![Figure 4.16. Site S: Comparison between reference evapotranspiration fraction ($E_{Trf}$) estimates derived from Landsat and AggieAir data in the northern and southern pivots](image.png)

ETrf estimates obtained from the both the high resolution imagery and the Landsat imagery, showed a high correlation (0.9) in the two center pivots. This implies
that both the METRIC-HR and METRIC models showed similar performance capabilities. The high resolution imagery was superior in the mixed pixel areas (bare soil and vegetation) specifically in the pixels in the outer contour of the center pivot. The northern center pivot in this site study had a more heterogeneous surface compared to the southern pivot. As a result, with respect to the northern pivot, a high resolution ET estimates would be more beneficiary compared to the southern pivot.

**Comparison in Site G**

Site G, a well-maintained vineyard, is irrigated by drip system. The irrigation design divides the vineyards of groups of 30–40 rows on average, each group creating a block. There are 19 blocks in the vineyard. Each block can be regulated independently with a ball valve upstream of the pressure regulator. The block is considered as the smallest manageable area in this study. The distribution of the blocks is visualized in Figure 4.17 as well as the ET_{rf} estimates of AggieAir and Landsat.

To test the results of the spatially distributed ET_{rf} estimates, all the pixels lying within the blocks were averaged. The average represented a single water demand that needs to be met by the water applicators.

The ET_{rf} estimates obtained from both models are shown in Figure 4.18. Visually, the Landsat ET_{rf} estimate has a more fuzzy appearance. Compared to AggieAir results, Landsat was underestimating ET_{rf} in 12 of the 19 blocks. The comparison of the ET_{rf} estimates generated by both METRIC and METRIC-HR showed the largest differences in Block 19. All the vegetative features in Block 19 are masked by the large Landsat pixel footprint; visually it is not recognizable as a vegetative area.
Figure 4.17. Mapping Evapotranspiration With Internalized Calibration (METRIC) reference evapotranspiration fraction (ETrf) on left, METRIC high resolution ETrf in middle, and 19 blocks of individual manageable areas on right.

The high-resolution AggieAir imagery enabled the METRIC-HR to sense evaporation occurring from the smallest block (Block 19), where METRIC could not.
The two estimates showed a correlation coefficient of .73. Figure 4.19 shows the two estimates plotted against each other.

*Figure 4.18.* The average reference evapotranspiration fraction (ETrf) estimates from Landsat and AggieAir inputs for each block.
Conclusion

The objective of this study was to assess the use of AggieAir, an unmanned aerial system, to estimate crop evapotranspiration at high spatial resolution. A high resolution METRIC (METRIC-HR) was derived from the well-established METRIC algorithm. High resolution inputs (RGB, NIR, TIR, DEM, NLCD) and weather data were used to develop an ET estimates at high resolution (0.15 m). A significant amount of spatial information was retrieved and detailed ET estimates was established over two sites S and G. This work demonstrated that it is possible to generate quantitative remote sensing products by means of a UAV equipped with consumer-grade cameras. However, these consumer-grade cameras require extensive calibration to relate spectral response to another scientific sensor (such as Landsat). The high spatial resolution provided make
this platform particularly suitable for precision agriculture and irrigation scheduling, where site specific critical management is required. The High resolution ET showed is a useful tool to monitor crop growth, and crop water demands when managing heterogeneous surfaces. This model lays the ground for the estimation of ET at high spatial resolution to be used in precision agriculture. The high resolution spatial distribution of ET helped evaluating the efficiency of irrigation applications per the smallest manageable area.

References


CHAPTER 5

SUMMARY

This dissertation has shown how data from consumer-grade sensors acquired by an unmanned aerial system (UAS), AggieAir, could be used in precision agriculture application. The high spatial, spectral, and temporal resolution makes this platform particularly suitable for precision agriculture and irrigation scheduling, where time-critical management is required. Chapter 2 presented the retrieval of chlorophyll content from thermal and multispectral optical imagery. A complex statistical regression model (Bayesian relevance vector machine) was trained on a dataset of in situ collected leaf chlorophyll measurements, and the machine learning algorithm intelligently selected the most appropriate bands and indices for building regressions with the highest prediction accuracy. Chapter 3, with a similar methodology to Chapter 2, discussed the estimation of leaf nitrogen content. The predicted estimates were averaged over the smallest manageable unit in the center pivot, thus providing a preliminary actionable information for nutrient management. Chapter 4 investigated the possibility of mapping evapotranspiration using the high spatial resolution data. Appropriate configurations were applied on the Mapping Evapotranspiration With Internalized Calibration algorithm to match the input data. Evapotranspiration estimates from AggieAir inputs were compared to those obtained from Landsat 8 data and showed agreement between the two. The estimates were averaged over the smallest irrigateable unit in the two study sites to assist in a more precise efficient irrigation scheduling. All these estimates, made at such fine resolutions in space and time, can aid farmers in assessing the heterogeneity of their
fields and subsequently implement needed actions accordingly. The high-resolution spatial information generated from AggieAir imagery could enable far greater precision in the application of various production resources (fertilizers, irrigation water). UAS facilitate enhanced monitoring with time-critical account of fine-scale variations in plant health and function.

