

Ground-based RGB imaging to determine the leaf  
water potential of potato plants

By

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

Department of Biosystems Engineering

University of Manitoba

Winnipeg, Manitoba, Canada

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## ABSTRACT

The determination of plant water status from leaf water potential ( $\Psi_L$ ) data obtained by conventional methods is impractical for meeting real time irrigation monitoring requirements. This research, undertaken first, in a greenhouse and then in the field, examined the use of artificial neural network (ANN) modeling of RGB (red green blue) images, captured by a ground-based, five mega pixel digital camera, to predict the leaf water potential of potato (*Solanum tuberosum* L). The greenhouse study examined cv. Russet Burbank, while the field study examined cv. Sangre. The protocol was similar in both studies: 1) images were acquired over different soil nitrate (N) and volumetric water content levels, 2) images were radiometrically calibrated, 3) green foliage was classified and extracted from the images, and 4) image transformations, and vegetation indices were calculated and transformed using principal components analysis (PCA). The findings from both studies were similar: 1) the R and G bands were more important than the B image band in the classification of green leaf pigment, 2) soil N showed an inverse linear relationship against leaf reflectance in the G image band, 3) the ANN model input neuron weights with more separation between soil N and  $\Psi_L$  were more important than other input neurons in predicting  $\Psi_L$ , and 4) the measured and predicted  $\Psi_L$  validation datasets were normally distributed with equal variances and means that were not significantly different. Based on these research findings, the ground-based digital camera proved to be an adequate sensor for image acquisition and a practical tool for acquiring data for predicting the  $\Psi_L$  of potato plants.

Keywords: nitrogen, IHS transformation, chromaticity transformation, principal components, vegetation indices, remote sensing, artificial neural network, digital camera.

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## LIST OF SYMBOLS

AGL	above ground level (m)
ANN	artificial neural network
AVHRR	advanced very high resolution radiometer sensor onboard NOAA-11
B	blue image band (8 bit)
CCD	charged couple device
CCCI	canopy chlorophyll content index
CIE	Commision Internationale de l'Eclairage
CV	coefficient of variation (%)
CWSI	crop water stress indicator
CWL	center wavelength (nm)
DAP	day after planting
ETM	enhanced thematic mapper sensor on Landsat 7 satellite
F	Bartlett's test for unequal variance
FC	field capacity or upper soil water limit allowable for plant growth
G	green image band (8 bit)
GBS	green blue slope (8 bit RV/nm)
GB <sup>-1</sup>	green blue simple ratio (dimensionless)
GNDVI	green normalized difference index,
GPS	global positioning satellite
GR <sup>-1</sup>	green red simple ratio (dimensionless)
GRS	green red slope (8 bit RV/nm)
H	hue transformation (8 bit)
H <sub>i</sub>	i <sup>th</sup> hidden neuron node
I	intensity transformation (8 bit)
ISODATA	iterative self organizing data analysis technique
LAI	leaf area index
log	logarithmic data transformation
MIR	middle infra-red region of the electromagnetic spectrum
N	nitrate (ppm) or nitrogen (kg ha <sup>-1</sup> )
ND	normalized difference
NDGBI	normalized difference green blue index (dimensionless)
NDGRI	normalized difference green red index (dimensionless)
NDRBI	normalized difference red blue index (dimensionless)
NDRE	normalized difference red edge
NDVI	normalized difference vegetation index (dimensionless)
NIR	near infra-red region of the electromagnetic spectrum
NOAA	National Oceanic Atmospheric Administration
p	probability
PC	principal component
PCA	principal component analysis
PWL	peak wavelength (nm)
PWP	permanent wilting point
R	red image band (8 bit)
RC	radio-control

$r$	correlation coefficient
$R^2$	coefficient of determination
$RB^{-1}$	red blue simple ratio (dimensionless)
RBS	red blue slope (8 bit RV/nm)
RMSE	residual mean square error
RGB	red green blue regions of the electromagnetic spectrum
RWC	relative water content a soil (%)
RI	relative importance of input neuron (%)
RV	reflectance value response from an image (8 bit)
S	saturation transformation (8 bit)
SD	standard deviation
SR	simple ratio vegetation index
$t$	student's t test of means for normal distributions
TDR	time domain reflectometry
VIAS	vertical image acquisition system
W	Shapiro-Wilk test for normality
WDI	water deficit index
$x$	exponentially normalized
X	chromaticity color coordinate transformation
Y	chromaticity color coordinate transformation
Z	chromaticity color coordinate transformation
$\alpha$	type 1 error significance level
$\Psi_L$	leaf water potential (MPa)
$\Psi_S$	soil water potential (MPa)
$\theta_V$	volumetric water content (%)

## NOTICE OF STUDENT CONTRIBUTION

The research in this thesis and the manuscripts submitted for publication was completed by the student. Additional contributions, in an advisory capacity, were made by the advisory committee members.

