ESTIMATING YIELD OF IRRIGATED POTATOES USING AERIAL AND SATELLITE REMOTE SENSING

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY in Irrigation Engineering

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ABSTRACT

Validating and Estimating Yield of Irrigated Potatoes Using Aerial and Satellite Remote Sensing

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Multispectral aerial and satellite remote sensing plays a major role in crop yield prediction due to its ability to detect crop growth conditions on spatial and temporal scales in a cost effective manner. Many empirical relationships have been established in the past between spectral vegetation indices and leaf area index, fractional ground cover, and crop growth rates for different crops through ground sampling. Remote sensing-based vegetation index (VI) yield models using airborne and satellite data have been developed only for grain crops like barley, corn, wheat, and sorghum. So it becomes important to validate and extend the VI-based model for tuber crops like potato, taking into account the most significant parameters that affect the final crop yield of these crops.

This research involved developing and validating yield models for potato crop in southern Idaho fields using high-resolution airborne and satellite remote sensing. High-resolution multispectral airborne imagery acquired on three dates throughout the growing season in 2004 was used to develop a VI-based statistical yield model by integrating the
area under the Soil Adjusted Vegetation Index (SAVI) curve. The model was developed using hand-dug samples collected in two center pivots based on soil variability and crop growth patterns to account for variability in the leaf area duration and yields. The three-date Integrated SAVI (ISAVI) model developed was then validated using 2005 spot yield samples collected from two center pivot fields and also tested for 2004 and 2005 whole field data over dozens of center pivot fields. The three-date model was applied using 2004 and 2005 satellite images and tested. The eight-date ISAVI yield model was also extended to satellite images to estimate the potato yield. The overall yield estimation using the eight-date ISAVI model was better than the three-date model as the image inputs covered the complete growth cycle of the crop from emergence to harvest.

Actual Evapotranspiration was also used as another independent variable in the model to improve the yield predictions. The actual ET was calculated using canopy reflectance based crop coefficient method for all the spot yield locations in 2004 and regressed with actual yield. Both actual yield and ET correlated very well. Multiple linear regression analysis was performed using two independent variables, namely, ISAVI and actual ET to predict the actual potato yield. The results showed a significant improvement in the correlation and the new model developed was validated using 2004 and 2005 whole field data. The results showed a reasonable RMSE and low MBE as well as a good linear correlation for both the years and a great improvement over yield estimated using only the three-date ISAVI in the simple linear regression model. A spatial variability analysis was also performed at different scales using airborne and satellite images to understand the typical spatial correlation within potato fields.

(145 pages)
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INTRODUCTION

General

The food for the growing world population is largely dependent on agriculture and its production. Increasing the food production becomes the focus of research in most of the developing countries. According to the Food and Agriculture Organization (FAO), the global population is expected to increase to eight billion by 2030 for which the growth in agricultural production should be more than sufficient to meet the population demand. The study reports also conclude that global food consumption will drastically increase in next 30 years. In order to meet the growing population demand for increased food production, the development of high yielding varieties, increased fertilizer application and efficient water management will be required.

For many years, farmers have been using more and more production inputs in an unscientific manner, which results in inefficiencies and poor response to these inputs by crops, ultimately increasing the cost of production and the threatening the soil and ecosystem health. Traditional farming practices treat the field uniformly without taking into consideration of inherent variability in soil properties and crop growth that may result in over or under application of inputs at specific locations in the field. Thus in recent years the concept of “precision agriculture” leading to sustainability in agriculture is gaining importance as a means of increasing crop production, improving the soil health and conserving the environment while also reducing the cost of cultivation. Precision crop management is location specific and addresses the soil and crop growth variability at a smaller scale rather than treating the whole field as one homogenous unit.
Precision agriculture relies on geospatial information to expand the prospects of agricultural crop production by adopting innovative approaches and technologies. Variability is well known to exist within many of agricultural fields. The causes of variability of crop growth in an agricultural field might be due to tillage operations, influence of natural soil fertility and physical structure, topography, crop stress, irrigation practices, incidence of pest and disease etc. Effective management of the crop variability within the field can enhance financial returns, by improving yields and farm production and reducing cost of production. Various inputs to the farm such as fertilizers, irrigation, pesticides, seeding, etc. can be adjusted and applied precisely according to the variability in soil properties and crop growth (Atherton et al., 1999). The introduction of geographic information system (GIS), global positioning systems (GPS) and remote sensing has resulted in more accurate and efficient mapping of field variability. Multispectral remote sensing plays a major role in precision agriculture due to its ability to represent crop growth condition on a spatial and temporal scale as well as its cost effectiveness. Multispectral remote sensing significantly helps in exploring the relationships between crop biophysical data namely vegetation development, photosynthetic activity (PAR), biomass accumulation, leaf area index (LAI), and crop evapotranspiration (ET), with crop production (Jayanthi, 2003). Many empirical relationships have been established in the past between spectral vegetation indices and leaf area index, fractional ground cover and crop growth rates through ground sampling. These relationships are then used by the crop growers to estimate the expected yield of crops prior to harvest in order to make crop management and production-related decisions for maximizing field productivity and market gains. In such instances, a complex spectro-agrometeorological model is more
likely to explain the variability in crop yields than a simple vegetation index (VI)-based yield model.

Multispectral satellite and airborne remote sensing has been playing a crucial role in precision agriculture providing data at different spatial, temporal and spectral resolutions. Both these platforms have advantages and disadvantages. Satellite images have problems like data masking due to cloud presence, lower spatial resolution, data not being available readily for real time management of crop growth due to fixed temporal frequency and correction of radiometric data because of atmospheric interference. However, satellite remote sensing has following advantages: it covers large areas and the analysis can be done in a single image consuming less time, data can be recorded in different wavebands which provide accurate information about the ground conditions, readily available historical data and the data can be acquired without any administrative restrictions. Compared to satellite remote sensing, aerial imagery is more applicable to precision crop management due to the following advantages:

1. Images can be acquired frequently over the study area throughout the crop growing season,
2. Image acquisition can be rescheduled to a cloud free day if there is data mask due to cloud on the day of acquisition,
3. Superior resolution- high spatial resolution showing soil and crop growth variability,
4. Cost per acre is relatively low when scanning large areas

Though aerial remote sensing is more relevant to precise crop management in terms of resolution, it does have problems like band to band registration, georectification
and mosaicking of images that involve manual efforts, bidirectional reflectance variations, and lens vignetting effects. Apart from these issues, aerial remote sensing offers the best soil and crop growth variability information with very high spatial resolution less than 0.5 m something which satellite sensors cannot. However in the future, several satellite sensors offering high resolution multispectral images less than 1 m might be launched that can provide timely inputs for precision crop management. In the current scenario, it is very important to validate the satellite data with the existing aerial images so as to develop a new and hybrid image analysis method that can provide precise remote sensing inputs to facilitate irrigated agriculture at different scales needed for precision agriculture. Also it becomes essential to address the complexity of issues in handling and acquiring these spatial and temporal remote sensing imagery. Following are some of the factors that farmers and decision makers have to be aware of and decide accordingly based on their needs to improve crop yield production.

1. Type of platforms, sensors involved in image acquisition, output products
2. Pre and post processing of digital image analysis and calibration of sensors.
3. Level of accuracy, size of resolution and geometric precision
4. Spectral resolution, pixel spectral response and interpretation of raw imagery of the same target area by same sensors on different platforms and the same sensors on the same platforms
5. Image quality assessment, extraction of spectral statistics from the target area in the image
6. Factors affecting crop yield explaining yield variance with a high degree of significance
7. Assessment and reliability of crop yield and soil variability maps and incorporating into variable rate technology (VRT) systems

8. Cost involved in image acquisition of the study area and also cost of the machines like GPS, VRT, yield monitors involved in precision agriculture.

Need for the Study

Remote sensing techniques have been used as an effective tool in assessing and monitoring vegetation parameters, crop stress and crop yield prediction. Liu and Kogan (2002) showed that remote sensing data provides high quality spatial and temporal information about land surface features systematically including environmental impacts on crop growth conditions. Various studies have reported that there is a good correlation between vegetation indices derived from remote sensing and the crop yield and biomass. (Gat et al., 2000; Groten, 1993; Liu and Kogan, 2002; Rasmussen, 1997). Crop yield studies done at regional levels covering very large areas using the coarse or low-resolution satellite images result in a generalization of the crop canopy conditions and crop yield estimates. For small agricultural plots with spectral data collected with ground based platforms or low lying platforms enable large degree of control over various environmental and management factors and results in high quality data and correlation between the measured and remote sensed data (Staggenborg and Taylor, 2000). Verma et al. (1998) conducted a study on grain (Cicer arietinum) crop and found high correlation between normalized difference vegetation index (NDVI) and dry matter. In order to monitor vegetation growth, predict yield and assess the crop yield, NDVI data has been widely used (Hayes et al., 1982; Benedetti and Rossinni, 1993; Quarmby et al., 1993).
Yang et al. (2000) studied the relationship between NDVI and grain yield and reported that NDVI can predict the yield with 89 percent accuracy. Murthy et al. (1994) studied the relationship of rice yield and NDVI at different growth stages of the crop. They showed that heading stage of rice indicates good correlation with NDVI and also with time composite NDVI.

Crop productivity and sustainability of irrigated agriculture can be enhanced by efficiently managing the supply of irrigation water. Crop evapotranspiration ET plays an important role in irrigation planning and decision making on a regional scale and it widely varies from crop to crop depending upon variation in crop canopy and climatic conditions. Water stress is a major factor that affects the yield and it’s directly related to crop evapotranspiration. Crop yield – ET relations are highly influenced by soil water levels in the root zone. Crop water stress as a result of soil water deficits have an effect on crop evapotranspiration and ultimately crop yield. Crop water stress can be quantified by the rate of actual evapotranspiration in relation to the rate of potential evapotranspiration. Crop water requirements should be fully met from the available water supply to prevent stress. The crop water requirement differs from crop to crop and also during the different stages of crop growth. Potato crops are very sensitive to water stress especially during the late vegetative and tuber initiation and yield formation phase. Water deficit during these stages damages the tubers and results in tubers with black hearts. However it is less sensitive during early vegetative and ripening period. In case of limited water supply, irrigation scheduling has to be carefully planned to avoid stress during the tuber and yield formation period. Saving in water can be achieved by allowing increased soil water depletion towards the ripening period and through improved timing and depth
of irrigation application thereby increasing the water use efficiency.

Most of the VI-based models account for the variability in crop growth resulting from soil influences, moisture stresses, pest and disease attack etc. Jayanthi (2003) developed a statistical VI yield model for two varieties of potato (Russet and Norkotah) using airborne images assuming the field to be under perfect irrigation management with no water stress. He collected spot yields for the crops and generated the soil adjusted vegetation index (SAVI) corresponding to yield location in the imagery. He developed different combination of SAVI (Single-date SAVI, SAVI integrated over critical growth period, SAVI integrated over the entire crop season (ISAVI) and correlated with collected yield samples. The results showed that integrated SAVI over the entire crop period correlated best with the yield of potatoes. Timing of image acquisition over the entire crop growth period is essential to make reliable estimates of potato crop yield. Prediction of yield for tuber crops could be more accurate if we can increase the frequency of the image acquisition but will depend on how reliable an estimate is needed and how significant is that for marketability. A study also conducted by Jayanthi (2003) showed that with an increase in the number of images acquired throughout the growing season used for yield estimation; better results would be obtained with less variability. However, the study did not involve actual evapotranspiration in the yield model. The integrated SAVI yield model developed was purely a statistical model and the crop response was assumed to be captured by ISAVI vegetation index. It is possible that two different sample sites with different yields might have same ISAVI values and sometimes there could be possible cases where similar yields for two sample sites had different ISAVI values.
Pathak (2005) attempted to validate the single and three-date SAVI model developed by Jayanthi (2003) and found that there was an over estimation of the yield. He reported that some of the possible reasons for over estimating the yield were due to imprecise image calibration and weed growth, which increase the VI values resulting in higher yield predictions and also could be due to the different length of the season as the Jayanthi (2003) model was developed for 100 days growing cycle.

The relationship between spectral VI and harvestable yield depends on the type of crop, stage, health, soil moisture characteristics, cultural and management practices. Remote sensing provides an effective way to study the spatial variability of crop growth and yields. Variable yields across the fields can be due to soil and environmental characteristics as well as irrigation system application non-uniformity. Soil properties that affect yields include texture, structure, moisture content, organic matter, and natural fertility and landscape positions. Environmental characteristics include weather, water availability, insects, weeds and disease. Tuber crops like potato are highly sensitive to water stress. Considering the large production investments involved and in order to maximize profits, extreme care should be taken to maintain optimal soil moisture in the root zone. Tuber crops such as potato and sugar beet are widely cultivated in certain areas on northwestern United States. In states like Idaho, Oregon and Washington, potato accounts for more than 80 percent of the irrigated areas and 30 percent of the national irrigated areas (Wright and Stark, 1990).

Various studies in the past using remote sensing showed a good relation between vegetation indices and the crop yield. However those yield models are restricted to grain crops like barley, corn, wheat, cotton, sugarcane etc. There are hardly any references in
the literature citing the development of VI yield models for potato using both airborne and satellite images.

Therefore, considering the factors and issues addressed above, it becomes important to extend the VI-based models to non-grain crops taking into account of the significant parameters that affects the final crop yield to a large extent. Considering past work with potatoes yield and remote sensing, actual ET is the most promising parameter to be added that could explain the variability and strengthen the model statistically. The factor ETᵦ/ETₘₐₓ has been shown by previous research (Doorenbos and Kassam, 1979; Stewart et al., 1977) to explain variability in yield on the ground. In other words, actual ET might be useful in explaining additional variance in the remote-sensing yield model.

In this study, efforts were made to evaluate the improvement of VI-Yield relationships by incorporating evapotranspiration (ET) or transpiration (T) of the crop using high spatial resolution airborne imagery and spot yield data. The validation of the improved yield model was done using Landsat TM5 satellite imagery from the same region, considering various environmental factors including management techniques that affect crop growth and yield. Mapping variability spatially and temporally over the entire field was also addressed.

Significance of the Research

Prediction of crop yield before the harvest period can be very helpful in areas that are categorized by climatic uncertainties. Reynolds et al. (2000) showed that conventional method of maize crop yield estimation would lead to poor crop yield assessment and crop area estimation which generally involves data collection for crop
and yield estimation based on ground-based field visits and reports that are often found to be subjective, time consuming and errors due to incomplete ground observation.

In some of the regions, yield models based on weather parameters have been developed. This kind of approach has problems including the spatial distribution of weather station, incomplete and unavailable timely weather data and weather observations that are not sufficient enough to represent the variability of important climatic variables over the large areas where crops are grown (Dadhwall and Ray, 2000). Another approach for predicting the yield of grain crops is by developing empirical models; however most of the models demand data that are not easily available. In case of agro-spectrometeorological yield models on large scales, the input data is usually not available, and if available, it becomes bulky to handle.

Multispectral satellite remote sensing data have been globally used to assess crop yields and soil variability. Satellite data can provide reliable and acceptable yield estimates with single crop grown over a large area. However, in areas with mixed cropping pattern, aerial remote sensing can be effectively used to delineate the crop type and land use. Efforts should be made to use both aerial and satellite data to strengthen the representative crop yield models taking in to account the soil and crop growth variability. The spectral signature captured by the aerial or satellite sensors within an area occupied by a single pixel represents the integration of many factors such as crop phenology, soil moisture stress, nutrient status, biomass and ultimately crop yield. Instead of measuring all these parameters individually on the ground, remote sensing data at a particular point in time, relates to the crop response to all these factors integrated into a single pixel response and provides useful information; spatial and temporal variability.
This research focuses on the yield prediction of tuber crops (potato) well before harvest on a large-scale basis using multispectral aerial and satellite remote sensing. These data provides a cost effective way to predict yield and map soil influences and crop yield variability. Thus the estimated yield and soil variability maps can be used as spatial databases and incorporated into variable rate technology systems (VRT) to provide precise field level inputs to better manage for spatial variations, maximizing production across the entire field. Images acquired during early season and during critical growth periods can provide details about emerging problems, watering issues, disease etc. These information could help the farmers and decision makers to make crop management and production related decisions for maximizing field productivity. In this way they can plan well in advance on how much to sell if there is any shortage or to store in case of surplus taking maximum advantage of future pricing. The government also can be alert of the crop production stage and can act accordingly during the famine times. For a large-scale area, predicting crop yield can be done using satellite remote sensing. This research is carried out to tackle various issues like in determining proper irrigation scheduling practices, mapping the variability of the crop yield, predicting potato yield prior to harvest.

