Assessment of two spectral reflectance techniques for the estimation of Fuel Moisture Content, Equivalent Water Thickness, and Specific Leaf Weight in Douglas-fir (*Pseudotsuga menziesii* (Mirb) Franco) needles

by

Fabio Visintini
B.Sc., University of Victoria, 2004

A Thesis Submitted in Partial Fulfillment
of the Requirements for the Degree of

MASTER OF SCIENCE

in the Department of Geography

Supervisory Committee

Assessment of two spectral reflectance techniques for the estimation of Fuel Moisture Content, Equivalent Water Thickness, and Specific Leaf Weight in Douglas-fir (*Pseudotsuga menziesii* (Mirb) Franco) needles

by

Fabio Visintini
B.Sc., University of Victoria, 2010

Supervisory Committee

Dr. K. O. Niemann, (Department of Geography)
Supervisor

Dr. M. S. Flaherty, (Department of Geography)
Departmental Member

Dr. D. Goodenough (Department of Computer Science)
Outside Departmental Member

Abstract

Supervisory Committee
Dr. K. O. Niemann, (Department of Geography)
Supervisor
Dr. M. S. Flaherty, (Department of Geography)
Departmental Member
Dr. D. Goodenough (Department of Computer Science)
Outside Departmental Member

In the wildfire community fuel moisture content (FMC) is the quantity of choice when it comes to assess vegetation water status in relation to fire risk and fire behaviour. Field measurements of FMC are both expensive and time consuming and, in addition, sampling is often spatially inadequate. Remote sensing could represent an almost ideal solution both in terms of spatial and temporal coverage, if a consistent relationship between FMC and spectral reflectance could be established. A review of the literature suggests that it is difficult to retrieve FMC for dense forest canopies with remote sensing platforms. This study took a step back and explored the relationship between spectral reflectance and vegetation water content at the leaf level, where several confounding factors present at the canopy level are eliminated or controlled for. It also considered a conifer species, because relatively little research has been produced on this topic for this type of vegetation. The main goal was to establish if FMC can be derived directly from spectral reflectance in the solar spectrum using two well known approaches, such as spectral indices and continuum removal. It is also aimed at exploring if an alternative, indirect way to measure FMC as ratio of Equivalent Water Thickness (EWT) and Specific Leaf Weight (SLW) is feasible and accurate. The results derived from Douglas-fir (*Pseudotsuga menziesii* (Mirb) Franco) needles used in this study suggested that FMC was not directly retrievable from spectral reflectance but vegetation water content could be assessed with sufficient accuracy in terms of EWT. Also the retrieval of SLW from reflectance of fresh foliage proved to be challenging. Finally, the study also highlighted several aspects in the relationships among foliar water content, dry matter content and reflectance that require additional research.

Table of Contents

List of Tables

List of Figures

Acknowledgments

It is surely conventional, and it would also be wrong not to, acknowledge first and foremost the person who made my journey through the Master possible: Dr. Olaf Niemann. To me, you are much more than a mentor.

Very, very special thanks also to Rafael Loos. We started this adventure together, we almost finished together, and we both know what we went through. All in all, you helped me way more than I helped you, but my upmost gratitude is for your friendship. I feel it so strong that I take it for granted, but I'm not quite sure to deserve it.

It is impossible not to commend all the people that have gravitated in and around the lab during these years. Some have helped with fieldwork, some have engaged in stimulating discussions, and all have contributed to a joyful workplace. Among those that are hopefully close to the finish line, one is especially dear to me: Roger, you've been through so much for so long, but do not give up now, the rewarding end is closer than you think and definitely within your reach!

Last, but by no any means least, Sara, you've always been supporting and you never complained for the time I spent after my studies. Thank you from the bottom of my hart, you and Elisa are my world.

Chapter 1 - Introduction

Fire is the very visible manifestation of a chain of chemical reactions involving some type of fuel, heat, and oxygen. When the fuel is living vegetation, fire may be seen as the reverse of photosynthesis (DeBano, Neary, and Ffolliot, 1998). Its untangling ambivalence is one of fire's most fascinating aspects: it can be as devastating and deadly as beneficial to the reshaping of ecosystem dynamic and the renewal of forest productivity and biodiversity (Arora and Boer, 2005; Bowman and Bogss, 2006; Úbeda and Mataix-Solera, 2008). Fire's interaction with humans adds another level of complexity. If in the western world the paradigm of the last hundred years or so has been the exclusion of fire from forests (Agee and Skinner, 2005; Hessburg and Agee, 2003), in most of the rest of the world, fire is still extensively used as a tool in slash-and-burn practices to clear land for agriculture, pasture, and land development (Viegas, 1998). It is now well known that the majority of forest fires are of human origin and that they are started voluntarily or involuntarily for a surprisingly wide range of reasons (Leone and Lovreglio, 2003).

While wildfires continue to burn hundreds of millions of hectares every year throughout the world, it seems that the intensity and severity of some of these fires are on an increasing trend because of the growing spread of forest/urban interfaces, changes in land use and, possibly, climate change (FAO, 2007). For forest fire managers finding methods to make better, and more timely, predictions of fire risk is a task of growing concern. For some, this task can be accomplished by strengthening the synergy between policy makers and the scientific community involved (DellaSala et al., 2004), and by increasing the emphasis on understanding the physical processes driving the ecological effects of fires (Johnson and Miyanishi, 2001). Fire behaviour models were first developed in the 1970s and continue to be upgraded and refined. A useful review of modeling approaches and fire models is that of Perry (1998). In simple terms, these models mathematically link a series of variables and parameters about fuels, weather, and topography to develop realistic scenarios of fire spread and intensity (Arroyo, Pascual, and Manzanera, 2008). One of these variables is fuel moisture content (FMC).

FMC affects combustion from pre-ignition to the flaming stage and, therefore, plays a central role in fire ignition and propagation (DeBano, Neary, and Ffolliot, 1998). As the name implies, fuel moisture content is used to express the amount of water in dead and live vegetation fuels, but dead and live fuel moisture contents are intrinsically very different. While the former is strongly dependent on meteorological conditions and it is estimated based on the time for the fuel to reach a given level of moisture equilibrium with the surrounding environment, the latter is largely governed by soil moisture availability and plant physiology (Hao and Qu, 2007; Nelson Jr, 2001). For this reason it is much more variable spatially and temporally than dead FMC. Reliable and timely estimates of FMC are difficult to obtain with field sampling, in particular for live FMC. Operational fire danger rating systems generally rely on meteorological indices to estimate FMC (Chuvieco, Aguado, and Dimitrakopoulos, 2004; Stocks et al., 1989; Taylor and Alexander, 2006) using data acquired at weather station locations. The meteorological approach not only uses proxy measures to estimate FMC, but for extensive forest areas weather stations can be very far away and extrapolation of data may be problematic at best. Overall, the natural variability of ecosystems and fuel complexes along with sampling issues makes the retrieval of FMC difficult. Compounding this lack of knowledge with that about the physical processes involved in the combustion and spread of forest fires results in questioning the relevance of FMC, in particular by researchers engaged in fire behaviour modeling (Cruz, Alexander, and Wakimoto, 2004).

Clearly, a remote sensing approach to the retrieval of FMC could overcome many of these issues, either empirically or by means of physical modeling (Chuvieco and Kasischke, 2007). Remote sensing may also be helpful to map forest fuels and fire regimes (Jia et al., 2006a; Jia et al., 2006b; Krasnow, Schoennagel, and Veblen, 2009; Rollins, Keane, and Parsons, 2004). It is already successfully used to characterize post-fire conditions and acquire information to assess short- and long-term effects on the landscape and the interrelated ecosystems (Boschetti et al., 2008; Epting, Verbyla, and Sorbel, 2005; Kokaly et al., 2007; Robichaud et al., 2007). While the potential of remote sensing to estimate vegetation water content both at the leaf and canopy was established some decades ago (Holben, Schutt, and McMurtrey III, 1983; Tucker, 1980), those to retrieve FMC are still arguable. The main reason can be, as we will see in the following chapters, that behind its deceivingly simple mathematical formulation, FMC encapsulates almost perfectly the nature of vegetation as composed of water and dry matter. In other words, measuring directly FMC by means of optical remote sensing means acquiring spectral information that is simultaneously related to the water and dry matter contents of vegetation. This information is somehow encrypted, in the sense that the spectral signal is affected at the same time by both components in an unknown fashion. Disentangling this information is probably both the greatest challenge and the key to improving FMC retrieval by optical remote sensing.