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## CHAPTER 1: INTRODUCTION

In terms of the global food supply, potato is the fourth largest crop produced in the world. In 2005, Canada produced nearly 4.4 million tonnes of potatoes (FAO 2006). The United Nations is declaring 2008 as the international year of the potato (FAO 2007). The potato was selected as the subject for this present research due not only to its relevance in the world's food supply but also to its importance regarding irrigation needs in this locality, which is one of Canada's largest potato producing regions.

With respect to potato, plant water stress reduces photosynthetic activity causing a decrease in total biomass and a decrease in both fresh and dry matter tuber yield (Costa et al. 1997). Gunel and Karadogan (1998) reported that for the first and second growth stages of potato, frequent irrigation increased specific gravity, dry matter, starch content and chip yield. Thus, plant water stress is of agronomic interest to potato producers. However, existing plant water status measurement methods are impractical for meeting real time irrigation monitoring requirements over large areas.

Previous research using remote sensing has developed methods for monitoring plant water status over large areas using combinations of the visible, NIR, MIR, and thermal-IR wavelengths (Barnes et al. 2000; Bausch 1995; Carlson et al. 1995; Moran et al. 1994). However, the combination of limited image availability and the expense of image acquisition in the NIR, MIR, and thermal IR regions have inhibited their implementation into an operational irrigation system. To satisfy the limitations for predicting plant water status over large areas using remote sensing requires the development of a plant water status model using a commercially available sensor with the ability to acquire images on a daily or weekly basis, under cloud free conditions.

Currently, based on economics, only retail, handheld digital cameras satisfy those limitations.

The overall objective of this thesis, therefore, was to predict the plant water status of potato plants using digital images obtained in the visible region using a digital camera as a practical approach for scheduling irrigation. A remote sensing approach with the potential for implementation into an irrigation system was investigated by using an economical sensor with fast image delivery mounted on a telescopic pole for flexible revisit rates to estimate plant water status ( $\Psi_L$ ). Soil-N or plant-N has an influence on leaf reflectance in the green region of the electromagnetic spectrum. The overall thesis question was to determine whether a commercially-available, 5-mega pixel digital camera acquiring red, green, blue (RGB) digital images at ground level could determine the  $\Psi_L$  of potato plants using an ANN model under different soil-N and soil water content levels. The feasibility of the thesis question was approached under both greenhouse and field conditions to address the following questions:

1. Can green leaf pigments be isolated from RGB digital images consisting of portions of the leaf, plant, and ground?
2. Is there a relationship between soil N and leaf reflectance in the green image band?
3. Can ANN modelling of RGB images predict the leaf water potential ( $\Psi_L$ ) of potato plants?
4. What is the relative importance of the input neurons used in the ANN model(s) in comparison to the relationships between  $\Psi_L$  and soil N?
5. Can a ground-based digital camera supply RGB images as an alternative to airborne-spaceborne imaging sensors?



The development of a remote sensing approach using RGB images and ANN modelling for measuring  $\Psi_L$  as an indicator of the need for irrigation has practical implications at the farm level for irrigation scheduling and at the watershed level for both licensing irrigation and the monitoring of community water supplies. In lieu of hyperspectral imaging, the use of ANN modelling as an image processing tool for wide-band images with attention given to changes in the relative importance of input neuron weights has implications for determining  $\Psi_L$  and other crop measures. Ultimately, the study has implications for water conservation.

## CHAPTER 2: LITERATURE REVIEW

The following is a literature review of factors underlying the development of a remote sensing model to predict the plant water status of potato (*Solanum tuberosum* L). The topics reviewed outline and introduce the factors required to understand the research protocol and to justify the thesis question, beginning with: (1) a literature review of the determination of plant and soil water status and their inherent limitations as measurements for scheduling irrigation, (2) the remote sensing of vegetation, (3) factors other than water stress that affect reflectance, and (4) the tools used for image analysis contributing to the research. The review of image analysis tools includes principal components analysis, artificial neural networks employing the weights method for justification, and spectral enhancement through vegetation indices and color coordinate transformations, radiometric image calibration, and image classification. A description of the sensor and ground-based sensor platform used in this research can be found in Appendix A.

### 2.1 Determination of soil and plant water status

Soil and plant water status measurements were required in this research. Soil water status, a conventional method for scheduling irrigation, is reviewed in the context of its inadequacy as a plant water status measurement. Plant water status is then discussed in terms of measurement and shortcomings for scheduling irrigation.