**Research Objectives**

The major objectives of this study are as follows:

1. To develop a remotely sensed vegetation index based yield model for tuber crop, potato using high resolution airborne imagery and involving ET of the crop.

2. To extrapolate the yield model developed with airborne imagery for use with
LandsatTM5 satellite data and validate the yield model by comparing with ground collected yield samples and field production data for several center pivots in Southern Idaho.

3. Prepare yield maps and assess the crop yield spatial variability at different scales using high-resolution multispectral aerial and satellite remote sensing.

**Hypotheses**

Vegetation density physically represents the subsequent yield from crops. Early yield prediction together with monitoring of crop growth is important. Crop canopy cover density and health can be monitored using multispectral images that measure photosynthetic activity and vegetation vigor. The spectral vegetation index profile helps in characterizing crop growth parameters that are related to the final yield. VI-based yield models using airborne and satellite data are restricted to grain crops like barley, corn, wheat and sorghum. In areas with soil and crop growth variability, high resolution satellite and aerial data are used to strengthen the crop yield models. The Vegetation index growth profiles for most of the grain crops are characterized by a sharp peak of VI and for non-grain crops, the VI growth profile is characterized by a prolonged phase between maturity and senescence stage. There are hardly any experimental studies citing the development of VI yield models for potato using both airborne and satellite images.

High resolution aerial and satellite remote sensing can be used to assess the objective relationship between evapotranspiration and crop yields influenced by varying soil, moisture and nutrient conditions existing in the field. High resolution aerial images best describe the spatial variability of yields and gives better information at the requisite
scales involved in precision agriculture. Crop yield estimation on a larger scale can be
achieved by satellite remote sensing with better results and less time involved.

Crop ET demands have to be met to achieve maximum crop yield. By applying
more water than the requirement does not necessarily improve the yield as crops only
transpire certain amount of water and it varies from crop to crop based on different
climatic conditions. The relationship between water use and crop yield has been studied
in the past years. Crop water use efficiency can be expressed as yield per unit
evapotranspiration (ET) or per unit transpiration (T) and crop yield can be expressed as
total dry matter yield or grain yield. Evaporation from the soil becomes limited when the
available soil water drops to a minimum level but transpiration will continue until the soil
moisture in the root zone drops below a critical level. Several studies in the past related to
water use and yield have reported that there is a strong linear relationship between
evapotranspiration and crop yield.

Based on the above, the following hypotheses are proposed:

1. There is significant relationship between SAVI, integrated SAVI and crop yield of
   potatoes both at small and large-scales.

2. There is significant relationship between Evapotranspiration and Yield.

3. High resolution multispectral images can be used to describe the spatial
   variability of yields.

4. Integrated SAVI-Yield models can be developed and applied to large areas using
   satellite imagery.
LITERATURE REVIEW

In recent years, the application of remote sensing techniques for crop yield estimation has been gaining importance due to the improvements in the spatial and spectral resolution of remotely sensed imagery. Crop growth and yield monitoring is important for the economic development of a country and with the aid of remote sensing it has become easier to monitor the area extent of agricultural crops. Several attempts have been made in the past to develop VI-based crop yield models for predicting the crop yield both at field levels and regional scales. Crop production and yield estimation both have a direct impact on the economic development of a nation and food management (Hayes and Decker, 1996). Airborne multispectral remote sensing has been used in assessing the crop yield conditions. It has been often used in estimating crop yield for a variety of crops in the past years (Yang, Bradford, and Weigand, 2001; GopalaPillai and Tian, 1999). Singh et al. (1992) studied the use of satellite spectral data in estimating the crop yield surveys.

Crop Yield Monitoring

Aerial and Satellite remote sensing plays a significant role in assessing and monitoring crop yield over a small or large area and provides useful information about the status of crop growth throughout the growing season. The spectral response from a crop can be well monitored using different spectral and spatial resolution depending upon the crop phenology and crop type. Several studies have shown that vegetation health can be very well measured using near infra red and red wavelength bands. Vegetation indices namely NDVI, SAVI are used by researchers all over the world to determine the status of
healthy vegetation and differentiate from other land use changes. Healthy, dense vegetation appears brighter and reflects more radiation in the near infrared region of the spectrum where as severely stressed vegetation appears dark and reflects less radiation. Healthy vegetation will have a high NDVI and SAVI values because of high reflectance in the infrared and low reflectance in the red band due to absorption by chlorophyll in the leaves.

Crop growth and final yield estimation can be done by learning the land cover change that happens during the crop growing season and also throughout the year. Crop growth seasonal change provides information related to agricultural management and the annual changes provides information about the cropped area or land cover change. The

Figure 1. Spectral reflectance curve of Vegetation, water and soil. (Source: Murai, 1996)
Figure 2. Spectral response curve of a healthy green vegetation. (Source: Hoffer, 1978)

The spectral reflectance of different surfaces and land cover is presumed to be different.

Figure 1 shows the spectral reflectance curves for three different land covers typically found in agricultural areas namely water, soil and vegetation and Figure 2 show the typical spectral response characteristics of a healthy green vegetation.

Healthy green vegetation has a unique spectral reflectance pattern based on the leaf structure and composition. In the visible part of the region, chlorophyll in a leaf absorbs light in the 0.45µm (blue) and 0.68 µm (red) portion of the spectrum and absorbs less in the green part of the spectrum resulting in a small peak at 0.5-0.6 µm that makes vegetation appear green to the human eye. Healthy vegetation reflects more in the near infra red region and relatively lower in the red region due to high photosynthetic activity and thus useful for vegetation classification and mapping. The moisture content in the
leaf results in water absorption at 1.45 µm and 1.9 µm respectively. The spectral reflectance of a crop canopy is influenced by different factors such as the crop canopy structure, crop condition, leaf area index, cultural practices, soil moisture stress and crop growth stage (Verma et al., 1998).

**Need for Crop Yield Estimation**

In general crop yield estimation can be done either by collecting ground samples from the field or by using various crop growth yield models. Each method has its own pros and cons in predicting the crop yield accurately. Ground-based yield prediction is time consuming, difficult, and expensive. On the other hand, the crop growth models sometimes become non-transferable to other cropped areas due to difficulty in incorporating the specific crop growth conditions.

**Ground-Based Crop Yield Prediction**

This technique was more common in the past when current technologies were not available. Nielsen (2004) studied the yield component method, which is the most simple and common technique to estimate crop yield. This technique involves a stratified random sampling procedure. The yield sample locations are selected from each of the study fields and the average yield obtained from each sampling site would be used to calculate per acre yield. In case of corn, the estimated yield is calculated by multiplying the ear number by average row number by kernel number and then dividing the result by 90, which represents the average kernel weight. For other sampling sites the same procedure described above was followed, and eventually the yield obtained from each
sampling sites was averaged to obtain the estimated yield for the entire field. This method, as said earlier, is time consuming, tedious, and inefficient as it does not account for the variation in field crop growth conditions.

**Remote Sensing Based Crop Yield Method**

This technique has been widely used in recent years. Unlike the ground-based method, this method is very easy to handle, not laborious, and most of all it results in spatial crop yield estimations. The yield can be basically achieved in two ways depending on the crop type, namely peak vegetation index based yield models and area under the vegetation index curve based yield models. Remote sensing of crop yields can be broadly grouped into two classes (Moulin, Bondeau and Delacolle, 1998): crop process or simulation models, and spectral vegetation index-based statistical yield models. Some of the previous research done to estimate crop yield based on these yield models are reviewed for the current research as follows:

**Crop Process or Simulation Models**

These models involve the mathematical function of various crop physiological factors such as photosynthesis, respiration, and relative growth rate to describe the crop growth changes under various climatic and environmental conditions. This type of model gives accurate estimation for small and homogenous fields but are less reliable for estimating yields of areas with soil non-uniformities and different agro climatic zones. The model at times becomes complicated as it needs several detailed inputs for simulation and makes the calibration process tedious to perform.
Sudduth et al. (1998) collected data on a 36-ha field in central Missouri to investigate methods for relating spatial grain yields to differences in those factors that can affect yields. They used CROPGRO-Soybean model to evaluate yield limiting factors across a range of climatic conditions. In order to account for yield variations due to excess water “run-on” from upland areas of the field methods were developed to account for water redistribution based on soil and topographic characteristics.

Paz et al. (2001) developed a procedure to calibrate CROPGRO-soybean model and to compare predicted and measured soybean yields, assuming that water stress, soybean cyst nematodes (SCN) and weeds were the dominant yield limiting factors. The result indicated that predicted soybean were in good agreement ($r^2 = 0.80$) with measured yield after calibrating three model parameters. Soybean yields were significantly reduced by an average of 626 kg/ha and 105 kg/ha as a result of stress and SCN, respectively. The effect of weeds on soybean yield was not significant.

Bazgeer et al. (2008) studied and established relationships between wheat yield and different agrometerological indices together with meteorological variables to predict wheat yield for various regions of Kordestan province in Iran. It was observed that the wheat yield prediction is better when all these parameters and indices are used in combination rather than when they used individually in the model. Similar work by Bazgeer et al. (2008) was done in Hoshiarpur district of Punjab, India to predict wheat yield using different agrometerological indices, spectral vegetation index (NDVI) and Trend estimated yield. It was reported that the agromet-spectral-trend combined yield model predicted the yield better than the other models. Similar positive results incorporating agromet-spectral-yield relations with Trend Estimated Yield have been
reported by Kalubarme et al. (1995) and Medhavy et al. (1995) for Punjab and Haryana (Verma et al., 2003) states in India.

**Vegetation Index-Based Yield Statistical and Area under (VI) Curve-Based Models**

The statistical models are developed based on the relationship between crop yield and various crop physiological parameters. These type of models are limited to a particular region for which they are developed and can’t be applied to other areas that have different climatic, environmental and management conditions. For vegetation index based model, the VI values at full cover are regressed with yield for maximum correlation. The area under VI curve based yield models are developed either by integrating VI during critical growth stages or integrating the entire area under VI curve using multi-temporal remotely sensed inputs and then finally regressed with yield (Benedetti and Rossini, 1993; Quarmby et al., 1993; Labus et al., 2002; Tennakoon, Murthy, and Euiiumno, 1992; Kalubarme et al., 2003).

Vegetation indices such as Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) are examples of indices that have been used in the past. These vegetation indices are most commonly used to monitor excessive moisture in fields, to detect drought areas and to assess the weather impact on vegetation growth and crop production (Unganai and Kogan, 1998; Kogan, 2001, 2002; Kogan et al., 2003; Singh, Roy, and Kogan, 2003). Most studies showed that NDVI has been very useful in predicting crop yield and assessing yield models using various approaches from simple integration to complex transformation.
The health of green vegetation is very well detected by NDVI, so it is effective in monitoring the crop growth conditions from the emergence period to the full cover though crop field conditions could slightly differ due to actions involved such as tillage, irrigation, fertilizer application etc. In order to monitor vegetation growth, predict yield and assess the crop yield, NDVI data has been widely used (Hayes et al., 1982; Benedetti and Rossinni, 1993; Quarmby et al., 1993). Murthy et al. (1994) studied the relationship of rice yield and NDVI at different growth stages of the crop. They showed that heading stage of rice indicates good correlation with NDVI and also with time composite NDVI. Various studies have been done on the spatial interactions in the CROPGRO-Soybean and CERES-Maize models and also on the comparison of estimated and measured data (Batchelor, Basso, and Paz, 2002).

Hatfield (1983) conducted a study on grain sorghum canopy reflectances using Exotech hand-held radiometer and related the ratio of VI (MSS7/MSS5) values at heading stage to potential yield. The author reported a r-squared of 0.92 and observed that there was no significant stress during the reproductive stage.

Huete (1988) presented a transformation technique to reduce soil brightness effect from spectral vegetation indices involving NIR and red wavelength and discussed the basis for soil-adjusted vegetation index (SAVI). The transformation nearly eliminated soil-induced variations in vegetation indices for cotton and range grass canopies with different soil backgrounds. He showed that a single adjustment factor (L=0.5) for SAVI reduced soil noise considerably with different range in vegetation densities compared to other vegetation indices.

Jayanthi (2003) conducted a study on yield estimation of potato using high-
resolution airborne multispectral imagery and developed various VI yield models for the same. He correlated the soil adjusted vegetation index (SAVI) with the hand-dug samples of potato for two varieties and then different combinations of integrated seasonal SAVI developed were regressed with collected yield samples. The results showed that Integrated SAVI over the entire crop period had good correlation with potato yield. The author also suggested that minimum of three flights or remotely sensed inputs occurring during early stages of vegetative growth, prior to full cover and peak vegetative cover were needed to develop a reliable VI yield estimate ($r^2 = 84$ percent) and showed that predicting yield would be more accurate with the maximum number of flights.

Bala and Islam (2007) used TERRA MODIS images for the years 2005 to 2006 to estimate the yield of potato in Munshiganj area of Bangladesh and validated using ground truth data collected from 50 farmer fields. Regression models developed using 2005 to 2006 years data was validated by using data from 2006 to 2007 seasons and reported that an average error of estimation was about 15 percent for the study area.

Pathak (2005) validated the existing potato yield model developed by Jayanthi (2003) in different environments. The model was tested for spot yield samples and whole field average yield from two years of data. He tested various SAVI yield models to estimate yield and compared with the actual yield. The results showed that single-date model underestimated the yield for 2003 data and overestimated for 2004, as the timing of image acquisition was different for both the years. The three-date ISAVI yield model also overestimated the yield for both spot and whole field samples. The author explained that the overestimation might be due to problems with calibration of imagery and different duration of crop growth period for the model developed and validated.
Haig (2003) conducted a study on a space borne satellite based NDVI to predict crop yield at field level in Birkoor Mandals, Nizamabad district, India. He investigated the relationship between satellite based NDVI and rice yield in irrigated fields with the combination of NDVI along with management and land factors for field prediction at field level. The results of the study also showed that there is a significant correlation between the remotely-sensed NDVI and field level rice yield with $r=0.52$ and $p=0.0$. It was also found that 25 percent of the yield variability at field level was explained by NDVI, 38.1 percent of yield variability by land and management factors where as the combination of all the factors including the NDVI accounted for 45.5 percent of the yield variability. It was also shown that not all the factors that affect yield also affect the NDVI.

Prasad et al. (2005) considered parameters such as soil moisture, NDVI, surface temperature, rainfall data of Iowa state for 19 years for crop yield assessment and prediction using piecewise linear regression method with breakpoint. A non-linear Quasi-Newton multi-variate optimization was utilized that minimizes inconsistency and errors in yield prediction. They suggested that crop yield prediction model would improve further with the use of long period dataset.

Sharma et al. (1993) described the procedures for district-wise wheat yield prediction using Landsat MSS and IRS-1A data for Haryana state in India for the 1988-89 growing season. They developed a linear yield spectral index model to predict the yield and found that the estimates from both the satellite data were in good agreement with one another. The authors reported that the maximum deviation of estimated yield by IRS-1A data was 18 percent when compared with the measured data.
Diker et al. (2002) studied the boundary effect on yield monitor data by successive clipping of yield monitor data. The results indicated that the correlations between grain yield and satellite derived NDVI on DOY 203 were improved as the field perimeter was clipped to 30.5 m inside of the field boundary. The coefficient of determination ($r^2$) between the yield and NDVI on DOY 203 improved from 0.67 to 0.76. They found that yield variability was higher in the clipped areas due to the speed of the harvester, headland harvest and time for yield monitor fill-up and emptying.

Baez-Gonzalez et al. (2002) developed and validated a method of monitoring and estimating corn yield using satellite and ground collected data. The factors such as photosynthetic active radiation (PAR), leaf area index (LAI), crop development stage (DVS), planting dates, and grain yield were considered in the growth model with the data collected from the field. The author developed a growth model to integrate the satellite and ground based data. The results showed that the model accounted for 89 percent of the variability in yield under irrigated conditions and 76 percent under non-irrigated conditions due to different soil patterns in the field. It is also showed that the methodology developed in this study seemed to be useful for large scale monitoring and assessment of corn yield.