1.1 - Objectives and research questions

This study investigates the estimation of the water content in samples of fresh Douglas-fir (*Pseudotsuga menziesii*) needles by optical remote sensing, both in terms of live FMC and its components equivalent water thickness (EWT) and dry matter content (DMC). It also compares two techniques, one of which relies on spectral information at specific wavelengths (spectral indices), while the other takes into account the spectral shape of absorption features (continuum removal). Dead FMC is not considered because optical remote sensing is not a viable option to measure it due to canopy closure. Therefore, in the course of this thesis, and unless otherwise specified, the term FMC is used to express live FMC. The specific questions that will be addressed in this study are:

- *Can FMC be estimated with spectral reflectance measurements using the spectral index and the continuum removal approaches?*
- *Is continuum removal more effective than a spectral index for estimating leaf water content?*
- *Is it possible to obtain estimates of FMC by combining spectral indices for EWT and DMC?*

- *How does the remote sensing approach to FMC estimation compare to the field observations?*

1.2 - Thesis outline

This document is organized in five chapters. A review of the literature pertinent to the concept and measurement of FMC is presented in Chapter 2. The study location, data acquisition, and processing are described in Chapter 3. The results of the study are presented and discussed in Chapter 4. Chapter 5 are summarizes the main findings along with few suggestions for further research.

Chapter 2 - Literature Review

Being a measure of water content in vegetation, FMC is related to a number of disciplines as heterogeneous as wildfires, forestry, ecology, plant physiology, and remote sensing. Research within each of these areas of study bring their knowledge contribution from different points of view and, above all, highlight aspects, issues, ideas, and controversies that would be difficult to grasp from the limited field of view of a single discipline. The price to pay for such "360 degree-view" of the subject, is having to deal with the shear volume of studies that has been produced in the scientific literature. Far from being exhaustive, this chapter is an effort to trace the most prominent pathways and connections in order to bring to the surface the hidden complexity of FMC. The approach followed is to address FMC as a single entity, along with a closer scrutiny of its two components because it seems to be the more suitable to be exploited in a remote sensing context.

2.1 - Fuel Moisture Content and Equivalent Water Thickness

FMC is one of many ways to express the water content of vegetation. It has been developed in the context of forest fire studies, and it is used almost exclusively by the wildfire research community. The most common mathematical expression for FMC is (Chuvieco et al., 2002; Danson and Bowyer, 2004):

$$FMC = (FW - DW) / DW \tag{2-1}$$

where FW is the fresh weight of vegetation and DW is the dry weight of vegetation. Sometimes, FW is used as denominator instead of DW, especially in plant biology, and in this case the term leaf, or canopy, water content is preferred to FMC.

Clearly, the nominator in (2-1) is the amount of water present in the vegetation sample, while the denominator represents its dry matter content. Equation (2-1) may therefore be re-written as:

$$FMC = WC / DMC \tag{2-2}$$

where WC is the amount of water present in the leaf or canopy and DMC is the corresponding leaf or canopy dry matter content. Because FMC is the amount of water per unit oven-dry matter of a vegetation sample it is a dimensionless quantity. However, the fraction is often transformed into a percentage of oven-dry matter by multiplying equation (2-1) by 100. Thus, in well-watered vegetation, FMC may have values well above 100%. It also important to note that because FMC is computed with (2-1) from samples collected in the field, its value cannot be obtained in real-time. The standard measure of dry matter requires the sample to be dried in an oven for 24 to 48 hours depending on the temperature setting, or at least until the sample dry weight does not change any longer with time.

The effects of moisture on the combustion of vegetation fuels are well explained by Nelson, Jr., (2001) and can be summarized as follows:

1. increase of the preheating time by increasing the heat required for the volatilization of the fuel;
2. decrease of fuel consumption by decreasing the rate of thermal decomposition of fuel and the flame temperature, and by diluting the available oxygen for combustion;
3. increase of the fuel particle residence time by reducing radiation transfer to adjacent fuel particles.

In common terms, this means that moist forest fuels require more heat for a prolonged amount of time to ignite, and that their combustion is rather inefficient and with a greater production of smoke. While this may seem intuitive, the systematic evaluation of the level of moisture for a fuel complex that will determine its ignition and burning characteristic is anything but trivial. Empirical and modeling studies have been conducted at the compositional level (Hosoya, Kawamoto, and Saka, 2007; Mamleev, Bourbigot, and Yvon, 2007a; Mamleev, Bourbigot, and Yvon, 2007b), leaf level (Alessio et al., 2008; Dimitrakopoulos and Papaioannou, 2001; Fonda, 2001; Fonda, Belanger, and Burley, 1998; Gill and Moore, 1996; Mak, 1988; Philpot, 1970), branch level (Xanthopoulos and Wakimoto, 1993), tree level (Babrauskas, 2006), up to the stand level (Butler et al., 2004; Cruz, Alexander, and Wakimoto, 2004; Cruz, Alexander, and Wakimoto, 2005; Stocks et al., 2004) without reaching a clear consensus on the role of FMC, without even considering its magnitude. For instance, burning experiments conducted at the leaf level are considered particularly useful because they can be carried out in a laboratory under controlled conditions and with standard equipment (Dimitrakopoulos and Papaioannou, 2001). Usually, the main goal of these studies is to provide insights on the flammability of leaves. However, comparisons are often difficult because:

a) different techniques have been used to perform the laboratory tests;
b) tests have been carried out on single or multiple layers of foliage;
c) tests results may refer to flammability as a whole, or any of its components (Anderson, 1970), as well as other types of variables.

Studies at the leaf level generally find an inverse relationship between FMC and flammability more easily than studies at the branch or tree level, but the magnitude of this relationship is inconsistent. At greater scales, Xanthopoulos and Wakimoto (1993) found empirically that FMC affected time of ignition in branches of three conifer species and that the results were in general agreement with the physical theory. On a burning experiment of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) trees, Babrauskas (2006) also found that FMC had a major impact on the effective heat of combustion. Moreover, he found evidence that FMC actually altered the combustion process and did not behave simply as an inert diluent. On the contrary Cruz et al. (2005) and Scott and Reinhardt (2001) found FMC a not significant predictor of crown fire rate of spread. Using the NEXUS fire model, Hall and Burke (2006) found that both the Torching Index and the Crowning Index were less sensitive to FMC than other variables such as canopy bulk density. According to Cruz et al. (2005) this is because FMC effects on fire dynamics are still not well understood, while Scott and Reinhardt (2001) invoked the fact that data on FMC are limited and of variable quality.

The lack, or poor quality, of data on FMC has also been noticed by Nelson, Jr.(2001), who has further pointed out that there is a need for models that can predict FMC changes in vegetation. A remarkable modeling study has been produced by Castro, et al. (2003), but it refers to fine FMC, namely the FMC of small branches and leaves of shrubs. The authors developed their modeling exercise combining a series of meteorological variables with components of the Canadian Forest Fire Weather Index, and were able to predict the FMC of *C. monspeliensis*, a Mediterranean shrub, over the period January 2001 to March 2002 with an R^2 of about 0.80 independently from the sample locations. Peterson et al. (2008) also produced a study in which they modeled the spatial and temporal variations in FMC for two California shrub functional types over a period of six years. However, robust models for the prediction of FMC for a more comprehensive range of vegetation types and with adequate temporal resolution are still not available. Nelson, Jr. (2001) argued that the limited knowledge about FMC may depend, in part, on the fact that the research in plant physiology is biased toward water potential and related water transport aspects, with some emphasis also on plant evapotranspiration. And yet, according to Weise et al. (1998), data on seasonal moisture content variability on various types of vegetation for fire management purposes have been collected in the USA since 1930s. It is interesting to note that some of the most thorough and known studies on FMC variability refers to conifers (Agee et al., 2002; Chrosciewicz, 1986; Gary, 1971; Keyes, 2006; Little, 1970).While the early studies were more exploratory in nature, the more recent ones explicitly interpret the data in terms of crown fire potential and aims at creating databases of FMC variability for fire risk assessment. FMC values in the range 100% - 120% were found appropriate by Agee et al. (2002) as a threshold in relation to crown fire risk, while Alexander (1988) reported values of FMC between 75% and 130%. On the other hand, the guidelines from Weise et al. (1998) are of moderate fire danger for FMC in the range of 80% - 120% and high fire danger with FMC between 60% and 80%. Although these are only suggested guidelines, and even taking into consideration that they are based on different types of vegetation in different ecosystems, the range of variation in FMC threshold values is an indication that there is a need to quantify FMC within reasonable bounds (Nelson Jr, 2001). One key problem may be the sample size needed to assure accurate estimates of FMC (Weise, Hartford, and Mahaffey, 1998), but even in this case, sample size estimates by Weise et al. (1998) varies by at least an order of magnitude from those of Agee et al. (2002).