The final findings presented in this dissertation are in general promising and encourage the development of future improvements. Plenty could be done to improve the collection, processing, and quality of the data. Perhaps the most urgent research topics to address are the automatic georeferencing of imagery, establishing a standardized procedure for orthorectification, and better understanding of the sensors calibration and performances. Also, data acquired by the UAS could be explored in different research within precision agriculture (e.g., crop stress, yield potential, crop disease). In addition, exploring UAS data with physical-based model approaches rather than with statistical and engineering approaches will create more robust algorithms that can be generalized over different kinds of crops. Perhaps closing the link between scientists who generate information from UAS data and farmers by presenting these findings in an actionable manner remains the biggest missing link for further adoption of precision agriculture and a significant research topic that needs to be addressed in future studies.

This work has demonstrated that the technology needed to produce actionable information is possible but unfortunately, the cost embedded in this technology is far from being affordable. The cost of flying the payload, collecting enough representable samples to train the models and processing the data exceeds the limits of the average
farmer and as a result restrain the technology to research purposes only. Another big challenge this technology presents is the big amount of data it produces. The “big data” itself has advantages and short comes. A prominent advantage of “big data” is the knowledge that emerges from the data. Such findings can change, modify or better inform us about the research in question. For example, exploring the TIR data and its relationship with chlorophyll estimation is something that haven’t been widely explored in the community and this finding opened the door to such interest. On the other hand, these “big data” sets are large enough to require supercomputers. Storing, managing and processing these data is beyond the ability of commonly used computers. Perhaps, the most fundamental challenge for big data applications is to explore the large volumes of data and extract useful information or knowledge for future actions.
APPENDIX
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Dear editors,  

I am requesting permissions to my paper in the “International Journal of Applied Earth Observation and Geoinformation”, as a Chapter in my dissertation.  

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From: Inga Maslova <maslova@american.edu>  
Date: Mon, Mar 21, 2016 at 8:02 AM  
Subject: Re: Permission  
To: Manal Al Arab <alarabmanal@gmail.com>  

Dear Manal,  

Yes, you have my permission to include the paper in your thesis.
Sincerely,
Inga Maslova
Assistant Professor
Department of Mathematics and Statistics
American University

On Mar 21, 2016 2:21 AM, "Manal Alarab" <alarabmanal@gmail.com> wrote:
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"ESTIMATING CHLOROPHYLL FROM THERMAL AND BROADBAND MULTISPECTRAL HIGH RESOLUTION IMAGERY FROM AN UNMANNED AERIAL SYSTEM USING RELEVANCE VECTOR MACHINES FOR PRECISION AGRICULTURE"

Best,
Manal

--
Manal Elarab, PhD
Civil and Environmental Engineering
Utah Water Research Laboratory - USU
Phone: +1 (435) 754-9299

From: Alfonso Torres-Rua <a.torres@aggiemail.usu.edu>
Date: Mon, Mar 21, 2016 at 6:48 AM
Subject: Re: Permission
To: Manal Alarab <alarabmanal@gmail.com>

Dear Manal,

You have my permission.

Alfonso

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Best,
Manal

--
Manal Elarab, PhD
Civil and Environmental Engineering
Utah Water Research Laboratory - USU
Phone: +1 (435) 754-9299

From: Andres Ticlavilca <andres.t@aggiemail.usu.edu>
Date: Mon, Mar 21, 2016 at 5:52 AM
Subject: Re: Permission
To: Manal Alarab <alarabmanal@gmail.com>

Dear Manal

You have my permission.

Best regards,

Andres

On Mon, Mar 21, 2016 at 2:21 AM, Manal Alarab <alarabmanal@gmail.com> wrote:
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AERIAL SYSTEM USING RELEVANCE VECTOR MACHINES FOR PRECISION AGRICULTURE

Best,
Manal

--
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Civil and Environmental Engineering
Utah Water Research Laboratory - USU
Phone: +1 (435) 754-9299

--
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CURRICULUM VITAE

Manal Elarab
alarabmanal@gmail.com 435-754-9299
(US Citizen)

Professional Profile
An Engineer scientist with extensive background in agricultural research and remote sensing geospatial analysis. Proven ability to generate innovative approaches in precision agriculture combining UAV data and machine learning algorithms. Practical experience working in a team performing research to apply in commercial applications. Excellent initiative, communication, problem solving and management skills.