**Estimation of Crop Evapotranspiration**

Evapotranspiration refers to the loss of water from the soil surface (evaporation) and canopy (transpiration). The estimation of ET in agriculture helps in the prediction of runoff, ground water recharge, land and water use planning, crop yield estimation, etc. (Kustas and Norman, 1996; Kalma and Calder, 1994). There are several methods to
estimate evapotranspiration depending upon available data. The conventional methods proved to be significant to small areas and cannot be applied for large areas as ET varies over time and space. Remote sensing is an effective tool for estimating ET over large areas through various approaches. Some of the previous research done to estimate crop ET both by conventional and remote sensing methods are reviewed for the current research as follows:

Tanner and Jury (1976) developed and tested an ET model for potato crop based on the potential ET formula of Priestley and Taylor and also with potential E and T estimates consistent with the potential ET estimate. They compared the ET estimates during cover development of potato for two years with lysimeter measurements and found the standard error of estimate varying from 0.4 to 0.94 mm/day depending up on the method for estimating E.

Tanner (1981) studied the transpiration efficiency of Russet Burbank potatoes grown in an experimental farm in central Wisconsin with three years of field data including periodic yield measurements and daily measurements of transpiration and saturation deficits. The results showed that the physiologically based constant k is equal to 0.065 plus or minus 0.007 mb for both tubers and total dry matter. Also the experimental derived k was found to be in good agreement with a k derived from physiological data for potato.

Jensen, Robb, and Franzoy (1970) defined reference evapotranspiration as the maximum ET that occurs over a field with a well-watered agricultural crop that has an aerodynamic rough surface namely alfalfa with 12-18 inches of top growth under given climatic conditions. He also stated that crop coefficients $K_c$ (ratio of potential evaporative
demands of field crop to the reference-evaporating surface) is the combined effect of
plant resistance to movement of water from soil to the evaporating surfaces and
resistance to the water vapor from the reference crop canopy surface to the atmosphere.
Mostly crop coefficients are represented based on environmental factors mainly
influenced by temperature or by analyzing the crop canopy development during the entire
growth period. Currently most of the studies conducted to estimate reference
evapotranspiration involve using either grass (Allen et al., 1998) or alfalfa (Wright, 1982)
as a reference crop depending up on the agro climatology of the areas.

Grattan et al. (1998) conducted a study on vegetable crops and developed a simple
crop coefficient method based on percent shading. They developed empirical
relationships between crop coefficients and percent ground cover and then validated with
concurrent lysimeter readings and Bowen ratio energy balance systems for various
vegetable crops. Ojo (2000) used the method developed by Grattan et al. (1998) and
computed the crop coefficient for onion cultivated in the Utah State University
experiment station, Greenville, in Logan, Utah. They reported that the use of percent
ground cover during the early and later stages of canopy growth caused difficulties in
deriving relationship between crop coefficient and percent shading due to an insignificant
number of leaves on the canopy surface.

Wright (1981) proposed a dual crop coefficient approach based on the combined
effect of crop transpiration ($K_{cb}$) and soil evaporation ($K_e$) fractions. The $K_{cb}$ component
refers to the crop evaporative conditions from the soil surface which is dry and the crop
growth that’s not limited by environmental, climatological or physiological factors. The
$K_{cb}$ curve is developed based on the time percentage between planting to effective cover
and time in number of days after effective full cover EFC (Crop growth stage when the
crop is at maximum ET relative to reference ET) to the harvest. The author developed
crop coefficients for several crops namely alfalfa, potato, snap bean, sugar beet, pea,
sweet and field corn, spring and winter wheat at Kimberly, Idaho. Wright (1982) also
conducted a study on leaf area at EFC of various crops and reported that it is different for
different crops.

Jayanthi, Neale, and Wright (2007) derived an average reflectance-based crop
coefficient (Kcrf) based on determining a representative average SAVI corresponding to
EFC stage aggregated from all the potato fields with soils predominantly of silt loam type
in the study area. It was derived through linear transformation of SAVI corresponding to
bare soil and SAVI at effective full cover with the basal crop coefficient (Kcb) values
corresponding to bare soil and effective full cover (EFC). In this study, average SAVI for
bare soil used was 0.0915 and that corresponding to LAI at effective full cover (3.5 for
potato according to Wright, 1982) was 0.691. The corresponding basal crop (Wright,
1982) coefficients used for bare soil and at EFC were 0.15 and 0.80. The authors
compared the simulated root zone soil water balance (using the kcrf for estimating the
actual crop evapotranspiration) and expected crop growth (using Kcb) with the average
soil moisture measured in the three neutron probe access tubes installed in the study field.
Daily reference crop evapotranspiration (ETref) was computed using the 1982 Kimberly-
Penman method. The results showed good agreement throughout the seasons and
validated the canopy reflectance-based crop coefficient method.

Jackson et al. (1980) developed crop coefficients based on canopy reflectance for
small grain and found similar results between Kc and to the ratio of perpendicular
vegetation index (PVI) for wheat to the PVI of wheat at full cover. Relationship between percent ground cover and canopy reflectance based PVI for alfalfa was developed. (Heilman, Heilman, and Moore, 1982). Neale, Bausch, and Heermann (1989) found a relationship between crop canopy reflectance and basal crop coefficients for corn and developed an operational technique for estimating actual ET. The author derived the crop canopy reflectance based crop coefficient ($K_{crf}$) by linear transformation of seasonal NDVI measured over bare soil and at effective full cover. The $K_{crf}$ value was then substituted in the place of $K_{cb}$ (Wright, 1982).

Garatuza-Payan and Christopher (2005) conducted a study to estimate the crop water requirements of irrigated vegetation combined with satellite based system and validated with field data in Yaqui valley, northwest Mexico. They derived relationships between NDVI and SAVI and crop coefficients using four different models with the ground based surface reflectance measured over the crop. Actual ET was computed as the product of predicted crop coefficients and reference evapotranspiration. The study also concluded that in comparison with the ground based data, RMSE values were found to be on the order of 1mm per day.

Hafeez et al. (2002) conducted a study on field evapotranspiration estimation in Central Luzon, Philippines using three different sensors namely Landsat 7 ETM+, Terra Modis and Aster. The study involved the application of SEBAL to all these three sensors to estimate actual ET that was computed during satellite overpass and then it was finally integrated for 24 hrs on pixel-by-pixel basis. The research included several combination and interrelationship of different sensor images in computation of ET and the results showed close relationship with daily ET estimated by these sensors as predicted by
SEBAL in comparison with other meteorological data. Results also concluded that the three sensors could be used for computing actual ET studies in the tropical climate but with necessary precautions.

Yang, Zhou, and Melville (1997) estimated local Evapotranspiration using Landsat Thematic Mapper (TM) data for sugarcane fields based on the concept of a Vegetation Index/Temperature Trapezoid (VITT). The author computed ET rate using surface temperature (Ts), moisture availability index (Ma) and NDVI derived from TM data.

The results obtained from this study were compared with results from a water balance model and estimating ET by VITT concept proved to be a useful method for sugarcane field at a local scale.

**Spatial and Temporal Variability of Crop Yield**

The process and properties that regulate crop performance and yield in most of the agricultural fields vary both in space and time. Application of technologies and principles of managing spatial and temporal variability associated with all aspects of agricultural production is essential for the purpose of improving crop performance and environmental quality. Some of the factors causing spatial variability of crop growth in an agricultural field are preplanting, preseason fertilizer application, planters consistency and its operation, weather related issues like low temperature at the time of sowing, soil moisture and soil fertility influence, field topography, irrigation scheduling practices, occurrence of precipitation events and incidence of pest and disease. To make precision agriculture efficient and useful, assessing variability of various above parameters that has
an impact on crop yield should be well known.

Variability of crop growth in an agricultural field is mainly governed by irrigation and soil type and management practices that influence the plant stand development during the critical period between germination and full cover. The factors affecting the variability of crop yield vary from one crop to another and also the causes of variability changes with time resulting in yield variation temporally. Tuber crops like potato are very sensitive to water stress which is directly related to crop evapotranspiration. ET varies regionally and seasonally according to weather and wind conditions. Incorporating actual ET in the crop yield model helps in estimating the yield in a precise manner and also best describes the spatial variability of crop yield by which farmers can be aware of the need and take appropriate remedial measures. Crop growth at the time of data acquisition marks the culmination of combined influences of weather, soil and management practices at that time. The spatial variability of crop in the field is mainly governed by the history of crop management and natural soil fertility and physical properties. The crop rotation and cultivation practices influence the field landscape over years and limit the rooting characteristics of the crops.

Spatial data analysis has been carried out using a variety of techniques, which incorporate sample locations to varying degrees in their analysis. Among various techniques, Geostatistics, which is based on the theory of regionalized variables, is the foremost tool for spatial variability analysis. It provides a set of statistical tools for incorporating the spatial coordinates of observed datas in processing, allowing for description and modeling of spatial patterns, predicting at unsampled locations and assessment of the uncertainty attached to these predictions. The results obtained from a
geostatistical analysis are dependent on a number of variables, such as sampling frequency and number, sampling spacing and accuracy and analysis parameter selections. Semivariogram parameters provide the basis for interpolation by kriging, which is a technique for optimal, unbiased estimation of properties at unsampled location with minimum estimation variance. This technique seem to be appropriate for studies of spatial variability of soil-water properties that could be estimated with known precision and low sampling costs to provide better options for management decisions. Proper interpretation of the semivariogram and selection of appropriate models are very important for the analysis process. Some of the previous research studying the variability analysis of yield is reviewed for the current research as follows:

Yang, Everitt, and Bradford (2004) conducted a study to evaluate Quickbird satellite imagery for mapping crop growth and yield variability in cotton fields. Both the satellite and airborne images were acquired for the same cotton fields for 2003 growing season and the yield data were collected at harvest from the two fields of cotton using cotton yield monitor. Various vegetation indices were calculated from the spectral bands for both the satellite and airborne imagery. The satellite images were then classified into 2-10 zones using unsupervised classification and mean yields of the zones were compared. The results indicated that the cotton yield was significantly correlated to both types of image data and the satellite images had similar correlations with the yield as compared to the airborne images. It was also showed that the unsupervised classification maps efficiently differentiated cotton production levels among the various zones involved and thus the study conducted eventually found to be useful in determining the crop growth patterns and yield variability using the high spatial resolution satellite imagery.
Redulla (2002) conducted a study on a commercial farm at Washington to investigate the causes of within-field spatial variability in potato. Soil samples were collected from four center-pivot-irrigated, uniformly fertilized fields on a 0.4 ha grid interval and analyzed for various soil properties. Correlation and stepwise regression analyses were conducted to test relationships between soil based and yield variables. It was found that soil texture components had stronger impact on yield than with the soil chemical properties measured.

Vieira and Gonzalez (2003) assessed spatial variability of soil properties and crop yield that were measured in a 10-m grid of a one ha field cultivated with crop sequences including corn, soybean, cotton, oats, black oats, wheat, rice and green manure under no tillage as a function of time, in two soil/climate conditions in Sao Paulo State, Brazil. Crop yield was measured at the end of each cycle in 2x2.5 m subplots and yield maps were constructed in order to visually compare the variability of yields and related soil properties. The results showed that the factors namely soil fertility, soil physical properties affecting the variability of crop yield varies from one crop to another and the results also suggested that change in yield from one year to another indicate that the causes of variability may change with time.

Zarco-Tejada, Ustin and Whiting (2005) conducted a study over a cotton field in California to develop various vegetation index calculated from the airborne visible and near infra-red (AVNIR) hyper-spectral sensor at 1 m spatial resolution. The yield data was collected using the yield monitor and it has been correlated with various vegetation indices related to crop growth, canopy structure, chlorophyll concentration and water content. Within field variability in cotton during different stages of growth was assessed.
using the time series indices developed from the imagery. The author reported that the structural indices related to LAI – Renormalized Difference Vegetation Index (RDVI), Modified Triangular Vegetation Index (MTVI) and Optimized Soil-Adjusted Vegetation Index (OSAVI) obtained the best relationship with crop yield and field segmentation (done using clustering method) during early growth stages. The hyperspectral vegetation indices related to crop physiological status namely Modified Chlorophyll Absorption Index (MCARI) and Transformed Chlorophyll Absorption Index (TCARI) were found to be best during the later stages of growth prior to harvest. The results showed that the overall accuracy of RDVI at early stages was 61 percent (k = 0.39) that dropped to 39 percent (k = 0.08) before harvest and the MCARI index was found to be sensitive to within field variability during late preharvest stage with an overall accuracy of 51 percent (k = 0.22).

Yang et al. (2000) used airborne digital imagery and yield monitor data to map plant growth and yield variability. They acquired CIR images and yield monitor data from a grain sorghum field five times during 1998 growing season. The correlation analyses showed grain yield was significantly related to the individual near infrared (NIR), red and green band of CIR images and the NDVI for the five dates. The results indicated that three images obtained at and after peak growth produced higher $r^2$ values (0.64, 0.66 and 0.61) than the other two early season images (0.39 and 0.37). The yield maps generated from the three best images agreed well with a yield map from the yield monitor data.

Pozdnyakova, Gimenez and Oudemans (2005) conducted a study on spatial analysis of cranberry yield at three scales with two support sizes. The yield data
calculated were fitted to either spherical (SS and LS) or exponential (MS) semivariogram models. The results indicated that the spatial properties of cranberry yield at MS were better defined in cranberry fields with more than 12 yr in production having small range and nugget variance and influenced by multiscale factors with nonlinear structure functions. It was also shown that the younger fields had greater range and nugget variance and a linear structure function. The study implied that precision agriculture practiced for perennial crops should consider temporal changes in the spatial variability of crop yield.

SunOk et al. (2000) conducted within-field variability study in a Korean rice paddy field. Measurements of rice yield, chlorophyll content and soil properties were obtained in a small (100 m by 30 m) rice field. Yield data was manually collected on 10 m by 5 m grids (180 samples with 3 samples in each of 60 grid cells) and chlorophyll content was measured using a Minolta SPAD 502 in 2 m by 2 m grids and soil samples were collected at 275 points to compare results from sampling at three different scales. They conducted a semi-variance analysis and point kriging to determine the variability of the measured parameters.

Bakhsh et al. (2000) conducted a field study to investigate the relationship between soil attributes and corn-soybean yield variability using four years yield data from a 22 ha field at Iowa. From GIS and statistical analyses, they concluded that interaction of soil type and topography influenced yield variability of this yield and by map overlay analysis it was found that areas of lower yield for corn at higher elevation were consistent from year to year whereas higher areas of yield were variable.

Johnson and Richard (2005) conducted a study to determine the variability of
sugarcane yield spatially and temporally at field level grown in south Louisiana. The fields were harvested at two locations and the yield data were obtained for three consecutive years in a grid pattern with a single row using the chopper harvester and yield monitor to determine cane yields. Sugar yield and quality were determined using random sampling from each grid cell. The results indicated that all the soil properties analyzed were spatially correlated with the range (lag distance) varying from 26 to 241 m. Cane and sugar yields at both locations were found to exhibit non normal distributions and the coefficient of variation (CV) ranged from 5 to 20 percent for all years and locations. The results also showed that the cane and sugar yields spatially correlated with a range varying from 26 to 187 m and the soil properties correlated with the sugar parameters at different locations varied spatially.

Lin-yi et al. (2002) analyzed the spatial correlation of maize yield in the middle and west of Jilin province in China using the method of geostatistics semivariogram taking NDVI of NOAA /AVHRR spectrum data as the regionalized variable to provide field sampling methods of yield estimation using remote sensing. The results showed that the crop yields were spatially correlated and the degree of range and correlation were found to be different both in west and middle regions of Jilin province. They suggested that the samples for crop yield estimation should be extracted based on the spatial distribution of crop yield.

Marques da Siva (2006) analyzed the spatial and temporal variability of maize yield over a period of three years for seven irrigated plots in Fronteira region of Portugal and found that the spatial variability for all the years was relatively great and disappeared over time. He suggested that that the crop needs should be managed in real time giving
importance to precision irrigation systems to reduce the risk of farm management investments.

Inamura et al. (2004) analyzed the yield, soil properties and crop management practices of paddy rice fields in a large scale farm in Sakurai, Japan using geostatistical techniques. They found that the agronomic factors such as the soil fertility, early growth and nitrogen dressing and uptake factors contributed significant variation to the yield.