In the absence of models predicting FMC, and with the possible issue of sample size for the direct estimation of FMC, remote sensing is considered a technique with potentially enormous advantages over traditional field work (Arroyo, Pascual, and Manzanera, 2008). Moreover, the detection of water status in vegetation is not a novelty for remote sensing. Gates et al. (1965) noticed that liquid water in plants absorbs in the infrared, particularly beyond 2000 nm, and much less at shorter wavelengths, while Allen et al. (1969) observed that the absorption spectra of corn leaves seems to be the result of the combined absorptions by chlorophyll and pure liquid water. The authors went further developing a plate model of a leaf and using it to retrieve moisture content as equivalent water thickness (EWT), in units of microns, from the leaf spectral properties. The introduction of EWT as a measure of moisture content is an important milestone because this quantity will become very important in remote sensing, and it can be linked to FMC.

Since the 1980s the remote sensing of vegetation water content has seen a conspicuous development both at the leaf and at the canopy levels by means of numerous empirical and modeling studies. However, while it became clear quickly that specific liquid water absorption features are located at about 970 nm, 1190 nm, 1450 nm, 1940 nm, and 2500 nm (Sims and Gamon, 2003), only in 1990 was it discovered that water is not the only chemical compound responsible for the absorption spectra of vegetation in the infrared between 1300nm and 2500 nm (Goetz et al., 1990).

Before turning our attention specifically to FMC, three aspects about the optical remote sensing of vegetation water content should be briefly discussed:

1) what are the main *methodologies* utilized to acquire information on plant water status;
2) what are the *techniques* utilized to acquire information on plant water status, and
3) what *quantity* or *quantities* related to plant water status can be retrieved.

As for the methods, there are only two ways to gain information on plant water status: direct and indirect. The direct method obviously aims at measuring directly the amount of water content present in leaves and plant canopies. Arguably, the use of radiative transfer models may also be placed in this category. The indirect method bases its estimates on proxy indicators such as chlorophyll content, or the degree of stress in plants (Ceccato et al., 2001). The indirect method has the of defining plant stress across species. In addition, both chlorophyll content changes and plant stress may be caused by factors different than water content changes. The indirect method is well suited only for localized areas with a clearly established relation between plant water content and its proxy indicator (Ceccato et al., 2001).

Independently from the conceptual methodology adopted for the estimation of vegetation water content, a variety of techniques are available to perform the actual retrieval. The most common are:

- spectral indices;
- spectrum matching;
- continuum removal;
- radiative transfer model inversion.

Less common techniques include hierarchical foreground/background analysis (Ustin et al., 1998), neural networks (Fourty and Baret, 1997; Trombetti et al., 2008), and genetic algorithm partial least squares (Li, Ustin, and Riaño, 2007).

The use of spectral indices is the most common technique in empirical or semi-empirical studies. Indices developed to estimate plant water content can be considered a special class of vegetation indices. A vegetation index is a mathematical transformation of two or more spectral bands that has the property to enhance the vegetation signal. Very often it takes the form of a ratio because this operation has signal normalization properties, but there are also new and more complex indices such as the difference of the integral of the reflectance derivatives, DD, of le Maire et al. (2004). However, most spectral indices for the detection of vegetation water content are ratios of Near-infrared (NIR) and Short-wave Infrared (SWIR) wavebands. This is because, as already mentioned, liquid water absorption features dominate the optical infrared between 900 nm and 2500 nm. A selection of the most common indices are summarized in Table 1.

Table 2-1: Common spectral indices for the estimation of vegetation water content

INDEX	FORMULA	REFERENCE
WI	R900/R970	(Peñuelas et al., 1997)
MSI	R1600/R820	(Hunt Jr. and Rock, 1989)
SRWI	R860/R1240	(Zarco-Tejada and Ustin, 2001)
NDWI	(R860-R1240)/(R860+R1240)	(Gao, 1996)
NDII	(R820-R1650)/(R820+R1650)	(Hardisky, Klemas, and Smart, 1983)
GVMI	((R820+0.1)-(R1600+0.2))/((R820+0.1)+(R1600+0.2))	(Ceccato, Flasse, and Grégoire, 2002)
TM5/TM7	R1650/R2218	(Elvidge and Lyon, 1985)
Datt 1	(R850-R1788)/(R850-R1928)	(Datt, 1999)
Datt 2	(R850-R2218)/(R850-R1928)	(Datt, 1999)
MI 1	(R880/R680)*(1/R1600)	(Toomey and Vierling, 2005)
MI 2	((R800-R680)/(R800+R680))*(1/R1600)	(Toomey and Vierling, 2005)
NDVI	(R800-R680)/(R800+R680)	(Rouse et al., 1974)
PRI	(R531-R570)/(R531+R570)	(Gamon, Peñuelas, and Field, 1992)

Techniques such as spectrum matching and continuum removal require high spectral resolution data. Spectrum matching consists of three basic steps (Goetz et al., 1990). First, absorption coefficients for the dry matter compounds and liquid water are mathematically derived from the measured reflectance spectra of vegetation and liquid water. Second, the coefficients are used along with a few adjustable parameters to compute a spectrum over a given wavelength range (approximately 200 nm or less). Third, the adjustable parameters are modified until the sum of squared differences between an observed vegetation spectrum and the computed spectrum are minimized. At the canopy level, further steps must be introduced to account for the effects of the atmosphere and non foliar reflective elements. Spectrum matching has been applied at the canopy level by Gao and Goetz (1995) to retrieve vegetation EWT from AVIRIS data, reporting a correlation coefficient between measured and retrieved EWT of 0.78.

Continuum removal is a well known mathematical procedure developed in the context of the spectroscopy of minerals to enhance individual absorption features by separating them from a " background" continuum spectrum resulting either from absorption caused by unrelated physical processes or by a mixture of compounds including the one of interest (Clark and Roush, 1984). The technique can be used either with reflectance or absorbance spectra. Tian et al. (2001) used continuum removal to measure relative water content (RWC) of wheat leaves within the 1650-1850 nm spectral region.

Along with the extensive production of empirical studies, there is also a keen interest in a modeling approach to evaluate vegetation biophysical and biochemical properties. Because the available models are physically based, they are potentially more powerful than empirical methods for developing a deeper understand of the natural processes that affect vegetation. For the same reason, they are also an attractive approach in the search for solutions to estimate vegetation parameters that are general in terms of space, time, and species composition. When used in the direct mode, leaf models can be coupled to canopy and atmospheric models to generate large synthetic datasets of vegetation reflectance at sensor level that account for most of the variability naturally observed across biomes. These data are useful in identifying wavelengths that are correlated to a given vegetation parameter, or to explore the correlation between the parameter and a spectral index designed to retrieve it (Danson and Bowyer, 2004). Model inversion is used to compute the value of a vegetation parameter from reflectance data. There are many examples of model inversion in the literature, but only a few deal with vegetation water content or forest fire related topics. Zarco-Tejada, Rueda, and Ustin (2003) estimated canopy water content by model inversion from MODIS equivalent synthetic spectra obtained coupling the PROSPECT and SAILH models. The method was also tested with real MODIS reflectance and ground data. The results of the study indicate that this approach is a potentially valid solution to monitoring vegetation moisture content by remote sensing. Kötz et al. (2004) extracted the main fuel properties of conifer stands by coupling the PROSPECT and GeoSAIL radiative transfer codes, but the success of the inversion partly relied on suitable *a-priori* knowledge. Riaño et al. (2005) investigated FMC retrieval both at the leaf level and at the canopy level using PROSPECT and the Lillesaeter models. The authors tried to recover separately plant water and dry matter content, which is in part the approach followed in this thesis. While the estimation of water content was successful, that of dry matter was more problematic. Danson and Bowyer (2004) and Bowyer and Danson (2004) have produced two correlation studies aiming at establishing the physical bases of the relationships between FMC, EWT, and spectral indices, while Ceccato et al. (2001) used both the PROSPECT leaf model and the Extended Fourier Amplitude Sensitivity Test (EFAST), which is a global sensitivity analysis, to set the foundations for the development of the Global Vegetation Moisture Index (GVMI). Virtually all these studies indicated that there are differences in the way water content is estimated with remote sensing.

In fact, the answer to which quantities related to plant water status can actually be retrieved with remote sensing requires particular care. In general terms, plant water content is usually estimated according to three main definitions: RWC, FMC, and EWT. The RWC is defined as the water volume of a leaf divided by the water volume for the same leaf at full turgor. RWC is a dimensionless quantity but, as FMC, it is also usually expressed as a percentage by means of the following equation:

$$RWC = 100 * ((FW - DW) / (TW - DW)) \qquad (2\text{-}3)$$

where FW is the fresh weight of vegetation, DW is the dry weight, and TW is vegetation weight at full turgor, or saturated weight.

As already discussed, FMC may be estimated with (2-1) and it is often given as a percentage.