Areas of Expertise
- Precision Agriculture
- Computational Modeling
- Geospatial Data Analysis
- Statistical Analysis
- Machine Learning
- UAV Application
- Spatial Evapotranspiration
- Spatial Data Mining
- Experimental Design

Experience
Graduate Research Assistant 2012-2015
Utah Water Research Laboratory, Logan, Utah
- Actively involved in development and calibration of UAV imagery—sensor selection, reflectance calibration, thermal calibration, orthorectification, ground data collection, comparative analysis, upscaling/downscaling data techniques
- Developed models to estimate leaf chlorophyll and plant tissue nitrogen using high resolution thermal and broadband multi-spectral UAV imagery combined with relevance vectors machine algorithm and validated by ground data
- Adapted METRIC model to estimate high resolution crop evapotranspiration using UAV data and evaluated against Landsat METRIC estimates

Graduate Research Assistant 2009-2011
American University of Beirut, Lebanon
- Designed and installed irrigation systems
- Conducted experiments on water saving in agriculture and deficit irrigation
Relevant Projects

Private Farm—Oats and Alfalfa, Scipio, Utah (2012 – 2013): Developed models to estimate plant chlorophyll and leaf nitrogen content using UAV high resolution data. Experiment was conducted over two center pivots.
- Designed data collection procedure, location and frequency
- Installed ground sensors and weather stations
- Collected field data over two growing seasons to develop and train statistical models
- Collected data to calibrate thermal and reflectance imagery
- Coordinated experimental activity with farmers—harvesting, irrigation scheduling, and fertilization

Gallo Commercial Vineyard, Lodi, California (2014-2015): Mapped Evapotranspiration over vineyards using UAV high resolution remote sensing data, funded by ARS-USDA.
- Designed and conducted data collection to calibrate thermal and reflectance imagery
- Corrected high resolution reflectance data (visual and infrared) to Landsat 8 imagery
- Developed Albedo coefficients customized to the UAV
- Adjusted METRIC model to accommodate the high resolution UAV data to estimate crop evapotranspiration

Education

Doctor of Philosophy in Civil and Environmental Engineering Dec 2015
Utah State University, Logan, Utah
Dissertation: The Application of Unmanned Aerial Vehicle to Precision Agriculture: Chlorophyll, Nitrogen, and Evapotranspiration Estimation

Masters of Science in Irrigation Engineering Dec 2011
American University of Beirut, Lebanon

Masters of Science in Plant Production May 2008
Lebanese University, Lebanon

Bachelor of Science in Agricultural Engineering May 2007
Lebanese University, Lebanon

Skills

Computational: WEAP, Arc Map, Matlab, R, Python, Erdas Imagine
Language: Fluent Arabic and English, Intermediate French
**Interests and Activities**

Cooking, Reading, Travelling, Hiking, Languages, Bowling and Mountain Biking

**Peer Reviewed Publications**


**Conferences**


**M. Elarab**, McKee, Mac; Torres-Rua, Alfonso FHassan-Esfahani, Leila; Jensen, Austin; “Use of UAS to Support Management in Precision Agriculture: The AggieAir Experience” ASA, CSSA & SSSA International Annual Meeting – Meeting 2015 – Poster Presentation

**M. Elarab**, A. Torres-Rua, M. McKee (2014). Oral presentation, Mapping ET at High Resolution using AggieAir Airborne Multispectral Imagery. ASABE International Symposium on "Evapotranspiration: Challenges in Measurement and Modeling from Leaf to the Landscape Scale and Beyond" being held in Raleigh, North Carolina, U.S.A. on April 7-10, 2014

**M. Elarab**, A. Torres-Rua, M. McKee (2014). Oral presentation, Mapping ET at High Resolution using AggieAir Airborne Multispectral Imagery. ASABE International Symposium on "Evapotranspiration: Challenges in Measurement and Modeling from Leaf to the Landscape Scale and Beyond" being held in Raleigh, North Carolina, U.S.A. on April 7-10, 2014

**Al-Arab, Manal**: Torres-Rua, Alfonso F; Ticlavilca, Andres; Jensen, Austin; McKee, Mac, “Use of high-resolution multispectral imagery from an unmanned aerial vehicle in precision


M.N Nimah, M. Al-Arab 2010 (keynote paper): Solutions for Sustainable Irrigated Agriculture and Food Security 2010 presented at the 1st Kuwait - Food security Expo, KISR- Kuwait 2010