Zhang et al. (2009) used multispectral image to analyze the variograms computed on various sample sizes on a field with broadleaf and grass weeds in Texas Agrilife research farm. A 100 by 100 pixel subset randomly chosen from the image with NIR, Green and Red bands along with NDVI dataset was used to conduct the spatial analysis. The results showed that half size of the subset image significantly estimated the variograms for NIR and Red wavebands and it was found that to map the variation on NDVI map within the weed field, the ground sampling interval has to be smaller than 12 m.
MATERIALS AND METHODS

Description of the Study Area

The data for this research were collected from the potato fields of Cranney Farms Inc., Oakley, Idaho. The total area occupied by potato fields in Cranney Farms in the 2004 and 2005 seasons were approximately 3700 and 3500 acres respectively. The duration of the crop growth season begins from April to September. According to Mr. Terry Helms, the manager of Cranney Farms, five varieties of potato were mainly being cultivated namely Russet Burbank, Rangers, Gem, Western, and Alturus. Figure 3 and Figure 4 show the layout of potato fields used in this research for 2004 and 2005, respectively.

Soils and Climate

Most of the study fields contain predominantly drax silt loam formed in alluvium derived from mixed sources of metamorphic and igneous rocks. Included with this soil, the area also has closely related soils of Goose Creek silt loam and Beetville loam making up 10 percent of the total unit. The soil type is a deep, moderately well drained level soil on broad valley terraces. The elevation of these soils in the study area ranges from 4100 to 4800 feet and the slope varies from 0 to 2 percent. The soil is moderately alkaline and found to be calcareous to a depth of 60 inches and slightly calcareous and noncalcareous thereafter. Permeability of this soil is moderate and the effective rooting depth goes up to 60 inches or more whereas the available water holding capacity ranges from 8.5 to 12 inches. Cultivated irrigated crops include sugar beets, potatoes, alfalfa hay,
Figure 3. Layout of Cranney Farm potato fields for the year 2004.
Figure 4. Layout of Cranney Farm potato fields for the year 2005.
wheat, corn and other small grains. Most of the fields are under center pivot irrigation systems designed to avoid excessive deep percolation and surface runoff.

The study area is located in a semi arid environment with an average temperature of 19.6°C in summer and the average daily maximum of 28.3°C. Figure 5 and 6 show the mean daily temperature in °C and mean monthly rainfall in mm for the 2004 and 2005 seasons, respectively. 2005 was cooler and wetter than 2004 with most of the rain falling in April and May whereas in 2004, it occurred in August during the late growing season of the crop. The average relative humidity varies from 39 to 44 percent throughout the year and humidity is always higher at night in all seasons. The possible sunshine percentage is around 78 in summer and 42 in winter, respectively. The prevailing wind direction is from the southwest with an average of 4.6 m/s.

![Graph showing mean daily temperature in °C during the crop growing season in 2004 and 2005.](image)

**Figure 5.** Mean daily temp in °C during the crop growing season in 2004 and 2005.
Airborne Multispectral Imagery Acquisition

The airborne images over the Cranney Farm fields were acquired using the USU airborne digital remote sensing system available through Remote Sensing Services Lab. The system consists of three Kodak Megaplus 4.2i digital cameras filtered for spectral observations in the green (0.548-0.552 µm), red (0.668-0.676 µm), and NIR (0.798-0.804 µm) bands of the electromagnetic spectrum. The images were captured at 8 bits with special digitizing boards mounted in a PC computer on board the aircraft, controlled with Epix frame grabbing board and specially designed software. The airborne multispectral images were acquired over different fields during 2004 and 2005 throughout the growing season. The three dates of image acquisition during the year 2004 season were July 05, July 30, and August 31. The images obtained for the 2005 growing

Figure 6. Mean monthly rainfall throughout the year in 2004 and 2005.
Figure 7. Piper Seneca aircraft for image acquisition, RSSL, USU.

Figure 8. RSSL airborne multispectral digital camera system, USU.
season were on July 08, August 04, and August 25. Figure 7 shows the USU remote sensing aircraft available through the remote sensing services lab for the image acquisition with Figure 8 showing the details of the airborne digital imaging system.

**Airborne Image Processing**

The binary files acquired on the aircraft were first converted to tiff format images. The individual green, red and NIR images were first registered to one another, layer stacked and corrected for vignetting effect to remove the illumination fall off at the edge of the images. The preprocessing and processing of images was done using the ERDAS Imagine version 9.0 software. The images were geo-rectified using GPS based coordinates taken at different points over the fields and at the center of the pivot.

**Calibration of Airborne Multispectral Imagery**

In order to convert the digital number in the images to a reflectance standard, images obtained have to be calibrated. Calibration of acquired aerial imagery is usually done by standard reflectance panel approach. But here in this study, it was not practical due to complications in setting up a panel in the region of the potato pivots close to Oakley, Idaho and also taking in to consideration the distance to Logan, Utah. So an alternative solution was found, which consisted in developing a relationship between solar irradiance measured over the panel and solar radiation measured with an Eppley pyranometer installed at a weather station in Kimberly, Idaho, that was located approximately 30 miles to the west of the monitored center pivots. The radiance was measured over a standard Halon panel with known and stable bidirectional reflectance
properties using an Exotech 4-band radiometer. The polynomial regression coefficients used for halon panel representing its bi-directional properties are listed in Table 1. The radiometer measurements were completed with a set of initial and final dark voltages.

**Bidirectional Reflectance from the Panel**

The bidirectional reflectance from the halon panel at the time of panel measurements was computed using the corresponding solar zenith angle as follows:

\[
R(0^\circ / \theta) = a_0 + a_1\theta + a_2\theta^2 + a_3\theta^3 + a_4\theta^4
\]  

(3.1)

where \(a_0\) to \(a_4\) are regression coefficients listed in Table 1.

The solar zenith angle was calculated using the following equation:

\[
\theta = \arccos[\cos\delta \cos\Phi \cos\omega + \sin\delta \sin\Phi]
\]  

(3.2)

where \(\delta\) is the earth’s declination angle in radians, \(\omega\) is the hour angle in radians and \(\Phi\) is the latitude of the study area. The hour angle was computed as follows:

\[
\omega = 15(T_{\text{std}} - \text{Noon}_{\text{std}}) \times \pi/180
\]  

(3.3)

where \(T_{\text{std}}\) and \(\text{Noon}_{\text{std}}\) are the local standard time and solar noon time. The solar time in hrs is given as:

\[
T_{\text{sol}} = T_{\text{std}} + [4(\Psi_{\text{std}} - \Psi_{\text{local}}) + E] / 60
\]  

(3.4)
where \( \Psi \) is the longitude in degrees. The equation of time (E) in minutes and \( \delta \) were calculated as follows:

\[
E = [ 9.87 \sin 2B - 7.53 \cos 2B - 1.5 \sin B ]
\]

\[
\delta = [23.45 \times \sin (B \times \pi / 180)]
\]

where B is in radians and defined as follows:

\[
B = 2\pi (\text{DOY} - 81.25) / 365
\]

where DOY is the calendar day of year.

**Solar Irradiance from the Panel**

The solar irradiance can be estimated from the radiance measurements over a standard reflectance panel as the following:

\[
[E] \times \cos(\theta) = \left[ \pi \times L_p \right] / \left[ R_p \left( 0^\circ / \theta \right) \right]
\]

where \( E \) is the incoming solar irradiance at time of the panel measurement (Wm\(^{-2}\)), \( L_p \) is the average radiance over panel (Wm\(^{-2}\)sr\(^{-1}\)), \( R_p \left( 0^\circ / \theta \right) \) is the bi-directional reflectance of the panel at the nadir point and \( \cos(\theta) \) is the cosine of the solar zenith angle at the time of measurement. The dark voltages measured before and after the panel setup were averaged and removed from each spectral band values.

The estimated \([E] \times \cos(\theta)\) was then plotted against the solar irradiance measured with Eppley pyranometer and finally the relationship was developed through statistical curve fitting and was used in the current study for calibrating the airborne images. The radiance over the panel at the time when the image was acquired is given as below

\[
L_p = \left( [E] \times \cos(\theta) \times R_p(0^\circ / \theta) \right) / \pi
\]

where \( E \) is the estimated irradiance developed from the relationship (Wm\(^{-2}\)) and \( L_p \) is
the average radiance over panel (Wm\(^{-2}\)sr\(^{-1}\)). The multispectral images obtained were calibrated to radiance images using the calibration coefficients developed for the USU airborne system. Eventually the images were transformed to reflectance images using the relationship:

\[
    \text{(3.10)}
\]

### Satellite Multispectral Imagery

Satellite images acquired by Landsat TM5 over the same region for 2004 and 2005 were obtained. The satellite images were carefully selected to avoid cloud cover and haze over the study area to avoid problems with calibration of the imagery. The images were selected from different path/rows (39 31 and 40 30) for the same scene so as to increase the number of images covering the complete crop growth from planting to harvest. Figure 9 shows Landsat TM5 scenes of the study area acquired from path/row 39 31 and 40 30. The path row and date for all the images used for both the years are given in Table 2.

### Calibration of Landsat TM5 Multispectral Imagery

The images acquired by LandSat TM5 images come as unprocessed (raw) images. The digital numbers from the raw images were first converted to radiance and then to spectral reflectance following the procedures below:

The digital number (DN) conversion to radiance received which is based on the linear relationship between the instrument response and the radiance registered by the sensor:
\[ L_{\lambda} = a_{0,i} + a_{1,i} \times D_{N_i} \]  

(3.11)

where, \( L_{\lambda} \) is the spectral radiance at the sensor’s aperture in \( W/(m^2 \cdot sr \cdot \mu m) \) and \( a_{0,i} \) and \( a_{1,i} \) are the sensor calibration coefficients for channel \( i \).

After the images were converted to radiance, they were corrected for atmospheric effects and converted to reflectance using the MODTRAN (MODe rate spectral resolution atmospheric TRANsmission) model that calculates atmospheric transmittance and radiance for frequencies from 0 to 50,000 cm\(^{-1}\) accounting for multiple scattering, absorptions, transmissions and emissions including default profiles. A MODTRAN graphical interface named MODO was developed to facilitate the preparation of input and output files. The following steps were involved in estimating the surface reflectance using MODTRAN:

1. Radiosonde data required in MODTRAN were collected for the date and time of image acquisition from the Boise airport weather station which is the nearest site representative of the study area.

2. The main input variables from the Radiosondes such as height, pressure (mb), air temperature (C), dewpoint temperature and relative humidity were entered to the tape5 input file. Other information like latitude and longitude, Julian day, visibility range, sensor zenith angle, starting and stopping altitude were also entered in tape 5.

3. MODTRAN was run for different values of surface reflectance namely 0.1, 0.5 and 0.9 so as to regress the at sensor radiance to surface reflectance. The output file tape6 was then exported to an excel spreadsheet including the calculated radiance and spectral responses in watts/m\(^2\). Multiple regression
was conducted using reflectance as Y variable and radiance spectral response as X variable for all the shortwave bands. Finally the intercept and slope coefficients obtained from the regression were used in an Erdas Imagine model to obtain the surface reflectance for the image. Figure 10 and Figure 11 show the sample tape 5 editor and model involved in getting the surface reflectance images respectively.

4. Modtran was run multiple times for all the images taken on different days and corresponding weather data was collected and used in the tape5 file.

Yield Sampling in the Study Fields

The yield modeling was performed at two levels namely point yield level and whole field level. The total yield from each field was monitored along with plant count densities, clod estimates and potato quality percentages and weights by Cranney Farms at the time of harvest. The point yield data were obtained in selected fields based on the variability of crop growth patterns within the fields that were monitored, visible in the aerial multispectral imagery. The yield sampling locations were chosen based on crop spatial growth profiles that fell into four categories namely (i) rapid growth-prolonged maturity and senescence (ii) slow growth-prolonged maturity and senescence (iii) rapid growth-short maturity and (iv) slow growth-short maturity, as observed from the multi-temporal airborne imagery. Each location for the spot yield data sampling was 10 ft x 4 rows in size. The boundaries of the sample locations were marked by placing small flags. The row spacing was approximately 0.55 m (22 inches). All potatoes from each sampling location were weighed using scales and then returned back to the furrows and covered
Figure 9. Landsat TM 5 scene of the study area from path/row 39 31 and 40 30.
Table 2 Path/Row scenes of TM5 with different dates for year 2004 and 2005.

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>Path/Row</th>
<th>Year</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2004</td>
<td>May 6</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2004</td>
<td>June 7</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2004</td>
<td>14-Jun</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2004</td>
<td>30-Jun</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2004</td>
<td>16-Jul</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2004</td>
<td>1-Aug</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2004</td>
<td>10-Aug</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2004</td>
<td>11-Sep</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2005</td>
<td>25-May</td>
</tr>
<tr>
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<td>2005</td>
<td>26-June</td>
</tr>
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<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2005</td>
<td>12-Jul</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2005</td>
<td>03-Jul</td>
</tr>
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<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2005</td>
<td>4-Aug</td>
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<tr>
<td>LandSat</td>
<td>TM5</td>
<td>3931</td>
<td>2005</td>
<td>13-Aug</td>
</tr>
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<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2005</td>
<td>20-Aug</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2005</td>
<td>5-Sep</td>
</tr>
<tr>
<td>LandSat</td>
<td>TM5</td>
<td>4030</td>
<td>2005</td>
<td>14-Sep</td>
</tr>
</tbody>
</table>

with soil. Differentially corrected GPS measurements were taken at all the sampling locations in the fields in order to identify the exact position of the corner of the sampling locations and allow the precise positioning of site in the airborne multispectral imagery.
Figure 10. Sample MODO tape 5 editor window.
Figure 11. Erdas imagine model to convert DN to surface reflectance values.
The spot yield sample data were collected from two fields in 2004 (WC 07 and OI16) and two fields in during 2005 (HF 12 and OI1) seasons. Figure 12, 13, 14 and 15 show the high resolution multispectral imagery of the fields where the spot yield samples were collected based on different crop growth profiles discussed above.

**Extraction of VI Statistics and Construction of Yield Models**

After the images were calibrated to reflectance, the vegetation index SAVI was obtained using the following equation

\[
SAVI = \frac{(NIR - RED)(1 + L)}{(NIR + RED + L)}
\]  

(3.12)

where

- \( L = 0.5 \) (approximate adjustment factor for brightness of the soil background)
- \( NIR = \) reflectance in the NIR band
- \( RED = \) reflectance in the Red band

Among the various vegetation indices, SAVI can better describe the crop growth variability as it was designed to minimize the effect of soil background reflectance which can change with surface soil moisture and other factors. For yield modeling purposes, the seasonal integrated SAVI (ISAVI) can be considered as a surrogate for leaf area duration as it covers the entire crop growth season and represents the area under the SAVI curve and from multi-temporal image data. The summation \( \Sigma (DOY_j - DOY_i) \) in equation 3.13 below represents the total crop duration from the date of emergence to the date of vine kill.
Figure 12. AOI of crop growth (Early Emergence Late Senescence) for Field 12, 2005.
Figure 13. AOI of crop growth (Late Emergence Early Senescence) for O16, 2004.
Figure 14. AOI of crop growth (Late Emergence Late Senescence) for OI1, 2005.
Figure 15 AOI of crop growth (Early Emergence Early Senescence) for OI6, 2004.
In this study, integrated SAVI was used in developing and testing the models with airborne and satellite images. The ISAVI was calculated as follows:

\[
\text{ISAVI} = 0.5 \times \left( \frac{\sum (\text{SAVI}_j - \text{SAVI}_{baresoil}) + (\text{SAVI}_i - \text{SAVI}_{baresoil}) \times (\text{DOY}_j - \text{DOY}_i)}{\sum (\text{DOY}_j - \text{DOY}_i)} \right)
\]

(3.13)

where ISAVI is the integrated SAVI.

DOY is the Day of year and

i, j represents the previous and present dates of image acquisition.

The hand-dug yield sampling locations were represented by AOIs (Area of Interest) - polygons digitized using ERDAS Imagine. These AOIs that represents the size, shape and location of the hand-dug samples collected in the fields were digitized over the geo-rectified images with the help of GPS readings and field observations. Yield models correlating actual yield and vegetation indices (SAVI and ISAVI) were developed using 2004 airborne multispectral images acquired with the USU airborne system. Spot yield samples collected after vine kill were used to develop the model using airborne images acquired on three different dates and was validated using whole field production data from 2004 and 2005 after applying the model to airborne images from those seasons. The 3-date ISAVI yield model was also applied to satellite images from 2004 and 2005 season and compared to whole field production data. The eight-date ISAVI model developed by Jayanthi (2003) was also applied to satellite images for both the years and the estimated yield values were compared to actual yield and tested statistically.