EWT is a more complex concept. The fact that it can be expressed either in dimensions of $[ML^{-2}]$ or simply of [L], is a sign that its physical meaning is not unique or unequivocal. In fact Seelig et al. (2008) have found four different interpretations in the literature:

- total water absorption path length of radiation reflected from leaves with dimensions of [L] obtained radiometrically. Downing et al. (1993) used the term Radiative-EWT to refer to this thickness;
- cross sectional water thickness of a leaf also with dimensions of [L], but experimentally determined;

- water content per unit leaf area or unit ground area of vegetated surface at canopy level, with dimensions of [ML^{-2}] and obtained experimentally;
- overall thickness of leaves times the RWC of leaf cells, with dimensions of [L].

Studies explicitly related to the retrieval of FMC with remote sensing started in the late 1980s. One of the earliest ones is by Paltridge and Barber (1988) who used low spectral and spatial resolution AVHRR data to develop a modified NDVI that could be related to the FMC of five Australian grassland sites. This study is the precursor of a series of works that have implemented the same basic concept: use of low-to-medium resolution satellite data to compute spectral indices that are then statistically correlated to FMC. Chuvieco et al. (2003; 2002) used both Landsat TM and AVHRR data to test a number of existing indices for the estimation of FMC for species of Mediterranean grassland and shrubland. In the Landsat TM study, the results based on simple correlation and multiple linear regression indicated that FMC was retrievable with comparable accuracies across the species of both types of cover, but with a slight edge for the shrub species. In the AVHRR study, the authors developed a synthetic FMC based on the NDVI, the Relative Greenness (RGRE) index, and the surface temperature to assess the spatial distribution and temporal variation of vegetation moisture content. Hardy and Burgan (1999) also correlated NDVI to FMC for a grassland, a sagebrush, and a conifer stand, but using an airborne high spatial resolution sensor mimicking the AVHRR spectral bands by means of optical filters. Temporal changes in moisture content were detected only for grassland. Ceccato, Flasse, and Grégoire (2002) designed a novel spectral index, the Global Vegetation Moisture Index (GVMI) specifically for the retrieval of canopy moisture content with the SPOT-VEGETATION sensor. The GVMI is a so-called optimized index because it has been developed using extensive modeling to correct for canopy and atmospheric effects and to maximize index robustness. The introduction of the GVMI represented a decisive shift from the past leaving behind the NDVI which, as already mentioned, may not relate to plant water status and displays saturation for dense forest covers. More importantly, it also established EWT over FMC as the preferred measure of vegetation water content by remote sensing. In the last decade, MODIS has become the sensor of choice for this task due to the greater number of spectral bands available. This allows researchers to test a greater number of indices. The majority of the most recent works has focused on FMC of chaparral vegetation (Dennison et al., 2005; Peterson, Roberts, and Dennison, 2008; Stow, Niphadkar, and Kaiser, 2005), or Mediterranean grassland and shrubland (Yebra, Chuvieco, and Riaño, 2008). Dennison et al. (2005) used linear regression to match FMC with NDVI and NDWI over twelve sampling locations in Southern California. NDWI performed clearly better than NDVI, but for both indices the coefficient of determination varied within a wide range from location to location. Stow et al. (2005) compared NDWI to VARI as predictors of FMC with a series of observations spanning over a period of almost two and a half years, and found that VARI was better correlated to FMC than the other index, perhaps due to specific phenological conditions and precipitation response over the selected time range. The authors also tried a multiple regression approach using both indices as predictors after verification of the degree of correlation between them. The multiple regression approach modeled FMC better than the separate bivariate models, obtaining an R^2 value as high as 0.95 for one of the three Southern California study locations. In a subsequent study Stow and Niphadkar (2007) extended the time range for the analyzed data and substituted the NDVI with NDII6 and a scaled version of VARI. An even more comprehensive study is that of Peterson Roberts, and Dennison (2008) which tested a greater number of indices for fourteen sampling locations, once more in Southern California, belonging to the chaparral and coastal sage scrub shrubland. The temporal coverage varied in ranges between 2000 and 2006 for the various sampling locations. Modeling the spatial and temporal variations of FMC was the main goal of the study, but the approach used to carry out the research was conceptually the same, namely, using multiple regression to estimate FMC by means of suitable spectral indices. Yebra, Chuvieco, and Riaño (2008) compared the empirical approach based on spectral index to a physically based one to model FMC of grassland and shrubland over a period of five years. Both methods were able to fit reasonably well the general trend of FMC variation in the time range investigated. When using the empirical approach, the results for grassland were better than those for shrubland. On the other hand, the simulated reflectance approach was more difficult to develop, but showed greater robustness. These latest semi-empirical studies have a background difference in comparison with the more prominent physically based modeling studies. The difference is that the former are trying to model variations of FMC over the long term with a seasonal or monthly time resolution, while the latter are focused on modeling FMC at a specific point of time simulating vegetation characteristics that is inclusive of a wide range of species and ecosystems.

The experience accumulated through these and other studies on the water content of vegetation has helped in shaping two crucial findings:

- FMC is perhaps retrievable with an acceptable degree of accuracy for grasslands, but inconsistently for shrublands, and especially poorly for forested areas;
- The dependency of FMC from both water and dry matter content limits the accuracy of the retrieval with a single spectral index while, at the same time, the moisture content of vegetation is preferably obtained in terms of EWT than FMC.

A formal relationship between FMC, EWT and SLW can be obtained multiplying and dividing both terms in equation (2-1) by leaf area (A):

$$((A/A) * FMC) = ((A/A) * (FW-DW / DW)) \tag{2-4}$$

Rearranging the second term in equation (2-4) gives:

$$(FW - DW) / A = EWT \tag{2-5}$$

and

$$A / DW = SLA = 1 / SLW \tag{2-6}$$

where SLA is Specific Leaf Area and SLW is Specific Leaf Weight. Therefore:

$$FMC = EWT / SLW \tag{2-7}$$

The mathematical equivalence of equations (2-1) and (2-7) offers the opportunity to improve the retrieval of FMC with remote sensing dividing EWT, which can be estimated with better accuracy, by SLW, which is a surrogate measure of dry matter content. The challenge, obviously, is to demonstrate that SLW can also be retrieved with spectral reflectance or transmittance.

2.2 - Dry Matter Content

Plants are composed of water and dry matter. On average, the proportion in terms of fresh mass for the fully hydrated Douglas-fir needles used in this study is about 60% water and 40% dry matter. As there is free and ligand water in plants, it should also be remembered that a portion of the dry matter is allocated to the solution phase with water and is not directly part of the leaf structure (Roderick et al., 1999). Before proceeding with a closer examination of dry matter, we must then look at the tight relationship between the water and the dry matter content in leaves, which is very relevant especially in comparative studies across species. The relationship between leaf water content (LWC) and leaf dry matter content (LDMC) is:

$$LDMC = 1 - LWC \qquad (2\text{-}8\ )$$

Thus, any spatio-temporal change in leaf water content entails a change in dry matter content. The practice of rehydrating the leaves before performing measurements of LDMC aims at standardizing for the known and well documented spatio-temporal variations of leaf water content. Similar and sometimes rapid fluctuations of non structural carbohydrates in plants have also been observed (Garnier et al., 2001b; Little, 1970; Palacio et al., 2008), but the rehydration procedure is unable to compensate for them. These dry matter fluctuations may produce variations in other related leaf traits, in particular specific leaf area (SLA), which is projected leaf area per unit dry mass, or its reciprocal the already mentioned SLW (Garnier et al., 2001b). These physiological aspects of the leaves should not be ignored because location and time of sampling in the field, as well as sample handling, may affect leaf status at the time of measurements and make comparisons difficult (Foley et al., 2006).

Content represents the amount of a given compound and, therefore, leaf dry matter content should be the mass of dry matter in a leaf. However, leaf dry matter content is by definition the ratio of leaf oven-dry mass to saturated fresh mass (Cornelissen et al., 2003; Garnier et al., 2001a; Garnier et al., 2001b; Vaieretti et al., 2007; Vile et al., 2005) and, as such, it is a unit-less quantity. However, LDMC is often expressed in units of mg/g, or as a percentage of saturated fresh mass. These units are traditionally, but improperly, used to define concentration. It is also worth notice that sometimes this important functional leaf trait is referred to as leaf tissue density (Ryser, 1996) on the assumption of a very close connection between leaf volume and leaf fresh mass. This has prompted some authors to suggest a relationship between LDMC, leaf thickness, and SLA, or SLW (Vile et al., 2005; Wilson, Thompson, and Hodgson, 1999; Witkowski and Lamont, 1991). Therefore, at least for laminar leaves, LDMC and SLA (or SLW) are often considered surrogates of one another. However, as we will see in chapter 4, this statement breaks down for needle-like leaves and, in general, for leaves with SLW greater than about 0.015 g cm^{-2} (Garnier et al., 2001b). Using SLW as a surrogate measure of LDCM automatically implies the measurement unit is that of mass per unit leaf area.