#### 2.1.1 Soil water content

Soil water is quantitatively expressed as volumetric water content ( $\theta_v$ , %), the volume of water in the soil per total volume of soil, and soil water potential ( $\Psi_s$ ), the free energy

status of water in the soil. Rather than measure the actual status of water in the plant quantitatively, soil water measurements quantify plant water status based on an ordinal scale ranging from a lower soil water limit, termed permanent wilting point (PWP), to an upper soil water limit, termed field capacity (FC). Due to temporal relationships in the soil-plant-atmosphere system, plants can be either favorably or adversely affected before the soil water reaches the PWP. The flow of water through the system is a function of the difference in water vapor concentration between the atmosphere and the plant, and the difference in water potential between the soil and the plant (Oke 1990). Soil water measurements, therefore, do not directly quantify plant water status resulting in a qualitative measurement that may not always be sensitive to the physiological response of the plant to water stress conditions. Soil water data therefore have inherent limitations.

Additional problems with soil water measurements used to model the availability of soil water are their dependence on the knowledge of the physical and chemical properties of the soil. Specifically, soil water models make assumptions occurring within the root zone with respect to soil texture and the purity of the soil water. Soil texture classifies soil particle sizes as a composition of sand, silt, and clay to identify and label an area with a soil type. Soil texture analysis tests are then interpreted to ascertain the ability of an area to attract, retain, and transport water across and within a soil column. However, soil particle arrangement or soil structure is of more value in comparison to soil texture since the structure of the soil determines the total porosity, as well as the shape and size array of soil pores (Hillel 1998). Hence, soil structure affects the content and movement of soil water more than soil texture. Soil water availability also assumes that the soil texture is constant throughout the rooting zone, that the plant roots

themselves are equally distributed throughout the rooting zone, and that all roots have the same ability for water uptake.

Another assumption with soil water availability measurements used to assess plant water status is that soil water is pure water, lacking impurities detrimental to plant growth. Soil water, however, is not pure water and should be considered as a solution containing water, nutrients, and minerals required for plant growth as well as contaminants or toxins that can be detrimental to plant growth. Hence plant stress may not be the result of low soil water availability, but of containments in the soil solution that negatively affect plant growth. Saline soils, for example, can negatively influence the osmotic water potential and thus inhibit the ability of the plant roots to uptake and transport water (Taiz and Zeiger 2002). Saline soils can also disrupt the plant metabolic processes and change the permeability of the soil.

Given the aforementioned disadvantages related to soil water content as a measurement of plant water status, leaf water potential ( $\Psi_L$ ) is a better predictor of plant water status. Measuring  $\Psi_L$  eliminates the need for knowledge of the physical and chemical properties of the soil and is therefore more appropriate for modeling plant water status by remote sensing.

### **2.1.2 Plant water status**

Leaf water potential ( $\Psi_L$ ) is a direct indicator of plant water stress, and is consequently one of the most widely regarded research approaches for measuring plant water status. Leaf water potential is a measure of the negative pressure that exists within leaf cells. The negative pressure results from plant water loss as water transpires from the leaf stomata during gas exchange with the atmosphere as a requirement for photosynthesis.

Hence,  $\Psi_L$  is a measure used to monitor water flux in plants. When a plant is under water stress, the stomata aperture will reduce or remain closed, increasing stomatal resistance, limiting gaseous exchange required for photosynthesis leading to a reduction in dry matter yield (Costa et al. 1997; Gunel and Karadogan 1998). Methods of measuring  $\Psi_L$  include the use of the relative water content (RWC) of leaves and such other in situ approaches as the psychrometer and the pressure chamber.

The first of these methods, RWC (Eq. 2.1) requires the mass of the leaf to be measured at three time intervals: at plant removal, at full turgor, and after drying (Lazcan-Ferrat and Lovatt 1999).

$$RWC = \left( \frac{FW - TW}{TW - DW} \right) \times 100 \quad (2.1)$$

where:

RWC= relative water content (%),  
FW = fresh weight of the leaf,  
TW = rehydrated turgid weight of the leaf, and  
DW = reweighed dry weight of the leaf.

Since the RWC technique requires the leaf mass to be measured when first removed from the plant, after leaf rehydration, and after leaf drying, this technique may be impractical for producers.

The other widely used approach in research for measuring  $\Psi_L$  in situ is the psychrometer method (Richards and Ogata 1958), which measures  $\Psi_L$  by calculating the difference in temperature between the leaf surface and a surface with a known water potential. For example, if the cooling surface is the known water potential, then the warming leaf surface has a lower water potential due to evaporation by the known water potential standard and absorption by the warming leaf surface via molecular diffusion (Taiz and Zeiger 2002).