Whole Field Average Yield Estimation

Actual average yield for the entire field was calculated by dividing the crop
production by the total area of the field. The whole field yield values were measured by Cranney farms by weighing the trucks of potatoes from each field. The area of all the study fields also was given by Cranney farms. Both the yield and image data available to those fields were used in this analysis. The ISAVI model developed for 2004 spot yield data was validated using a total of 15 fields from multispectral airborne images for the year 2004 year and 13 fields in 2005. The center pivot fields involved in spot yield sampling and developing the model were excluded in the whole field data analysis. The model was also tested using 2004 and 2005 satellite images for the same study region. A total of 10 fields were chosen from 2004 and 13 fields from the year 2005. The Integrated SAVI images for all fields were obtained spatially and the three-date ISAVI model was applied to get the spatially distributed yield maps for all the fields. One big AOI corresponding to all the fields was created for the whole field. The field AOI was then applied to get the yield statistics and the actual production from the field was plotted against the estimated production and compared.

**Yield Evaluation**

The predicted yield and actual yield values were evaluated using the mean bias error (MBE) and root mean square error (RMSE) using the equations below:

\[
MBE = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{X_i^E}{X_i^O} - 1 \right)
\]

\[
RMSE = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{X_i^E}{X_i^O} - 1 \right)^2}
\]

where \( n \) = number of pairs used for comparison
\( X(E)_i \) = Estimated value and
\( X(O)_i \) = Observed or actual value.

Both these statistics provide a good measure of how closely two independent data sets match and also quantify the degree of over or under prediction by the model.

**Building Evapotranspiration Into the Crop Yield Model**

As potato crop is highly sensitive to water stress, maintaining optimal soil moisture in the root zone is required to obtain high quality yields and profit. Both over and under irrigation affects potato yield and quality. An attempt to improve the remote sensing based statistical yield model was done by conducting a soil water balance in the root zone of the crop and incorporating cumulative seasonal actual ET into the yield model as a method to improve yield predictions.

The soil water balance was conducted in all of the study fields using the reflectance based crop coefficient method (Neale et al, 1989; (Jayanthi, Neale, and Wright, 2007) for estimating daily ET. The soil water balance model used to assess the soil moisture status in the crop root zone is as follows:

\[
SM_{j+1} = SM_j + I + P - ET_c - DP
\]

where \( SM \) represents the soil moisture, \( j \) and \( j+1 \) denotes the current time step and a succeeding time step \( j+1 \). \( I \) represents the irrigation amount applied and \( P \) is the precipitation. \( ET_c \) is the crop evapotranspiration, and \( DP \) is the deep percolation.

The daily reference crop ET was computed using the 1982 Kimberly-Penman method calculated for southern Idaho. The actual crop ET was calculated based on reflectance based crop coefficient \( (K_{crf}) \) (Jayanthi, Neale, and Wright, 2007) estimated
using both the airborne and satellite images for the study area replacing the basal crop coefficient $K_{cb}$ in the conventional basal crop coefficient approach. The input parameters namely reference ET, wind speed, rainfall, max and min temp were obtained from the Cranney Farms weather station. Information regarding soil properties was obtained from USDA soil county maps. Crop yield, emergence date, vine kill date and depth of irrigation applied for all the study fields were provided by Cranney Farms. A brief description about the method involved in calculating actual ET is given below.

**Basal Crop Coefficient Method**

Wright (1982) proposed this method of estimating the total crop ET at a given time. The theory behind this method is as follows:

$$\text{ET}_{\text{crop}} = K_c \times \text{ET}_{\text{ref}}$$  \hspace{1cm} (3.17)

$$K_c = K_{cb} \times K_a + K_s$$  \hspace{1cm} (3.18)

$$K_a = \ln(A_w + 1)/\ln(101)$$  \hspace{1cm} (3.19)

$$K_s = (1-K_{cb}) \left[1-(t_w/t_d)^{0.5}\right] \times f_w$$  \hspace{1cm} (3.20)

where $K_{cb}$ is the basal crop coefficient; $K_a$ is the coefficient (dimensionless) that represents plant stress due to soil moisture deficit; $A_w$ is the percentage available water (100 percent at field capacity and $K_a =1$); $K_s$ represents the soil evaporation coefficient; $t_w$ indicates the time after rain or irrigation in days where as $t_d$ is the time taken for soil to dry in days, which varies according to soil texture.

**Canopy Based Reflectance Crop Coefficient Method**

The theory behind this method is that the SAVI can be scaled to represent the basal
crop coefficient and is sensitive to the actual crop growth conditions in the field (Bausch and Neale, 1987; Neale, Bausch and Heermann, 1989). $K_{crf}$ is the reflectance-based crop coefficient obtained through linear transformation of SAVI corresponding to bare soil and SAVI at effective full cover with the basal crop coefficient ($K_{cb}$) values corresponding to bare soil and effective full cover (EFC). The resulting transformation is:

$$K_{crf} = \frac{SAVI - SAVI_{baresoil}}{SAVI_{EFC} - SAVI_{baresoil}} K_{cbEFC} - K_{cbBaresoil} + K_{cbBaresoil}$$

(3.21)

The remote sensing-based $K_{crf}$ for this study was derived using the equation developed by Jayanthi, Neale, and Wright (2007) for an alfalfa reference crop:

$$K_{crf} = 1.085 \times SAVI + 0.0504$$

(3.22)

**Multiple Linear Regression Analysis**

Yield is a function of actual evapotranspiration and incorporating seasonal ET in the yield model should better explain the variability of the yield on ground. Here in this study, multiple linear regression analysis was performed using yield as the dependent variable with ISAVI and seasonal actual ET as independent variables to test if the yield model has been improved compared to the three-date linear model developed. The multiple regression model has the following form:

$$Y = c_0 + a_1 x_1 + a_2 x_2$$

(3.23)

where $Y$ is the dependent variable yield and $X_1$, $X_2$ are the independent variables (ISAVI and seasonal ET). Analysis of Variance parameters were used to test the significance of
the model and also the individual variables using the null and alternate hypothesis. The multiple regression model was developed for 2004 hand dug samples and was tested using 2004 and 2005 whole field actual yield data.

Assessing and Mapping Spatial Variability of Yield

The spatial variability of crop growth can be seen very well in high resolution multispectral images. The frequency distribution of spectral reflectance in a multispectral image is assumed to follow a known statistical normal distribution based on the assumption that each data point is independent in its occurrence. The preliminary variability analysis of crop growth was studied using simple statistical measures of central tendency. The most common indicator of variability within the sampled data is standard deviation from the mean. Descriptive statistics of various factors affecting crop yield including mean and standard deviation were estimated to describe the spatial variability of crop growth within a field. Other measures of describing the variability include the coefficient of variance, skewness, kurtosis, etc. Yield maps showing different spatial patterns of crop growth were studied and their temporal growth trends were used to summarize the differences in crop growth within the study field. Both airborne and satellite images of the different pivots were organized for visual assessment of soil and crop growth variability and studied. Plate 1 shows the typical temporal series of False Color Composite (FCC) images of WC4 field showing soil and crop growth variations during the 2004 season. Temporal variations in the reflectance based crop canopy coefficients was studied in combination with the integrated SAVI yield estimates to show the effect of ET over crop yield.
The assumption in analyzing multispectral image data is that each individual pixel value is independent of other pixel but in reality it is more likely that the values are similar to the neighboring ones. Spatial samples data are tend to more correlated than those are far apart. To take into account of this spatial dependence, Geostatistic techniques, one of the powerful tools in describing spatial variability were also conducted in this study. They deal specifically with the dependency of spatial data using “variogram” as a function to describe the spatial variation in a feature. Semi-variance is a measure of the degree of spatial dependence between the observation pairs and the equation to calculate semi-variance between any two pixels at a lag \( h \) is given as

\[
\gamma(h) = \frac{1}{2} \sum (Z(x) - Z(X + h))^2
\]  

where \( \gamma(h) \) is the semi-variance at a distance separated by \( h \); \( Z(x) \) is the value of the pixel at location \( X \).

If the region of interest has \( N(h) \) pair of pixels separated by a distance \( h \), its semi-variance is given by the equations as

\[
\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(X_i) - Z(X_i + h)]^2
\]

where \( N(h) \) is the total number of pair of pixels separated by a distance \( h \) for \( i=1, 2, \ldots, N(h) \); \( Z(X_i) \) and \( Z(X_i + h) \) are the pixel values at location \( X \) and \( X+h \), respectively. The semi-variance \( \gamma(h) \) measures the dissimilarity between spatially distributed regionalized variables. The similarity between two pixels increases as the value of semi-variance decreases. The semi-variance values plotted against the distances between the data pairs
Plate 1. Temporal series of False Color Composite (FCC) Images of WC4 field showing soil and crop growth variations during the year 2004.
is referred to as semivariogram. The semivariogram models are characterized using three parameters (Figure 16) namely a) Sill – which represents the total variation present when the semivariogram reaches the plateau, b) Range – the distance at which semivariogram reaches the sill and all successive values are independent of each other, and c) Nugget representing the vertical extent of discontinuity at the origin of the semivariogram.

Some of the main semivariogram models (Figure 17) include spherical, gaussian, power, exponential, linear, etc. and among which spherical model is the most commonly used model in analyzing experimental data. However in this study both spherical and exponential models were used. The equations for the spherical and exponential models are given as

\[
\gamma(h) = \begin{cases} 
  c_0 + c \left\{ \frac{3h}{2a} - \frac{1}{2} \left( \frac{h}{a} \right)^3 \right\} & \text{for } h < a \\
  c_0 + c & \text{for } h \geq a 
\end{cases}
\]

(3.26)

\[
\gamma(h) = C_0 + C \left[ 1 - \exp\left( -\frac{3h}{a} \right) \right]
\]

(3.27)

where \(c_0\) is the nugget variance, \(c\) is the auto-correlated variance or sill, \(a\) is the range of correlation or scale of spatial dependence for the variable, and \(h\) is the separation distance between the pixels. The semivariogram model was generated for SAVI images in order to test the correlation and spatial dependence of yield for some of the study fields. The whole field subset image was created for all the study fields from both airborne and Landsat TM image covering the area identified by different climatic and environmental factors. The X and Y coordinates of the image pixel were used to calculate the distances.
between the pixels. All these data sets were exported as ASCII text files and imported into GS+ statistical software and converted to geostatistical datasets. The best fitted spherical and exponential models were fitted to those variograms and all the parameters of the semivariogram (sill, range, and nugget) were identified and analyzed for the input variable to test the spatial dependency of the yield data.

Kriging is also one of the geostatistical techniques that uses an optimal interpolation technique for generating best linear unbiased estimate for each location and applies semivariogram model to determine the values at un-sampled locations. All these techniques were used to describe the spatial variability of crop yield for the study field. The implications on using these methods were examined at different scales using both airborne and satellite images.

Figure 16. Example of a semivariogram form.
Figure 17. Semivariogram models showing parameters namely nugget, sill, and range.
RESULTS AND DISCUSSION

Development of VI-Yield Model

The spot yield sample data collected during the 2004 growing season were used in developing the SAVI based statistical yield model. A total of sixteen hand dug yield locations were chosen based on soil and crop growth patterns from two center pivots fields (WC 7 and OI 16). Airborne images were acquired three times during critical stages of crop growth. The first image was acquired on July 05 which is approximately five to eight days before the crop reached the effective full cover stage which corresponds to the period of peak ET. The second image acquisition flight was on July 30 capturing the peak vegetative growth of the crop. The final image was acquired on August 31 when the potato fields were at the senescence stage of growth and captured the variability in crop senescence rates in the field.

First, an NDVI-based linear relationship using single date imagery (July 5\textsuperscript{th}, 2004) was developed to compare against a similar SAVI based relationship to assess the effects of soil background and differences in vegetation growth on these VI. The hand-dug samples from 2004 were used to obtain the relationships and 2005 hand dug samples were used for testing the NDVI and SAVI based relationships. Figure 18 shows the single-date NDVI based linear yield relationship resulting in a r-squared value of 0.62 as compared to an r-squared of 0.72 for the SAVI based relationship (Figure 19). These single date models were then applied to the hand dug samples collected in the 2005 season and the estimated yield versus the actual yield were plotted as shown in Figure 20 and Figure 21.
Figure 18. NDVI based single-date yield model developed using 2004 spot yield data.

Figure 19. SAVI based single-date yield model developed using 2004 spot yield data.
Figure 20. Estimated versus actual yield using NDVI based single-date yield model applied to spot yield samples collected in the 2005 season.

Figure 21. Estimated versus actual yield using SAVI based single-date yield model applied to spot yield samples collected in the 2005 season.
The SAVI-based relationship resulted in a better correlation with yield ($R^2 = 0.88$) and lower RMSE of 0.06 than the NDVI relationship ($R^2 = 0.60$ and RMSE= 0.47) due to the ability of SAVI of minimizing soil background reflectance effects caused by natural variability in soil reflectance in addition to varying surface soil moisture due to irrigation or rainfall.

The single-date SAVI model was developed for the image captured on July 5th as it best correlated with the yield compared to other image dates. The image acquired during this period captured the crop growth intensity from emergence till that date which are usually related to the higher producing areas in the field but also slow growing areas due to poor soil conditions which are related to lower leaf area duration and lower yields. This agrees with the findings reported by Jayanthi (2003) that best correlation for a single date model could be obtained from the aerial image captured 7 to 10 days before the effective full cover. Despite the better correlation, the single-date SAVI model over predicted the 2005 yield with a mean bias error (MBE) of 0.3 kg/sq.m. Here in this case, the single-date model over predicted based on the fact that the SAVI image used in 2005 was acquired 4 to 5 days before effective full cover and had more leaf area present than the 2004 image used for model development which was acquired at an earlier stage relative to effective full cover and this might have caused the over estimation.

The single-date yield model is based on the assumption that spot yields are independent and randomly distributed covering the entire range of crop yield variability and also assumes normal growth duration of the crop, estimating the yield accordingly. Potato crops, being an indeterminate variety have a vegetative growth curve with no pronounced peak VI and the final yield is related to the duration of the green leaf area
and not only to the peak leaf area index. A more precise and better relationship should be obtained by considering the entire crop growth season and relating the yield with integrated area under the SAVI curve over the complete crop growth cycle.

A three-date integrated SAVI model was developed using a total of 16 hand-dug yield samples collected in 2004. The integrated SAVI images were generated from the three images acquired on July 05, July 30 and August 31, 2004 and corresponding average SAVI values were extracted from the pixels within the area of interest (AOI) polygon corresponding to the field sampling sites. The results are shown in Figure 22 with an r-squared of 0.81 and standard error of yield estimate of 0.41 kg/sq.m. The assumption of null hypothesis in simple linear regression is that the independent variable is not significant or unimportant in predicting the dependent variable Y and the alternate hypothesis proves that the independent variable is significant in predicting the dependent variable yield. The test of significance for the independent variable was analyzed from the ANOVA table. It was concluded from the results, that the independent variable ISAVI was significant (p < 0.05) in predicting the yield. Therefore, the null hypothesis was rejected as the P value was very small and hence the alternate hypothesis was accepted. This test proved that there existed a good correlation between the independent variable ISAVI with yield on the potato field.

Validation of Three-date Integrated SAVI Yield Model for Spot Yield Data

The three-date integrated SAVI yield model developed using 2004 spot yield data was validated using hand-dug potato yield collected during the year 2005. A total of eighteen hand dug yield locations were chosen based on soil and crop growth patterns.
and the samples were collected from two sprinkler irrigated center pivots fields (HF 12 and OI 1). The first image in the year 2005 was acquired on July 08 which was approximately one week before the effective full cover stage of the crop. The second image was on August 04 which captured the peak vegetative growth of the crop and the yield formation on ground. The final image was acquired on August 25 when the crops were in the senescence stage and best captured the variability of crop senescence rates in the field. An integrated SAVI image was produced from SAVI images derived from the imagery acquired on the three dates. The AOI polygons were created on the integrated SAVI image for each spot yield location and corresponding average integrated SAVI values were extracted for each AOI location. These values were then used with the three-date yield model developed and estimated yield for all the sampling locations were obtained. Figure 23 shows the comparison between actual and estimated yield values.
The model predicted the yield better than the single-date model with an MBE of 0.07 kg/sq.m and RMSE of 0.24. The yield data values are falling around the 1:1 line and resulted in a good linear correlation (r-squared = 0.89) though the model slightly over predicted for some of the yield sampling locations at the higher end.