Content should not be confused with concentration. While dry matter content is leaf dry mass per unit leaf fresh mass, dry matter concentration is leaf dry mass per unit leaf volume (Roderick, 2000; Shipley and Vu, 2002). Despite the aforementioned connection between leaf volume and leaf fresh mass, content and concentration will be the same only if the density of the leaves is equal to the density of water. Shipley and Vu (2002) have been able to show that LDMC and leaf dry matter concentration are at least proportional to one another to a certain degree, which means that leaf density is approximately constant across species. Roderick (2000) has also aptly pointed out that, despite contributing extremely little to leaf mass, variations in leaf internal air spaces are a simple but effective way to alter all relationships among leaf area, mass and volume. In relation to this, there is a long standing and compelling amount of evidence that these internal air spaces also alter the optical scattering properties of leaves (Allen et al., 1969; Gates et al., 1965; Gausman, 1974; Kumar et al., 2001).

In the remote sensing literature on leaf and canopy biochemistry, the terms content and concentration have been very often used as synonymous, especially in the early work. In more recent work, a quantity expressed in units such as g/g is considered concentration, while content is measured as mass per unit leaf area. Clearly, neither are formally correct. Although this may look simply like a matter of proper terminology it is, in reality, a matter of substance because there is evidence that, when using multiple linear regression, the reflectance or transmittance of leaves are better related to the amount of absorbing chemicals per unit leaf area and not by concentration expressed in units of absorber mass per unit fresh, or dry, leaf mass (Fourty and Baret, 1998). Therefore, it is very likely that there are other factors influencing the reflectance and transmittance of leaves alongside with the absorption characteristics of the biochemicals of interest. Leaf cell structure, multiple scattering, and complex overlapping of absorbing chemicals are considered the most likely sources affecting the retrieval of foliar biochemistry by means of its spectral properties (Grossman et al., 1996).

The chemical composition of vegetation dry matter includes a large number of organic compounds and minerals. For sake of simplicity, these are usually grouped in a few broad categories. In the context of this study, the dry matter of leaves may be considered composed of two major carbohydrates along with starch and other sugars, lignins, a well known group of pigments, proteins, lipids, and inorganic material generally described with the term ash (Almeida and De Souza Filho, 2004; Kumar et al., 2001). The two major carbohydrates are cellulose and hemicellulose which, along with lignins, provide, the structural skeleton of plants. Holocellulose (cellulose plus hemicellulose) and lignins are the two most abundant biopolymers on Earth. It is estimated that lignins alone account from 25% to 30% of the organic carbon in the biosphere (Boerjan, Ralph, and Baucher, 2003; Boudet, Lapierre, and Grima-Pettenati, 1995). On the other hand, cellulose is also a renewable resource with a relevant industrial and economic value that, besides its traditional uses, may potentially be utilized in the food industry or as a raw material for the production of bioethanol from genetically modified plants (Hoch, 2007;

Joshi and Mansfield, 2007; Taylor, 2008). Thus, the interest in detecting these biochemicals in vegetation with spectroscopic techniques goes beyond the realm of pure scientific research. Cellulose, hemicellulose, and lignins constitute the bulk of the dry matter content of vegetation. They account for 70% to almost 100% of dry weight in wood and about 50% to 65% of dry weight in needles of three western conifers (Nelson Jr, 2001). The other substantial components of leaf dry matter are sugars and nitrogen-based proteins. Despite being insoluble in water, an important chemical property of these three molecules is their exposed hydroxyl (OH) groups which allow for the formation of strong hydrogen bonds with the highly polar molecules of water. The highest affinity for water is that of hemicellulose, the lowest is that of lignins, which actually waterproof the walls of specialized plant cells. On the other hand, most of the main organic compounds in plant dry matter have O-H, C-O, C-N, and N-H bonds. This has deep implications on the spectral properties of these compounds (Curran, 1989; Curran et al., 1992; Kumar et al., 2001). The three most significant consequences are:

1. the fundamental absorption features, due to vibrational bending and stretching of the molecules of these compounds, are generally located beyond the Visible, Near-Infrared (VNIR, 350-1100 nm) and Short-wave Infrared (SWIR, 1100-2500 nm); secondary, weaker, absorption features observed particularly between 800 nm and 2500 nm are due to harmonics, overtones, and combination bands of the main features;
2. many of these secondary features are broadened due to multiple scattering and may overlap with one another due to the chemical similarities in the organic compounds;

3. these very same features also overlap, in many cases, with much stronger liquid water absorption features located at about 970 nm, 1190 nm, 1450 nm, 1940 nm, and 2500 nm.

The remote sensing of foliar and canopy biochemistry built up on the Near Infrared Reflectance Spectroscopy (NIRS) laboratory techniques developed in the 1960s and refined until the mid 1980s to predict crop biochemical composition and forage quality (Curran, 1989). The basic NIRS protocol relies on multiple linear regression to develop a calibration equation between the reflectance of dried, ground leaves and the amounts of the chemical constituent of interest. A different equation must be developed for each chemical compound or micronutrient present in the leaf. Very often, along with the reflectance (R), a log transformation of reflectance called pseudo-absorbance, and the first and second difference of reflectance or of log (1/R) (as an approximation of the derivatives) are used in the regression procedure. Transforming the reflectance curve as log (1/R) allows the researcher to plot the data in a form similar to an absorption curve according to the Beer-Lambert law (Serrano, Peñuelas, and Ustin, 2002), and also reduces the effects of non linearity in the reflectance response to biochemical concentration (Bolster, Martin, and Aber, 1996). Tacking the derivative of the same curve is operationally more significant because it seems to compensate, or at least mitigate, the effects of shifts in the baseline and interfering absorptions (Bolster, Martin, and Aber, 1996; Demetriades-Shah, Steven, and Clark, 1990; Wessman et al. 1988). The technique has reached such a level of sophistication that it consistently provides results comparable with those of laboratory wet chemistry, and is now used in a wide range of application fields (Benito, Ojeda, and Rojas, 2008; Stchur et al., 2002). A generalization of multiple linear regression called partial least squares (PLS) regression has become rather popular, along with other multivariate techniques and less traditional methods such as genetic algorithms, neural networks, and wavelets (Estienne et al., 2001; Wold, Sjöström, and Eriksson, 2001).

Foliar NIR spectroscopy relies on consistently prepared laboratory samples and instrumentation with adequate spectral resolution and signal-to-noise ratio. It also requires that the samples used in calibration encompass the range of variation of those for which the calibration equation(s) will be used for prediction (Kokaly, 2001; Wessman et al., 1988). The extension of the NIRS technique to non-agricultural vegetation rarely, if ever, satisfied the basic requirement about the sample representativiness (Card et al., 1988; Wessman et al., 1988). The application to fresh, instead of dry, foliage and to whole forest canopies also exacerbated other methodological issues and made the interpretation of the results more problematic (Gastellu-Etchegorry et al., 1995; Kupiec and Curran, 1995; Martin and Aber, 1997; Peterson et al., 1988; Zagolski et al., 1996). Moreover, imaging spectrometers such the Airborne Imaging Spectrometer (AIS) and the early version of AVIRIS, did not have an adequate signal-to-noise ratio at least on part of the SWIR spectral range to detect canopy biochemistry (Smith and Curran, 1996). Although these and other studies up to the end of the century found statistically significant correlations between several biochemical compounds and the optical properties of tree leaves and canopies, it is reasonable to say that their most important goal was "to establish that chemical information can be obtained from spectra of tree foliage" (Card et al., 1988). These authors were also well aware of the limitations of the technique and developed strategies to overcome them. To name a few: scrambling of compounds content (concentration) to gain knowledge of the level of correlation between the absorbing chemicals and the spectral measurements in order to mitigate the risk of inflating the value of the coefficient of determination (Card et al., 1988; Grossman et al., 1996); limitation on the number of wavelengths selected by multiple linear regression and cross validation also to avoid overfitting (Card et al., 1988; Peterson et al., 1988); use of constrained regression to create models with a better theoretical basis (Grossman et al., 1996; Wessman et al., 1988); smoothing and filtering of data (Card et al., 1988; Curran et al., 1992); spectrum matching (Gao and Goetz, 1994; Goetz et al., 1990) and decoupling techniques (Curran et al., 1992) to subtract or reduce the effects of water absorption and chemical overlapping. The trends that have emerged from the results of these studies are that a) using pseudo-absorbance or an approximation of derivative of pseudo-absorbance generally improves estimate accuracy, and b) biochemical retrieval works better if compounds are expressed in terms of mass per unit area (Fourty and Baret, 1998; Grossman et al., 1996). A somehow surprising finding is that smoothing or filtering of data did not improve the accuracy of estimations (Curran et al., 1992) and, actually, the introduction of random instrumental noise was found effective by Fourty (1998) at least to retrieve water content. Two issues that have never been fully understood and resolved are why wavelengths that are not associated with any known biochemical are often selected by means of multiple linear regression and, vice versa, why some of the wavelengths that are associated with specific compounds may be omitted by multiple linear regression (Curran, 1989). The lack of consistency in wavelength selection, as well as a lack in the robustness of the relationships empirically developed by means of multiple regression are still major issues in the remote sensing of foliar and canopy biochemistry. The most common explanations for these problems invoke bond chemical similarity among compounds (Ferwerda, Skidmore, and Stein, 2006; Kokaly and Clark, 1999; Soukupová, Rock, and Albrechtová, 2002; Wessman et al., 1988) or, alternatively, intercorrelations among compounds (Curran, 1989). Other plausible reasons are disturbances in the bonding energy configuration (Wessman et al., 1988), as well as the fact that some of the most important constituents of vegetation dry matter have more than one molecular weight, such as cellulose (Taylor, 2008), or are not yet chemically well defined, such as the class of lignins (Ralph et al., 2004). The lack of robustness is generally associated with a lack of physical basis in the empirical models (Fourty and Baret, 1997). Some studies have also found that the accuracy of the estimates depended on the choice of the dataset for calibration and/or on the way in which the stepwise multiple regression was run (Grossman et al., 1996; Jacquemoud et al., 1995). Compounding these methodological issues with those of chemical and physical nature previously mentioned, have prompted Grossman et al., (1996) to strongly question the meaning of all results obtained up to the mid 1990s about foliar and canopy biochemistry.