**Validation of Three-date Integrated SAVI Yield Model**

**for 2004 and 2005 Whole Field Yield Data**

The Three-date integrated SAVI yield model developed for 2004 spot yield data was validated using 2004 whole field airborne and yield data involving a total of 15 fields. The integrated spatial SAVI images for all fields were created from imagery acquired on three airborne multispectral acquisitions on July 05, July 30 and August 31.

![Three-date ISAVI model (07/08, 08/04, 08/25 2005)](image)

$r^2 = 0.89$

MBE = 0.07 Kg/sq.m

RMSE = 0.24

Figure 23. Comparison of estimated versus actual yield using 2004 three-date ISAVI yield model for spot yield samples collected in the year 2005.
The three-date integrated ISAVI model was applied to the image to obtain a spatially distributed yield map. The field AOI created was applied to the yield image to obtain the yield statistics. Figure 24 shows the comparison of estimated versus the actual average yield for the whole field. The model slightly overestimated yield with a MBE of 0.16 kg/sq.m and a RMSE of 0.29. The estimated field production from all the fields was calculated by multiplying the area of each field with the average estimated yield for the whole field. Actual weighed production from each center pivot field was plotted against the estimated production (Figure 25) showing a good linear correlation (r-squared 0.95) with a RMSE of 144.63 and a slight overestimation, an MBE of 66.47 metric tons (MT). The reason for this overprediction might be due to the fact that the three-date integrated SAVI model developed did not cover the complete growth cycle and interpolations had to be conducted to obtain the seasonal integrated SAVI at the beginning of the season between crop emergence date and the date of the first airborne image acquisition as well as at the end of the season between the date of the last image and the vine kill date.

A better yield estimation can potentially be achieved by developing a model using more images from multiple acquisition dates covering the growing season from emergence to vine kill. Also potato yield is influenced by many factors such as crop ET, temperature, soil properties, land and crop management practices, etc. All these factors need to be considered in estimating the yield accurately.

The three-date integrated SAVI yield model developed for 2004 spot yield data was also validated using 2005 whole field data from 13 fields. The spatial ISAVI images for all the fields were created from the three airborne multispectral images acquired on July 08, August 04 and August 25. The three-date integrated ISAVI model was applied to
the image to obtain a spatially distributed yield map. The field AOI created was applied to the yield image to obtain the yield statistics. Figure 26 shows the comparison results with a MBE of -0.15 kg/sq.m and RMSE of 0.25. The actual weighed production from all the fields was compared with the estimated production (Figure 27) showing a good linear correlation (r-squared 0.96), an RMSE of 105.98 and a MBE of -60.59 (MT) which is similar to the 2004 whole field results in value but underestimated.

**Estimating Yield Using Landsat TM5 Satellite Imagery**

To further test the performance of the three-date integrated SAVI yield model developed for 2004 spot yield data using airborne images, satellite images from 2004 and 2005 were used involving a total of 10 fields in 2004 and 13 fields in 2005, respectively. The ISAVI images for all the fields for both the years were created spatially using TM
Figure 25. Comparison of estimated versus actual yield production in metric tons using 2004 whole field data.

Figure 26. Comparison of estimated versus actual yield using 2005 whole field data.
Figure 27. Comparison of estimated versus actual yield production in metric tons using three-date model applied to 2005 whole field data.

images acquired on June 30, August 01, September 11 for 2004 and July 03, August 04 and September 05 for 2005 season, respectively. The three-date ISAVI model was applied to get the yield map. The image statistics were extracted from the spatially distributed yield image. Figure 28 shows the comparison of estimated versus actual whole field yield. The model over predicted the yield with a MBE of 90.51 MT and RMSE of 203.74 for 2004 and under predicted the yield for 2005 with a MBE of -150.33 MT and RMSE of 247.09 (Figure 29), similar trends to the observed estimates from airborne imagery in the same year. These differences in the yield prediction between airborne and satellite might be due to different pixel sizes and also the fact that the field AOI on satellite images was difficult to establish along the edges due to the pixel size. In addition, the dates of the satellite image acquisition did not match the three airborne acquisition dates but were selected to be close to those dates. Also each field had
Figure 28. Comparison of estimated versus actual yield production in metric tons using three-date model applied to 2004 TM5 satellite whole field data.

different duration lengths from emergence to vine kill for both the years. An additional image of the potato field should be used in late season to capture the length of tuber bulking and crop senescence pattern that helps to better predict yield variability. Also, soil water stress during tuber bulking might reduce the yield and so incorporating actual crop evapotranspiration in the yield model might improve yield assessments.

Verifying an Eight-date ISAVI Model with Landsat TM Satellite Data

The eight-date integrated SAVI model developed by Jayanthi (2003) was applied to the 2004 and 2005 satellite images to estimate yields and compare with whole field production data. A total of 10 fields in 2004 and 13 fields in 2005 were used to estimate the yield. The ISAVI images for all the fields for both the years were created spatially
using the satellite images listed in Table 2.0. The three-date ISAVI model was applied to get the yield map. The image statistics were extracted from the spatially distributed yield image. Figure 30 shows the comparison of estimated versus the actual average yield for the whole field. The model over predicted the yield with the MBE of 67.32 MT and RMSE of 175.72 for 2004 and an MBE of 51.74 MT and RMSE 207.35 of for the 2005 season (Figure 31). However, overall the yield predictions were better than the three-date model for both years with the data falling around the 1:1 line and very low bias. The use of more images improved the characterization of in-field variability in SAVI resulting in more accurate ISAVI values and yield estimations. It is evident that the model developed using high resolution (1 m) airborne images can be very well applied to satellite images.
Figure 30. Comparison of estimated versus actual yield production in metric tons using eight-date model applied to 2004 TM5 satellite whole field data.

Figure 31. Comparison of estimated versus actual yield production in metric tons using eight-date model applied to 2005 TM5 satellite whole field data.
Incorporating Actual ET into the Yield Model

In order to improve the yield predictions by incorporating actual ET in the model, a soil water balance in the crop root zone for the hand dug locations was conducted throughout the 2004 season and seasonal actual ET was included as another independent variable in the model. The soil physical property data such as water retention capacity used in the water balance analysis were collected from USDA soil survey report for the study area. The basic soil data used in the water balance analysis includes field capacity ($\theta_{fc}$) 320 mm/m and wilting point ($\theta_{wp}$) 160 mm/m. The crop characteristics data namely initial root depth was set to 0.15 m and final as root depth at 1.27 m. The final crop canopy height was considered to be 0.76 m and the management allowed depletion (MAD) used in the computation was 40 percent. The reference ET was computed using 1982 Kimberly-Penmann method using weather data provided by the Cranney farms weather station. The water balance analysis conducted estimated the actual ET using canopy reflectance based crop coefficient method ($k_{crf}$) (Jayanthi, Neale, and Wright, 2007). A total of ten images from both airborne and satellite images covering the entire growing season were used to create the $K_{crf}$ images. The hand dug sampling location AOI polygons were overlaid on the $K_{crf}$ images to extract image statistics.

The potato crop was planted on April 09, 2004, emergence occurred around the last week of May (DOY 148) and the crop was harvested by the last week of September (DOY 270). The water balance was computed starting from emergence date and the daily actual ET was estimated using $K_{crf}$ method for all the AOIs based on soil and individual crop growth patterns (Figure 32). The graph shows the daily actual ET for four of the sampled locations based on the four seasonal crop growth categories previously
Figure 32. Daily actual ET for four different AOIs based on different crop growth patterns in the WC7 field during 2004 season.

described. The arrow marks on the graph indicate the irrigation dates. The cumulative ET was found to be higher for the AOIs that had early crop growth start and senesced late in the season and lower cumulative ET for the AOIs with crop emerging very late and senescing early. It is evident from the graph that the daily ET values were very low during the initial phase of crop development when most of the water was evaporating from the soil surface and less was used in transpiration. ET increased as the plants started growing at a rapid rate utilizing maximum water in the root zone. Similar pattern existed for all other sampled locations and the cumulative seasonal ET derived from all the locations were used in multiple linear correlation analysis along with the ISAVI as two independent variables and actual yield as the dependent variable. The cumulative actual ET for the different hand dug sampled locations are shown in Figure 33. The graph shows
a good linear correlation (R-squared 0.87) between the actual yield and ET with ET values ranging from a minimum of 639 mm to a maximum of 700 mm.

The results of the multiple linear regression analysis are shown in Table 3. The results showed a great improvement in the model correlation compared with the three-date ISAVI model (r-squared 0.81) with 88 percent of the variability explained by the variables involved. The null hypothesis in multiple linear regression assumes that the independent variables are not significant or unimportant in predicting the dependant variable Y and the alternate hypothesis proves that at least one variable is significant in predicting the dependant variable. The test of significance for individual variables and overall test significance were analyzed from the ANOVA table. The results indicate that the independent variable ET was more significant (p < 0.05) than ISAVI variable in predicting the yield on ground. However, the overall test for significance seemed to reject the null hypothesis as the P value was very small and hence the alternate hypothesis was
accepted. This test proved that there existed a good correlation between the independent variables with yield on the ground. The resulting multiple linear regression (MLR) model was:

\[ Y = 5.56 \times \text{ISAVI} + 0.0359 \times \text{ET}_{\text{as}} - 21.397 \]  

(4.1)

where \( \text{ET}_{\text{as}} \) is the cumulative seasonal ET. The independent variables in the above equation have different units with \( \text{ET}_{\text{as}} \) (mm) having a larger magnitude compared to ISAVI (Dimensionless).

**Validating the MLR model Using 2004 and 2005 Satellite Imagery**

The MLR model performance was tested by applying it to 2004 and 2005 satellite imagery and testing against whole field production data for the center pivot fields monitored. To obtain cumulative ET, the soil water balance in the crop root zone was conducted for all the study fields for which the whole field yield was available. A total of 10 fields during 2004 and 13 fields during 2005 were chosen for the analysis. All the information regarding potato crop planting, emergence and harvest data were obtained from Cranney farms. The soil data used in the water balance analysis were collected from USDA soil survey report for the study area. Most of the study fields had uniform soil type (Silt loam) with the exception of few fields having a mixture of silt and sandy loam. The water balance analysis was carried out in the same way as the AOI sampling sites used in the model development i.e. by using the reflectance based coefficient method \( (k_{crf}) \) to track the real growth of the potatoes in the fields. A total of ten images from both airborne and satellite images covering crop growing season were used to create the \( K_{crf} \) images. The whole field AOI polygons were used on the \( K_{crf} \) images for each of the study
fields involved to extract image statistics (means and standard deviations). The average value of $K_{crf}$ for each of the study fields on each image acquisition date were used in computing the water balance to obtain the cumulative seasonal ET (ETas) for each field to be used in the MLR model along with the calculated integrated SAVI values. Figure 34 and Figure 35 shows the estimated yields plotted against the actual yield for the 2004 and 2005, respectively. The results indicate an excellent linear correlation ($r^2$ 0.97) with a MBE of 44.13 MT for 2004 and $r$-squared of 0.75 and MBE of -39.34 MT for 2005. For both the years, the results showed a great improvement compared to the yield estimated using the three-date ISAVI simple linear regression model. Thus it can be concluded that cumulative seasonal ET explained additional variability.

**Yield Maps Based on Integrated SAVI Model**

The yield maps were produced using the integrated SAVI model with both the airborne and satellite images. Some of the study fields from 2004 and 2005, season namely, HF19, WSA09, OI10, HF4, and WC4, were chosen based on soil and crop growth variability patterns and the yield estimates of those fields were compared. The false color composite (FCC) of these study fields are shown Plate 2 and Plate 3. The yield maps were created using the three-date integrated SAVI model with the airborne images and Eight-date integrated SAVI model was applied to satellite images to get the estimated yield maps for the whole fields. The yield maps were compared with the FCC images to check if the crop growth pattern followed the yield pattern. Plate 2 shows the FCC images of HF19 and WSA09 from 2004 season. The total whole field production from
Table 3 Summary output of the multiple linear correlation analysis using two independent variables ISAVI and ET<sub>as</sub>

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<td>4.091827534</td>
<td>1.358474022</td>
<td>0.197420264</td>
<td>14.39849734</td>
<td>-3.281214527</td>
<td>14.39849734</td>
</tr>
<tr>
<td>SAVI Variable</td>
<td>0.035973046</td>
<td>0.012789868</td>
<td>2.812620468</td>
<td>0.014670929</td>
<td>0.063603877</td>
<td>0.008342215</td>
<td>0.063603877</td>
</tr>
<tr>
<td>ET Variable</td>
<td>0.035973046</td>
<td>0.012789868</td>
<td>2.812620468</td>
<td>0.014670929</td>
<td>0.063603877</td>
<td>0.008342215</td>
<td>0.063603877</td>
</tr>
</tbody>
</table>
Figure 34. Comparison of estimated versus actual yield production in metric tons using MLR model applied to 2004 TM5 satellite whole field data.

Figure 35. Comparison of estimated versus actual yield production in metric tons using MLR model applied to 2005 TM5 satellite whole field data.
these two fields were 2607 MT and 2637 MT with an average yield of 5.03 kg/sq.m and 5.43 kg/sq.m respectively. The yield maps created for both the fields clearly indicate that the crop growth pattern directly affects the yield pattern (Plate 6). Some portions of the fields resulted in distinct patterns where eroded soils clearly caused a lower yield which was very evident from the yield maps. Most of the areas in HF19 field were having variable growth patterns with lower yields especially in areas with highly eroded soils where the crops were struggling to keep their photosynthetic process active and thus affecting the whole field average yield. However in areas with non-eroded soils such as in field WSA 9, the plants emerged early and were growing healthy on the ground for a longer period contributing to a higher ISAVI and resulting in high yields. Field wsa09 also had a patch of eroded soils where the yield was very low as evident from the yield maps while other portions of the field were distributed with medium to high yields. The Plate 3 also shows the FCC images of HF4 and OI10 fields from the 2005 season. The whole field production from these two fields was 3330.56 MT and 2956.76 MT with an average yield of 6.05 kg/sq.m and 5.62 kg/sq.m, respectively. The yield maps were produced for OI10 field and the map clearly indicates similar patterns of crop growth and yield from this field as well (Plate 6). The FCC satellite images for field WC4 (Plate 4) show soil and crop growth variations which can be observed with more detail in the FCC airborne images for the same field (Plate 5). The yield maps produced using both airborne and satellite images for WC4 field were also compared (Plate 7). From both the yield maps, it can be noted that the yield variability from aerial image is more distinct than satellite yield map but yield estimates followed the same pattern. It is important to note that the whole field yields in the 2004 season were lower than the yields attained
during the 2005 season. This might be due to the extreme dry and hot weather condition that occurred in 2004, while the 2005 season had normal temperatures and higher precipitation rates.

**Spatial Variability Analysis Using Descriptive Statistics**

The spatial variability of yield in potato fields was analysed based on soil and crop growth differences caused by highly variable soil conditions as well as land and crop management practices and differences in landscape elevation in the fields. Plate 5 shows the FCC airborne images compared to the Landsat TM5 images for the WC4 field depicting soil and temporal crop growth variability during the 2004 season. The WC5 potato field under production in 2005 was selected as an example to show the spatial variability in yields resulting from the presence of streaking soil layers throughout the field (Plate 8). This field was planted during the second week of April (DOY 102) with plant emergence occurring around the third week of May (DOY 140). The mostly bare soil image of DOY 145 (May 25th) captured the soil layer streaks showing eroded (white areas on the east side) and non-eroded areas throughout the field. Effective full cover was reached on the good soils of the field by July 12th and on most of the poor soils by August 4th. Senescence rates were faster on the poor soils and were captured by the August 20th, Sep 5th and Sep 14th 2005 images. SAVI images were generated for all image dates. AOI polygons were created for eroded and non-eroded soils within the field and basic statistics were extracted for these polygons and also for the entire field. The statistics included the minimum, maximum, mean and standard deviation for the SAVI which was used as the surrogate for yield and water use (Table 4).
Plate 2. FCC aerial images of HF19 field (Top) and WSA09 (Bottom) showing soil and crop growth variations during the year 2004.
Plate 3. FCC aerial images of HF04 field (Top) and OI10 (Bottom) showing soil and crop growth variations during the year 2005.
Plate 4. Temporal series of FCC satellite images of WC4 field showing soil and crop growth variations during the year 2004.
Plate 5. FCC images of airborne images (Top) comparing with LandSat TM5 (Bottom) for WC4 field showing soil and crop growth variability during 2004 season.
Plate 6. Yield maps showing the variability in yields for field HF19, WSA9 during 2004 and OI10 during 2005 season.
Plate 7. Yield maps showing the variability in yields for field WC4 using airborne images (Left) and satellite images (Right) during 2004 season.
Plate 8. Temporal series of FCC satellite images of WC5 field showing soil and crop growth variations during the year 2005.
Table 4. Summary statistics of SAVI images for WC5 potato field in eroded, non-eroded and whole field during 2005 growing season

<table>
<thead>
<tr>
<th>Date</th>
<th>Unit</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-May-05</td>
<td>Whole field</td>
<td>0.054</td>
<td>0.120</td>
<td>0.108</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.093</td>
<td>0.138</td>
<td>0.127</td>
<td>0.004</td>
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<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.104</td>
<td>0.148</td>
<td>0.139</td>
<td>0.004</td>
</tr>
<tr>
<td>26-Jun-05</td>
<td>Whole field</td>
<td>0.286</td>
<td>0.412</td>
<td>0.366</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.313</td>
<td>0.390</td>
<td>0.331</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.351</td>
<td>0.406</td>
<td>0.381</td>
<td>0.009</td>
</tr>
<tr>
<td>3-Jul-05</td>
<td>Whole field</td>
<td>0.321</td>
<td>0.544</td>
<td>0.451</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.380</td>
<td>0.506</td>
<td>0.417</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.442</td>
<td>0.521</td>
<td>0.497</td>
<td>0.013</td>
</tr>
<tr>
<td>12-Jul-05</td>
<td>Whole field</td>
<td>0.502</td>
<td>0.769</td>
<td>0.680</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.529</td>
<td>0.703</td>
<td>0.580</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.663</td>
<td>0.746</td>
<td>0.728</td>
<td>0.017</td>
</tr>
<tr>
<td>4-Aug-05</td>
<td>Whole field</td>
<td>0.335</td>
<td>0.794</td>
<td>0.750</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.687</td>
<td>0.760</td>
<td>0.724</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.751</td>
<td>0.781</td>
<td>0.770</td>
<td>0.007</td>
</tr>
<tr>
<td>20-Aug-05</td>
<td>Whole field</td>
<td>0.399</td>
<td>0.766</td>
<td>0.719</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.612</td>
<td>0.744</td>
<td>0.678</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.706</td>
<td>0.752</td>
<td>0.736</td>
<td>0.007</td>
</tr>
<tr>
<td>5-Sep-05</td>
<td>Whole field</td>
<td>0.312</td>
<td>0.663</td>
<td>0.556</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.355</td>
<td>0.566</td>
<td>0.486</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.552</td>
<td>0.604</td>
<td>0.572</td>
<td>0.013</td>
</tr>
<tr>
<td>14-Sep-05</td>
<td>Whole field</td>
<td>0.250</td>
<td>0.598</td>
<td>0.481</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>Eroded soils</td>
<td>0.250</td>
<td>0.511</td>
<td>0.389</td>
<td>0.057</td>
</tr>
<tr>
<td></td>
<td>Non-eroded soils</td>
<td>0.481</td>
<td>0.556</td>
<td>0.505</td>
<td>0.015</td>
</tr>
</tbody>
</table>
The SAVI mean and standard deviation (SD) curves for eroded and non-eroded soils over the growing period are shown in Figure 36. From the curve, it is clear that both the curves follow the same pattern but the SD for eroded soils were higher than the non-eroded soils contributing to higher spatial variability over the entire field. The SAVI mean for eroded soils was lower than the non-eroded soils indicating sub-optimal growing conditions for the crops on these soils. Crop growth variability as a result of soil variability was observed in many fields with field WC5 having distinct areas of eroded and non-eroded soils.

The FCC Images of OI1 field showing temporal crop growth patterns and senescence rates for 2005 growing season are presented in Plate 9. This field was used to study the spatial variability of potato yield caused by changes in landscape elevation.

The potato plants in this field emerged around the last week of May and reached effective full cover during the second week of July. The previous and present land management practices showed a slight difference in the landscape elevation of 2.5 m in this field from south to north direction with south portion at higher elevation. From Plate 9, it can be seen that peak crop growth was reached by mid-July and by the end of August, the plants started to lose their photosynthetic activity observed in the SouthWest-SouthEast (SW-SE) direction with less water available as a result of eroded soils. It is very evident that the crop growth and senescence rates were high towards NorthWest-NorthEast (NW-NE) orientation and had more yield when samples were collected compared to south section. This might be due to the fact that more water and nutrients moved from upslope positions and affect the portions at higher elevation (SW-SE portion) eventually resulting in lower yields.
The minimum, maximum, mean, and standard deviation were extracted for all the dates from the SAVI images for areas covering pertaining to NW-NE and SW-SE portion (Table 5). The SAVI mean and standard deviation curve for both northern and southern portion of the field over the growing period are shown in Figure 37. From the curve, it can be seen that the SAVI mean for NW-NE portion was slightly higher than the SW-SE areas of the field. The SD for both NW-NE and SW-SE areas of field was more or less similar until the effective full cover but the deviation was more in SW-SE portion of the field towards the end when the crops were at maturity and senescence stage contributing to higher spatial variability. This note of information is useful in precision agriculture point of view where the farmers can assess and apply the right amount of farm inputs on the field at the right time on a real time basis thereby increasing the yield.

Variability Analysis Using K<sub>crf</sub> Images

The integrated SAVI yield estimates were used in conjunction with the K<sub>crf</sub> images over the period of time to show the variability of yields. The K<sub>crf</sub> images over the critical growth period and also the corresponding yield image produced using integrated SAVI image for field WC4 during 2004 season are shown in Plate 10. The calibrated FCC images for each date were converted to SAVI images and then transformed to SAVI based reflectance crop coefficient images. The reflectance based crop coefficient images were classified into different ranges of K<sub>crf</sub> and different colors were given to the varying K<sub>crf</sub> ranges. From the k<sub>crf</sub> and yield images, it is very clear that the crop growth during the complete growth cycle follows the soil patterns varying over the entire field. The K<sub>crf</sub> images for the growing season are very important in terms of irrigation scheduling to
apply required depth of irrigation on a real time basis from the multispectral images. The advantage of using $K_{crf}$ method over $K_{cb}$ method is that $K_{cb}$ estimates theoretical maximum water requirement assuming ideal crop growth conditions which might lead to over or under estimation of irrigation depth depending on the crop growth stage and location in the field. In addition, $K_{cb}$ is valid for conditions in which it had been developed. However the actual crop growth conditions that are present in the fields are far from the ideal conditions in which $K_{cb}$ has been developed. In contrast, $K_{crf}$ represents the actual crop water needs based on the actual crop condition assessed using remote sensing data.

Spatial Variability Analysis Using Geostatistics

Geostatistics using semivariogram analysis was performed for some of the study fields to show the spatial dependence of yield data based on SAVI data and to characterize the spatial variation in the region of interest. A total of eight study fields from satellite and airborne images were chosen for the semivariogram analysis based on soil and crop growth variability. The geostatistical parameters and the fitted models for those fields are given in Table 6. The semivariograms computed for different study fields are shown in Figure 38 and Figure 39. The semivariogram results show that the crop yield in all the fields were spatially correlated.

The maximum value of variance is known as the sill and nugget variance represents the data that were spatially uncorrelated. The measure of spatial dependency of the data is given by the ratio of nugget variance to sill. Cambardella et al. (1994) defined the spatial dependency of data based on the ratio of nugget to sill into three categories: If the ratio is less than 25 percent, there is a strong spatial correlation of the data, medium
Plate 9. FCC satellite images of O11 field showing variability in crop growth patterns and senescence rates due to land and management practices for 2005 growing season.
Figure 36. SAVI mean and standard deviation for eroded and non-eroded soils over the 2005 growing period for potato field WC5.

Figure 37. SAVI mean and standard deviation for north and south portion of potato field OI1 over the 2005 growing period.
Table 5. Summary statistics of SAVI images for OI1 potato field from NW-NE and SW-SE during 2005 growing season

<table>
<thead>
<tr>
<th>Date</th>
<th>Unit</th>
<th>No. of pixels</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-May-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.084</td>
<td>0.154</td>
<td>0.125</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.075</td>
<td>0.141</td>
<td>0.129</td>
<td>0.005</td>
</tr>
<tr>
<td>26-Jun-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.467</td>
<td>0.577</td>
<td>0.533</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.445</td>
<td>0.635</td>
<td>0.574</td>
<td>0.023</td>
</tr>
<tr>
<td>3-Jul-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.485</td>
<td>0.663</td>
<td>0.615</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.523</td>
<td>0.698</td>
<td>0.650</td>
<td>0.024</td>
</tr>
<tr>
<td>12-Jul-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.667</td>
<td>0.780</td>
<td>0.749</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.597</td>
<td>0.797</td>
<td>0.769</td>
<td>0.019</td>
</tr>
<tr>
<td>4-Aug-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.438</td>
<td>0.737</td>
<td>0.719</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.632</td>
<td>0.739</td>
<td>0.710</td>
<td>0.015</td>
</tr>
<tr>
<td>20-Aug-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.565</td>
<td>0.706</td>
<td>0.684</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.546</td>
<td>0.698</td>
<td>0.651</td>
<td>0.020</td>
</tr>
<tr>
<td>5-Sep-05</td>
<td>NW-NE</td>
<td>150</td>
<td>0.468</td>
<td>0.586</td>
<td>0.532</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>SW-SE</td>
<td>150</td>
<td>0.387</td>
<td>0.552</td>
<td>0.480</td>
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<tr>
<td>14-Sep-05</td>
<td>NW-NE</td>
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<td>0.356</td>
<td>0.481</td>
<td>0.432</td>
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</tr>
<tr>
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<td>SW-SE</td>
<td>150</td>
<td>0.278</td>
<td>0.446</td>
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</tbody>
</table>
Plate 10. Temporal series of FCC images (Top) of WC4 field showing soil and crop growth variations during the year 2004 and corresponding $K_{crf}$ images (Bottom) compared with ISAVI yield estimates.
Table 6. Variogram parameters and best fitted model for the study field during 2004 and 2005 seasons

<table>
<thead>
<tr>
<th>Fields</th>
<th>Variogram model</th>
<th>Nugget</th>
<th>Sill</th>
<th>Nugget/Sill Ratio</th>
<th>Range</th>
<th>RSS</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>WC4</td>
<td>Exponential</td>
<td>0.00050</td>
<td>0.13000</td>
<td>0.0038</td>
<td>386</td>
<td>1.22E-04</td>
<td>0.99</td>
</tr>
<tr>
<td>Becker</td>
<td>Exponential</td>
<td>0.00100</td>
<td>0.15400</td>
<td>0.0065</td>
<td>564</td>
<td>7.80E-05</td>
<td>0.96</td>
</tr>
<tr>
<td>HF5</td>
<td>Spherical</td>
<td>0.00053</td>
<td>0.00146</td>
<td>0.68</td>
<td>148</td>
<td>1.26E-07</td>
<td>0.90</td>
</tr>
<tr>
<td>OI9</td>
<td>Exponential</td>
<td>0.00420</td>
<td>0.03340</td>
<td>0.126</td>
<td>256</td>
<td>1.36E-05</td>
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</tr>
<tr>
<td>OI10</td>
<td>Spherical</td>
<td>0.00539</td>
<td>0.01088</td>
<td>0.49</td>
<td>520</td>
<td>1.91E-07</td>
<td>0.99</td>
</tr>
<tr>
<td>Field 8</td>
<td>Exponential</td>
<td>0.00360</td>
<td>0.11460</td>
<td>0.0314</td>
<td>451</td>
<td>1.18E-04</td>
<td>0.98</td>
</tr>
<tr>
<td>WC1</td>
<td>Exponential</td>
<td>0.00240</td>
<td>0.11420</td>
<td>0.021</td>
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<td>1.07E-04</td>
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</tr>
<tr>
<td>WC7</td>
<td>Exponential</td>
<td>0.00270</td>
<td>0.12840</td>
<td>0.021</td>
<td>358</td>
<td>1.83E-04</td>
<td>0.99</td>
</tr>
</tbody>
</table>

when the ratio is between 25 and 75 percent and the correlation is said to be weak if the ratio is greater than 75 percent. From Table 5, it can be inferred that all the study fields were strongly correlated except for OI10 and HF5 which had weaker correlation of yield data spatially compared to other fields. The sill value indicates the degree of spatial variability. Higher values of sill indicates larger spatial dissimilarity of the yield data and viceversa. Here in this analysis, the spatial dissimilarity in the yield data were larger for all the study fields compared to OI9, OI10 and HF5 which might be due to the fact that the yields were comparatively uniform in these three fields than the other fields. This can be seen in the yield maps produced for field OI 10 (Plate 6) which had uniform yields compared to WC4 field that had variable yields all over the field (Plate 7). The range
Figure 38. Semivariogram curve for the study fields WC4, WC7 (Top Left to Right) and HF5 and OI9 (Bottom Left to Right).
Figure 39. Semivariogram curve for the study fields HF8, WC1 (Top Left to Right) and Becker, OI10 (Bottom Left to Right).
represents the distance over which the data are correlated. The yield data located in places closer than the range are said to be correlated statistically and data away from the range are not. The range of correlation for all the study fields varied from a distance of 150 m to 520 m with field OI10 having the higher range and HF5 field with the lowest range compared to other fields. The data for all the study fields in this analysis were best fitted by exponential model except field HF5 and OI10 that were best fitted by spherical model.

All the variogram parameters analyzed for the study fields showed that there was a strong spatial correlation of the data and that the mathematical models fitted can be used to do kriging analysis, an interpolation technique of point data to produce surface maps. The semivariogram parameters have to be further investigated using coarser resolution imagery for a large area and compared. In this research, the variogram analysis studied using both airborne and TM images provided a useful information about the spatial dependency of the data and the maps produced by kriging analysis can be used as a reference in doing the sampling work at field scale. Yield monitor data, if available combined with geostatisitical methods, could provide a better spatial and temporal distribution of the data over the field. The surface maps created by kriging using the yield monitor data could be used as an excellent guide by the farmers to improve crop management practices by taking crop growth and soil variability into account. However, this research has shown that spatial yield maps from remote sensing could be used for the same purpose.
Detailed Discussions and Observations from This Study

Multispectral remote sensing offers an excellent means of providing multispectral images of features on the earth surface at various scales and on a real time basis. This is being used as an effective tool in the field of yield modeling and prediction for several crops. The spectral reflectance of a crop depends on crop stage and health and could be effectively monitored using multispectral remote sensing. Research in the past has shown the relation between leaf area duration, vegetation indices and crop yield. The crop growth in a field would follow a pattern at different places and depends upon several factors including soil type, management practices, fertilizer application etc. In the case of potato, the crop which emerges very early and stands on the ground healthy for a longer duration will eventually have high yield and portions of the field where crop emerges very late and senescence occurs very early leading to lower yields. These variations in the growth rates and duration are well captured by multitemporal remote sensing images. Determining the ratio of near infra red and red wavelength offers useful information regarding the crop vegetation health. Healthy cropped areas have high SAVI values and would appear bright compared to stressed vegetation that would appear darker in the images. All these factors formed the basis in developing the yield model in this study. The model was developed using airborne images acquired on three different dates and applied to satellite images. The model developed in this study showed that there was a good correlation between yield on ground and ISAVI and also showed that reliable yield estimation can be achieved using remote sensing data. Jayanthi (2003) suggested that when using three date images, the first image for the growing season has to be seven to ten days before the effective full cover. This image at vegetative stage phase of the crop
shows the soil and crop growth variations throughout the field indicating low and high yielding spots. Areas with low yield might be due to various factors such as low soil natural fertility, uneven application of irrigation, fertilizer deficiency, etc. Spatial yield maps can be useful for farmers to identify the problematic areas by matching the coordinates of the location in the image and take necessary action to improve the yields. Some of the remedial measures include such as adding fertilizer at low yielding spots or applying differential application of irrigation water and ensure proper irrigation timing to avoid crop stress. The second image should be acquired ten to fifteen days after the effective cover stage of crop has been reached in the good portions of the field. This image shows the crop development at its maximum covered with high biomass over the entire field. Areas with both good and poor soils have attained peak growth of the crop. The third flight acquisition should be towards the end of the season around two weeks before the vine kill date. The image captured at this stage shows the variable senescing rates in the field related to good and poor soils. Image acquisition using aerial remote sensing in this study followed the same general timing of image acquisition dates mentioned above.