In remote sensing, the classic alternative to the empirical studies is that of physical modeling. This is carried out using radiative transfer models either in direct or inverse mode, depending on the application. The inversion of leaf models such as PROSPECT (Jacquemoud and Baret, 1990) or LIBERTY (Dawson, Curran, and Plummer, 1998) allows the computation of the specific absorption coefficients of the biochemicals of interest from knowledge of their concentration in leaves. Once these specific absorption coefficients are known, the radiative code can be used to compute the concentration of the biochemical compounds in other leaf datasets. Leaf models can also be coupled to canopy models to investigate the biochemistry of forest canopies. Noticeable studies that have used radiative transfer models to investigate foliar and canopy biochemistry are those of Fourty et al., (1996), Fourty and Baret, (1997), Dawson et al., (1999), and Riaño et al., (2005). It is worth notice that while most of the empirical studies have tried to retrieve information on specific plant biochemicals and nutrients, the physical approach has succeeded only in partially retrieving dry matter content. Success depends, in part, on the merits of the specific models, and on the fact that no model is advanced to the point of including a detailed representation of foliar biochemistry. For instance, the latest version of PROSPECT includes specific absorption coefficients for pigments, but it is still unable to separate the contributions of chlorophylls a and b (Feret et al., 2008). The strong absorption of liquid water is also a problem both at the (fresh) leaf and canopy levels because it tends to mask the absorptions due to other biochemicals.

Two other techniques that have been used with some success in the investigation of foliar and canopy biochemistry are those of partial least squares and continuum removal. In contrast to multiple linear regression, partial least squares regression, or PLSR, is a multivariate technique that can take advantage of the information contained in the full reflectance spectrum of leaves or canopies without concerns for multicollinearity and, perhaps, less sensitivity to noisy data. Bolster, Martin, and Aber (1996) used PLS to evaluate the biochemical content of samples of fresh deciduous and conifer foliage and found that this technique performed better than multiple linear regression. Once more, it must be stressed that the wavelengths selected by the two methods were different depending as a function of both data processing and chemical compound. A similar study with similar results, but on dried ground leaves, was carried out by Petisco et al. (2006) who confirmed the validity of the NIRS technique for this type of investigation.

The first study that applied continuum removal and band depth along with multiple regression to analyze the biochemistry of dried, ground leaves was by Kokaly and Clark (1999). The authors concentrated their investigation on three SWIR absorption features in the foliage spectra associated with nitrogen, lignin, and cellulose obtaining positive results for all three compounds, but particularly high correlations for nitrogen. In addition, they used simulated data based on the Hapke radiative transfer model to investigate the effect of water on the retrieval of dry matter compounds. Kokaly (2001) used again continuum removal to study the 2100 nm absorption features in the spectra of three pairs of dry conifers needles selected for their difference in nitrogen content and found compelling evidence of a band broadening in the absorption feature of the spectra of samples with greater nitrogen content. Curran, Dungan, and Peterson (2001) further tested continuum removal and band depth analysis for a range of twelve biochemicals in samples of dried, ground slash pine needles. They also compared these methods to the more traditional first derivative of reflectance. All three methods were correlated with the biochemicals' contents with regression analysis. The continuum removed reflectances were found more effective than the derivatives of reflectance for analyzing the biochemistry of the foliar samples, confirming that this type of spectral treatment may be quite effective in enhancing the signal contained in spectral absorption features.

However, much more testing is necessary, especially with fresh foliage and at the canopy level, to fully understand the effectiveness and the limitations of continuum removal. The strength of water absorption may hinder the use of this technique with fresh vegetation.

Different than the case of water content, there are no specific spectral indices developed for the estimation of vegetation dry matter content. The Cellulose Absorption Index (CAI) developed by Daughtry et al. (1996) to discriminate crop residues from soil may be considered an adaptation of the continuum removal technique (Daughtry et al., 2005). It is based on three SWIR wavelengths at about 2000 nm, 2100 nm, and 2300 nm that can be correlated to a broad cellulose absorption feature. The Lignin Cellulose Absorption (LCA) index (Daughtry et al., 2005) is based on three ASTER spectral bands located between the 2100 nm and 2300 nm absorption features of cellulose and lignin respectively. Also, this index may be used for the remote sensing of crop residue. Serrano, Peñuelas, and Ustin (2002) proposed the Normalized Difference Lignin Index (NDLI) for the estimation of canopy lignin in shrub vegetation. The index is similar to the NDVI, but it uses pseudo-absorbance values at 1680 nm and 1754 nm.

Chapter 3: Study Location, Data Acquisition and Processing

3.1 - Introduction

This thesis describes a laboratory study conducted at the leaf level to investigate how well water content in terms of EWT and FMC can be measured by means of spectral indices. The main reason to carry out the study at the leaf level in a laboratory setting is to avoid the complications arising from measurements at the canopy level, where soil background effects, illumination and viewing conditions, and atmospheric absorption and scattering are very difficult to control for. The dehydration procedure may also be quite problematic at the canopy level in a natural environment. In fact, it will require masking the tree canopy from precipitation, as well as creating an artificial barrier around the tree root system to limit soil moisture and water uptake. Even with these precautions in place, complete isolation of a tree from moisture uptake would likely not be achieved. Moreover, the study would need an extended period of time to allow for a progressive, but unmanageable, depletion of the plant internal water reserve.

The spectral indices approach was selected because it can be very easily implemented in an operational system to measure FMC in near real time. If it can be shown that the concept works at the leaf level, a study to upscale the results at the canopy level may then be planned. Another possible outcome is to set the basis to develop field equipment that may be used to expand and expedite acquisition of FMC data in the field.

For practical reasons, only one species could be considered for this study. A trade-off had to be achieved to balance manpower, sample size and work load. A small pilot study was carried out to infer the amount of time to handle a single sample and the length of the de-hydration procedure to cover a wide range of FMC values. The pilot study results indicated that a maximum of 40 samples per day would be feasible, and that 10 days of sample de-hydration would allow for the desired range of variation in FMC.

The choice of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) needles was based on the fact that there is a limited number of studies that have investigated the relationships between spectral reflectance and water content in conifers (Stimson et al., 2005). In addition, this conifer species is very common on Vancouver Island.

3.2 - Study Location

The location of the study is a regrowth plot on the hydrographic left of the Rithet Creek Valley within the Greater Victoria Sooke Lake Watershed on Vancouver Island, British Columbia (Figure 3-1). A close up view of the plot along with a 3-D view of the Rithet Creek Valley is displayed in Figure 3-2. Sampled trees locations are marked with yellow dots.