More flights or images throughout the growing period would be optimal to perform the integrated SAVI calculation and improve yield predictions. Additional images would capture emergence and vegetative growth rates while late season images would better capture the rates of senescence up to vine kill. All these factors have been considered in this study using satellite images and the eight-date integrated model developed by Jayanthi (2003).

Initially linear regression analysis was carried out with yield data and average
SAVI\textsubscript{mean} of all the study fields for all dates using 2004 and 2005 satellite data (Bala et al. 2009). The mean SAVI values were extracted from the pixels within the area of interest (AOI) for all the study fields and then the average of SAVI\textsubscript{mean} for all the dates for different study fields were calculated and regressed with yield data. The results showed a poor linear correlation with very low r-squared value. The problem with this method of averaging the SAVI\textsubscript{mean} values for all the dates is that it clusters all the values of pixels that have soil and crop growth variability over the entire field. Also this method, does not involve the area under the SAVI curve which is related to the leaf area duration. Therefore, an integrated SAVI approach spatially involving pixel by pixel calculations followed by regressing with the whole field yield data was performed.

The planting and emergence date of the crop along with the vine kill date are the necessary information for developing a yield model using ISAVI which involves the integration of area under the crop growing curve. This information was used in this study for the model development and validation. In practice, this piece of information will be hard to get for all the fields if the yield estimation is being conducted over a large area. Therefore the model was tested using satellite images with and without using the emergence and vine kill dates. The model did not result in a significant difference in the yield estimation for most of the fields since the satellite images covered the complete crop growing curve from emergence till vine kill. So the duration of crop growth was obtained using multitemporal satellite images covering emergence to vine kill period and was integrated accordingly. However the dates of emergence and vine kill was necessary for developing the model using three image acquisition dates or less when the image acquisition is not available for the full crop growing season. Frequent image acquisition
using aerial sensors for the complete growing season of the crop might be quite expensive but can provide better results. This study showed that the three-date model can be used to reliably predict yield when the dates of image acquisition are appropriately distributed throughout the crop growing season. Also this study showed that the three-date and eight-date ISAVI yield model developed using airborne images can also be applied to satellite images to predict yield and it resulted in good prediction for most of the fields.

Water stress is a major factor that affects the yield and quality of potatoes and is related to both crop evapotranspiration and soil water storage. Crop yield and ET relations are highly influenced by soil water levels in the root zone. Potato crops are very sensitive to water stress especially during the late vegetative and tuber initiation and yield formation phase. Actual ET is the best parameter that could be added to the remote sensing yield model to explain the variability and strengthen the model statistically. Therefore a soil water balance in the root zone was conducted for the study fields and ET was included as an additional variable in multiple regression analysis. The model showed a significant improvement in the correlation and better explained the spatial variability in yield.

The spatial variability in an agricultural field is inevitable in most cases due to various factors causing the variability. Some of the main causes of variability in crop growth are due to natural soil variability or impacts of erosion, land and crop management practices, and relief of the land. The other factors affecting the crop growth include fertilizer deficiencies causing soil nutrient variability, variability due to pest/disease attacks and water application non-uniformity during the crop growing season. This study used the high resolution aerial images and satellite images to conduct
a variability analysis using classical and geo-statistics. The classical statistics analysis showed that there is spatial variability in most of the fields and differences between good and poor soils. Geostatistic techniques explained the spatial dependence of data for the study fields. The use of semivariogram has to be further investigated using very low resolution images (example MODIS) and compared for different areas having the same crop. However, in this study semivariogram analysis was performed for both Landsat TM and airborne images for the potato crop for the same area. The semivariogram parameters (nugget, sill and range) analyzed was different for different fields and showed how the yield data varied spatially.
SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This research involved developing and validating yield retrieval models for potato crop in southern Idaho fields using high resolution airborne and satellite remote sensing. High-resolution multispectral aerial data acquired in 2004 was used to develop a VI-based statistical yield model based on a three-date ISAVI. The model was developed using hand dug samples collected at the end of the season based on soil and crop growth variability. The model developed was then validated using 2005 spot yield samples collected from two center pivot fields and also tested for 2004 and 2005 whole field production data obtained from the grower. The developed three-date ISAVI model was tested with satellite images on dozens of fields and verified. The eight-date ISAVI yield model previously developed by Jayanthi, 2003 was also tested using 2004 and 2005 satellite data. Actual ET was used as an additional independent variable in the three-date model to improve the yield predictions. The spatial variability analysis was also performed at different scale using airborne and satellite images.

During the 2004 season, airborne images were acquired three times during critical stages of the crop growth season namely on July 05, July 30 and August 31. The three-date integrated SAVI model resulted in a r-squared of 0.81 and the standard error of yield estimate was 0.41 kg/sq.m. The ISAVI was significant (p < 0.05) in predicting the yield. The 3-date model was validated using hand-dug potato yield collected during the 2005 season with an MBE of 0.07 kg/sq.m and RMSE of 0.24. The yield data values fell around the 1:1 line and resulted in a good linear correlation (r-squared = 0.89) though the model slightly over predicted for some of the yield sampling locations at the higher end.

The three-date integrated SAVI yield model was also applied to airborne imagery
and validated using 2004 whole field production data for a total of 15 fields. The model resulted in a slight over prediction with a MBE of 0.16 kg/sq.m and RMSE of 0.29. The total production from all the fields was also plotted against the estimated production and the model over predicted with a MBE of 66.47 metric tons (MT). The reason for this over prediction might be due to the fact that the integrated 3-date SAVI model developed did not cover the complete growth cycle between emergence and vine kill period. Thus the period between crop emergence and the first image date and the period between last image and vine kill needed to be linearly interpolated possibly artificially increasing the ISAVI. It was hypothesized that a better yield estimation could be achieved by using more image acquisition dates over the growing period starting from emergence to vine kill date.

The three-date integrated SAVI yield model was also validated against the 2005 whole field production data for a total of 13 fields. The model slightly under predicted the yield with an MBE of -0.15kg/sq.m and RMSE of 0.25 and the estimated production showed a good linear correlation (r-squared 0.96) with the MBE of -60.59 (MT).

The model was then applied to 2004 and 2005 satellite imagery and yield estimates were tested against whole field production data involving a total of 10 fields in 2004 and 13 fields in 2005. The model slightly over predicted the yield with a MBE of 90.51 MT and RMSE of 203.74 for 2004 and under predicted the yield for 2005 with a MBE of -150.33 MT and RMSE of 247.09, similar trends to the observed estimates from airborne imagery in the same year. These differences in the yield prediction might be due to different pixel size resolution between airborne and satellite images. In addition, with the satellite images, the acquisition dates did not match the three airborne
flight dates and were chosen to be close. In addition, each field had different season
duration length from emergence to vine kill for both years. An additional image of the
potato fields late in the season to capture the length of tuber bulking and crop senescence
pattern is ideal to better explain the yield variability.

An eight-date integrated SAVI yield model previously developed using airborne
images was tested using the 2004 and 2005 satellite images and compared to whole field
production data. The model slightly over predicted the yield with the MBE of 67.32 MT
and RMSE of 175.72 for 2004 and an MBE of 51.74 MT and RMSE of 207.35 for the
2005 season. The overall yield estimation using the eight-date ISAVI model was better
than the three-date model proving that an increased number of images better captures the
crop growth variability and seasonal duration in portions of the field.

In order to further improve the yield retrieval model, a soil water balance in the
root zone of the crop was conducted to obtain actual seasonal ET and incorporate it into
the yield model to improve yield predictions. The cumulative seasonal actual ET was
calculated for all the spot yield locations in 2004 and regressed with actual yield. Both
actual yield and ET correlated very well with an r-squared of 0.87. The results obtained
from multiple linear regression analysis showed a great improvement in the correlations
and 88 percent of the variability was explained by the variables involved. The validation
results of MLR model also indicated an excellent linear correlation (r-squared 0.97) with
the MBE of 44.13 MT for 2004 and r-squared of 0.75 and MBE of -39.34 MT for 2005
season. For both the years, the results showed a great improvement compared to the yield
estimated using the three-date ISAVI simple linear regression model. Thus it can be
concluded that cumulative seasonal ET explained additional variability.
Yield maps were created using the three-date integrated SAVI model with the airborne images and eight-date integrated SAVI model was applied to satellite images to get the estimated yield maps for the whole fields. The yield maps produced were compared with the FCC images to check if the crop growth pattern followed the yield pattern. The yield maps produced for the study fields clearly indicated that the crop growth pattern directly reflected the yield pattern in most of the study fields.

The spatial variability of yield in potato fields was analysed based on soil and crop growth variations caused by highly varying soil conditions and changes in landscape elevation. Some of the potato fields were chosen to do the variability analysis using classical statistics. The minimum, maximum, mean and standard deviation were extracted for all the dates from the SAVI images for the study fields chosen and the statistics proved that there existed the spatial variability over the field. The K_{crf} images were used in conjunction with the corresponding yield image produced using integrated SAVI image for the study fields. The K_{crf} and yield images clearly indicated that the crop growth during the complete growth cycle followed soil patterns varying over the field.

The spatial dependence of the yield data was tested using semivariogram analysis for some of the study fields with the aid of satellite images. All the variogram parameters studied for the study fields showed that there was a strong correlation of the data spatially and the mathematical models fitted can be used to do kriging analysis. The semivariogram parameters namely nugget, sill and range varied from field to fields. All the semivariogram parameters analyzed could be used as a guide for sampling work and to do kriging analysis to produce yield maps.

This research involved developing remote sensing yield models using both
airborne and satellite images at field level and validated them using different sets of yield data. However, there is a need for further research to identify additional factors affecting the yield and that can further explain the variability in yield and improve predictions further. Based on this research, the following recommendations are suggested:

1. The yield model developed in this study should be further validated using yield monitor data for each field. A spatial autocorrelation model that involves the distance for each point data (yield) can be developed and compared with linear model and yield maps then can be produced accordingly.

2. Though the potato loss from the harvesters is small, attempts should be made to include those on-farm losses to obtain the actual yield accurately improving reliability.

3. This study didn’t take into account previous land and crop management practices that may have a lingering effect on crop growth and yield. These effects have to be assessed properly and should be considered in the model they make a significant difference in the yield predictions. A detailed study on the soil physical and chemical properties at field level should be done. The soil properties such as pH, Electrical conductivity, Water holding capacity, NPK fertilizer/nutrient availability in the field etc. have a significant effect on yield. All these properties should be analyzed so that remedial measures can be taken accordingly.

4. Quality of the potato tuber must be investigated further using high resolution multispectral images and spatial yield data obtained with yield monitors. This can help the farmers improve the quality of their product with changes in crop
management.

5. Some of the agro-meteorological parameters like growing degree days (GDD), Photothermal Units (PTU), Heliothermal units (HTU) were not considered in this study. These parameters combined with spectral indices (SAVI or ISAVI) could be incorporated in the model to possibly improve yield predictions.

6. The yield model developed using high resolution airborne data was applied to Landsat TM images in this study. Further research should be conducted using coarser resolution images (MODIS) to extend the yield model developed with airborne imagery or, develop a model using low resolution images for comparison. This model can be either based solely on spectral indices or combined with other significant parameters for application over large areas (e.g. for a complete county or state) which would be of significant use in terms of cost and time.

7. Further research in this area can be done studying the relationship of fPAR, leaf area index with yield on the ground. These parameters can also be incorporated in the model if found to be significant in the yield predictions.

8. The actual ET involved in this study was computed by doing a water balance analysis in the root zone based on reflectance based crop coefficient method. Actual ET derived spatially from multispectral inputs using energy balance models such as SEBAL (Surface Energy Balance Algorithm for Land) should be tested and compared.

9. The procedure and methodology described in this study was used only for potato crop but might be applicable to other tuber crops.


CURRICULUM VITAE

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OBJECTIVE

Highly committed and qualified Agricultural /Irrigation engineer seeking a challenging opportunity in the fields of Geographical Information Systems and Remote Sensing.

EDUCATION

- Utah State University, Logan UT 84322-4105
  - Ph.D in Irrigation Engineering, 2011 (GPA 3.72/4.00)
- Tamil Nadu Agricultural University, Tamil Nadu, India
  - Master of Science in Agricultural Engineering, 2003 (GPA 3.65/4.00)
- Tamil Nadu Agricultural University, Tamil Nadu, India
  - Bachelor of Engineering in Agricultural Engineering, 2000 (GPA 3.52/4.0)

WORK EXPERIENCE

Utah State University, Remote Sensing Services lab (July 2005 - Present)
- Worked in various independent projects for the lab. Work involves
  - Preprocessing and processing of Optical and Thermal airborne and satellite imagery (band-band registration, geo-rectification, mosaic making, calibration, digitizing classification and map making) for various projects.
  - Produced calibrated (surface temperature) thermal imagery maps for various areas of Yellowstone National Park
  - Collection of yield sampling, develop yield model and produce yield maps.

Precision Farming Center, Tamil Nadu Agricultural Univ., India (June 2001 – April 2003)

- Research Assistant under Dr. P. Natarajan. Worked in the projects explained below:-
  - Development of Precision farming technology for enhancing the yield of horticultural crops.
  - Analyzing and Interpreting Yield, soil and topography maps using Arcgis for various crops and writing reports.
- In-situ moisture conservation & Micro water harvesting in dry land horticultural systems

Agricultural Engineering Dept. Tamilnadu, India (Oct 2000 – April 2001)
- Underwent a training at Chief Engineer’s Office- Different farm equipments operation and maintenance
- Delineation of Watershed map, land use planning and irrigation water management using GIS softwares namely Arcview, Arc info, & Idrisi 32.

RESEARCH EXPERIENCE

  - Develop a yield model using airborne and satellite data and validate the model
  - Produce Yield maps at different scales and compare
  - Analyze spatial and temporal variability of yield using geostatistics tool (R and GS+)

- “A GIS based spatial variability analysis of soil properties towards Precision Farming”, 2003 (M.E. Thesis)
  - Grid Sampling method to collect soil samples
  - Analyze soil physical and chemical properties of the soil
  - Analyze spatial variability of soil properties using geostatistics and produce maps

- "Design of Drip Irrigation Laterals using C++ programming language”, 2000 (B.E. Project)

RELEVANT COURSES

- Ph.D. – Remote Sensing of Land surfaces, GIS for civil engineers, Site-Specific Agriculture management, Crop Physiology, Sprinkler and Drip Irrigation design, Principles of Irrigation Engineering and Drainage Engineering.
- M.E. – Remote sensing and GIS, Farm Irrigation systems and design, Command area development, Geostatistics, Operational research, Watershed development, Open channel hydraulics

COURSE AND LAB PROJECTS

- Land use and Land cover mapping of Coimbatore district using RS and GIS techniques
- Assessing spatial variability of physio-chemical properties using geostatistics as a tool
- Estimation of crop ET using airborne multispectral imagery
A report on comparing various GIS software at Farm and Engineering levels

COMPUTER SKILLS
- Operating Systems: Windows, Linux, DOS
- GIS and RS Tools: ArcGIS, ArcView, Arcinfo, SST, HGIS, ErdasImagine, SEBAL, MODTRAN and Idrisi32
- Statistic Tools: Minitab, R, GS+
- Office Softwares: MS Word, MS Excel, MS PowerPoint

TEACHING EXPERIENCE
- Taught three classes of “Evapotranspiration”, for SWC605, at Tamil Nadu Agricultural University, India.
- Handled tutorials for “GIS and Remote Sensing softwares”, for SAC603 at TNAU, India.

PROFESSIONAL MEMBERSHIPS
- Student Member of SPIE (Society of Photographic Instrumentation Engineers)
- Student Member of USCID (United States Committee of Irrigation and Drainage)

HONORS and ACTIVITIES
- Tamil Nadu Agricultural University (TNAU) Merit Scholarship holder (2001-2003)
- Received Certificate of Achievement for successful completion of training program on field evaluation of irrigation system conducted by International Irrigation Center, USU, 2004.
- Dean’s honor list student with a GPA of 3.92/4.0 (Fall 2005)
- Rhythmalaya and Placement cell Secretary, College of Agricultural Engineering (CAE), TNAU, (1998-1999)

PUBLICATIONS