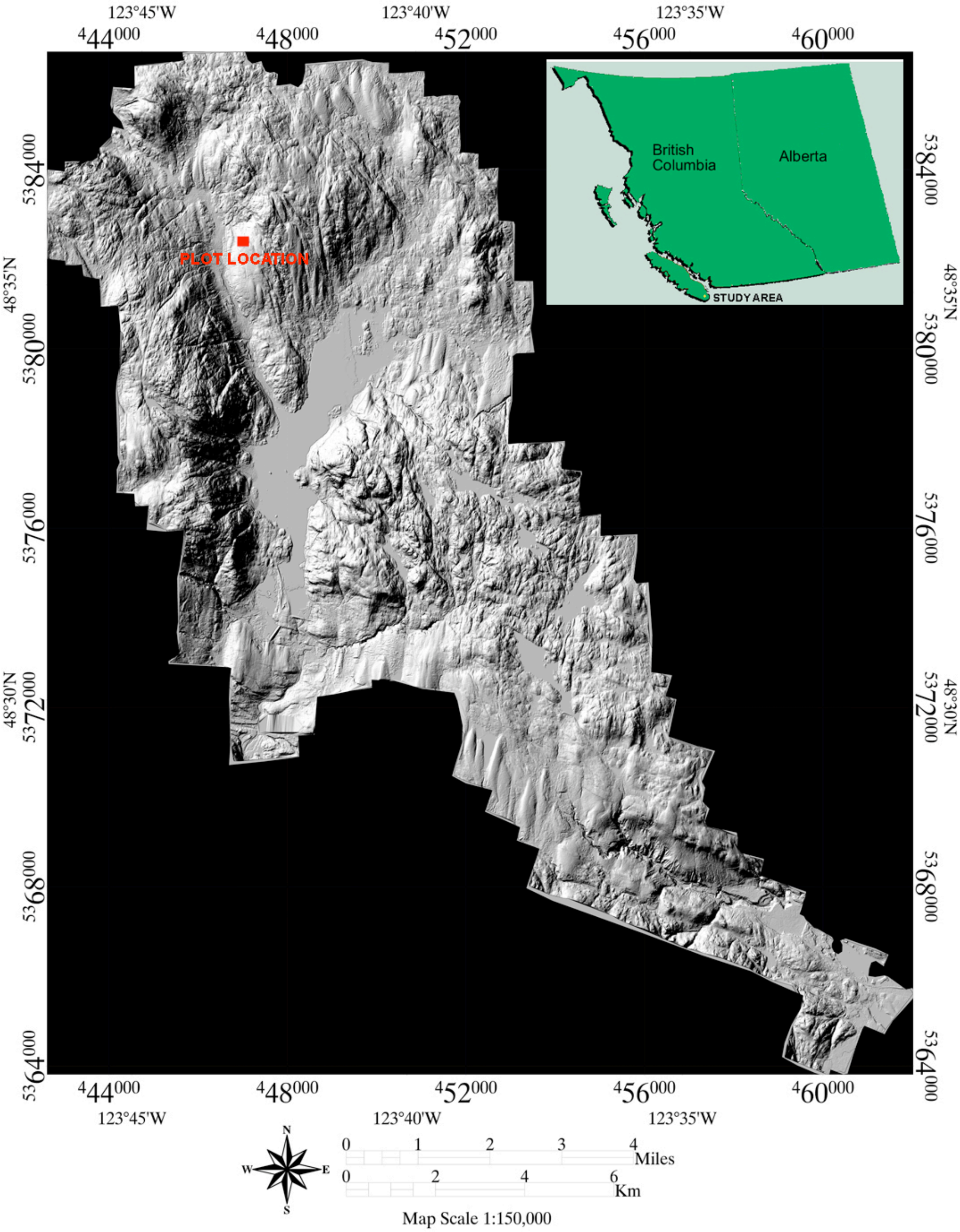

Figure 3-1: Study location.

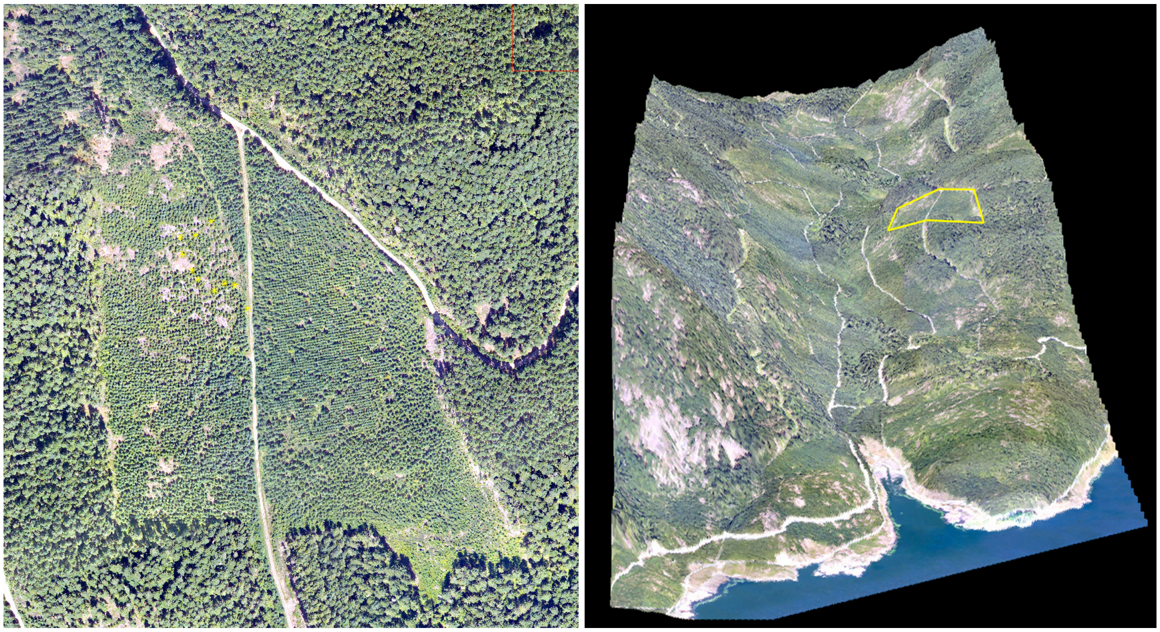

Figure 3-2: Close-up view of the tree plot sampling location (left). Sampled trees' locations are marked in yellow. 3-D view of the Rithet Creek Valley with the tree plot boundary of the sampling location marked in yellow (right).

The plot is situated at an elevation of 365 m above sea level and is dominated by Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) with some western hemlock (*Tsuga heterophylla* (Raf.)). The understory is mainly represented by salal (*Gaultheria shallon* Pursh) and grass species.

Sampling was carried out between 11 o'clock and 15 o'clock on August 23, 2005. Ten trees were selected for sampling following these criteria:

a) trees of same, or very similar, age/height class;

b) trees separated from each other;

c) trees should look healthy, but represent a range of growing conditions such as exposure, soil, and competition for light with neighbouring individuals in order to maximize the variation of foliar dry matter content.

The trees sampled were approximately 10 to 12 years old. Each tree location was recorded by means of a Global Positioning System (GPS). Four branches were sampled from each tree. Two were cut at a height of about 1/3 from the tree base (lower crown) and the other two at 2/3 from the tree base (upper crown). The branches had North and South exposures respectively, and were clipped as close as possible to the tree bole. The assumption implicit with this sampling strategy was that the upper crown has different anatomical/physiological characteristics from the lower crown because of less competition for light. Differences were also thought to derive from the North-South exposure of the branches. Each selected branch was tagged after cutting and immediately stored in a black plastic bag. After sampling two trees, the branches were brought back to a main collecting location and stored in bins with about 25 cm of water at the bottom.

3.3 - Sample Re-hydration and De-hydration

Once in the laboratory in the same afternoon, the branches were re-cut under water to minimize the possible effect of cavitation and favour re-hydration. On average, 12 inches at the base of each branch were cut off. The branches were then wrapped in a double layer of black plastic wrap to isolate them from the light, and left to re-hydrate in the bins for 24 hours. Figure 3-3 displays the average initial water content in percentage for each tree as an indication of the process of re-hydration. Only one tree did not completely re-hydrate.

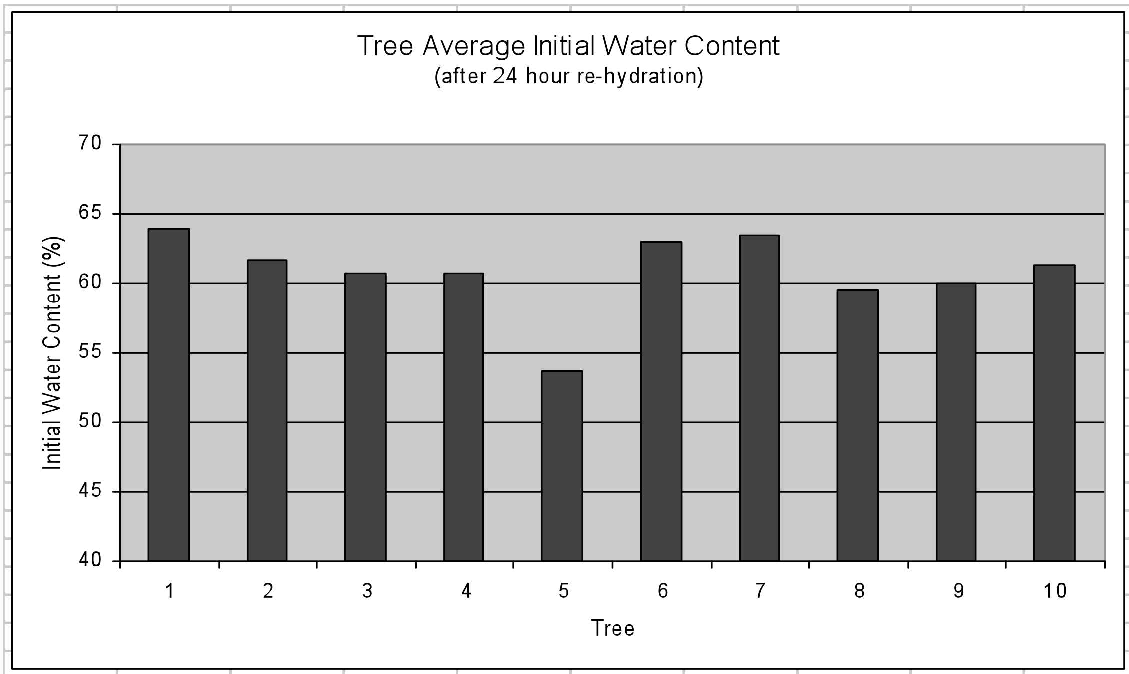

Figure 3-3: Average tree water content after 24-h re-hydration period.

All branches were then individually photographed and subjected to de-hydration at room temperature hanging from the ceiling room (Figure 3-4). The temperature of the room was thermostatically controlled and varied between 18˚ C and 21˚ C for the time period of the study.

Figure 3-4: Some of the 40 sample branches at day 1 of the 10-day de-hydration period.

Starting from August 24, 2005, and for 10 consecutive days, a twig from each of the 40 branches was cut from a similar position on each branch, and needle samples were collected from the central portion of each twig for measurement. Special care was used to select only previous year twigs and needles. Current year twigs/needles were not sampled. An average of 15 to 20 needles were selected for spectroscopic measurements from each twig, while another 25 or 35 needles (depending on needle size) were selected for weight and area measurements. The twigs were then discarded. Therefore, the total number of samples that have been measured for this study is:

(10 trees) x (4 branches/tree) x (1 twig/branch/day) x (10 days) = 400 samples

3.4 - Fresh Weight Measurements

Immediately after the needles were removed from the twig, the fresh weight was measured with an XE series, Model 100 A analytical scale of Denver Instrument Company. Prior to any measurement acquisition, the scale was levelled and calibrated with a calibration gauge. Fresh weight measurements were acquired in grams. To determine the accuracy of the scale, the weight of a batch of 35 needles was measured ten times obtaining an average weight of 0.2280 g and a standard deviation of 0.0007 g. Depending on needle size, only batches of 25 or 35 needles were measured in order to avoid large inconsistencies in fresh weight. These needles were then stored in individual air-tight vials for further measurement.

3.5 - Reflectance Measurements

After fresh weight measurement, some of the remaining needles were carefully attached to black tape with their adaxial face up to acquire their spectral signature. The needles were aligned as close as possible to each other in order to minimize background effects on the spectral measurements. An example of needles prepared for spectral reflectance measurement is displayed in Figure 3-5.

Figure 3-5: Douglas-fir needles prepared for spectral reflectance measurement.

Reflectance measurements were carried out over the range 350 - 2500 nm with the 6442 FieldSpec Pro Spectroradiometer model FSP350-2500P by Analytical Spectral Device of Boulder, Colorado (USA). The spectroradiometer is actually composed by three separate units: one Visible/Near Infrared (VNIR) spectrometer and two Short-wave Infrared (SWIR) spectrometers. The fixed VNIR unit cover the range between 350 and 1050 nm with a Full Width at Half Maximum (FWHM) spectral resolution of approximately 3 nm at 700 nm. The radiation dispersed by the grating is filtered by an ordered separation filter before reaching the 512-channel silicon photodiode detector array. Because the 700 nm range is dispersed over the 512-channel array, each channel collects a 1.4 nm bandwidth radiation. The two scanning SWIR spectrometers cover the ranges 900 to 1850 nm and 1700 to 2500 nm respectively. The units have two scanning concave holographic gratings which sequentially direct the dispersed radiation onto their respective single-channel indium gallium arsenide (InGaAs) detectors. The spectral resolution of the SWIR ranges varies between 10 and 12 nm, with a sampling interval of about 2 nm.

In order to stabilize the sensor dark noise, the instrument was allowed to warm up for a minimum of 30 minutes prior to any measurement. A Spectralon white plate was used as a reference standard to transform radiance into relative reflectance. The end of the spectrometer fibre optic was set at a height allowing 1.0 cm^2 of needle area to be probed by the spectrometer. An Analytical Spectral Device Pro Lamp holder equipped with an Hushio 14.5 Volt, 50 Watt halogen lamp that mimic the Sun light spectrum was used to illuminate the sample and the reference plate. The reflectance measurement layout is displayed in Figure 3-6.

Figure 3-6: Instrumentation layout for reflectance measurements.

A series of five white reference plate spectra was collected before each sample measurement. Each plate spectrum was an average of ten measurements. Needle spectra were acquired at three 120˚ orientations to take into account possible bidirectional reflectance distribution factor (BRDF) effects. For each orientation were recorded five spectra and each spectrum was, in turn, the average of ten measurements. The total number of spectra for each needle sample was then averaged in post processing. Every ten needle samples measurements the spectrometer data acquisition parameters were re-optimized using the instrument control software to avoid possible drift in sensor response.

3.6 - Leaf Area Measurements

After the completion of the reflectance measurements, the fresh needle area was acquired using a Li-COR model LI-300 leaf area meter. Before taking any measurement, the instrument was allowed to warm up for 20 minutes to stabilize the lamp brightness. The instrument was also calibrated using both a metal disk and a bar mask of known areas. To perform the measurement, the needles were aligned between two plexiglas plates with the adaxial face up and scanned through the area meter. Three area measurements, in unit of cm^2, were acquired for each needle sample and then averaged together. While the average area of each individual sample varied between 4.9170 and 13.0087 cm^2, the standard deviation varied between 0.0015 and 0.1197 cm^2, although 381 samples out of 400 have a standard deviation below 0.0500 cm^2 (Figure 3-7).

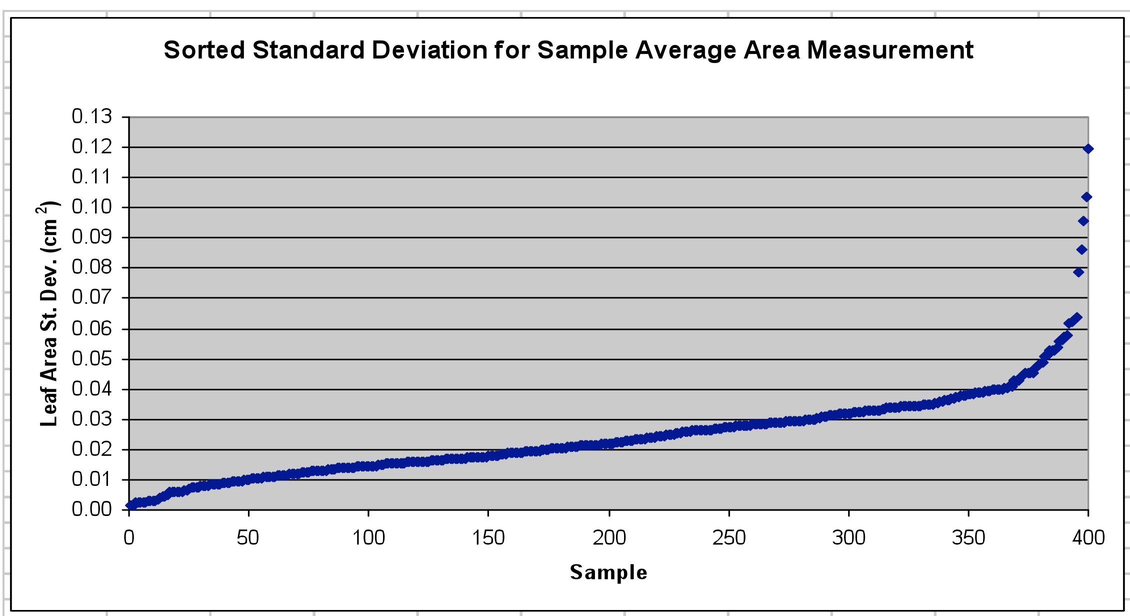

Figure 3-7: Standard deviation (sorted from low to high) of sample average leaf area.

The area meter calibration was verified every ten samples measurements using a bar mask. A drift was observed in the area measurement of the calibrated bar mask (Figure 3-8). However, as seen in Figure 3-9 for the calibration checks performed in day 2 of the study, there is no clear evidence that the area measurements of the mask can be considered statistically different. In addition, the variable "leaf area" will be used in this thesis to compute EWT and SLW, and because these two quantities will be ratioed to derive FMC, the "leaf area" variable will cancel out. Therefore, no leaf area corrections were applied to compensate for the instrumental drift.

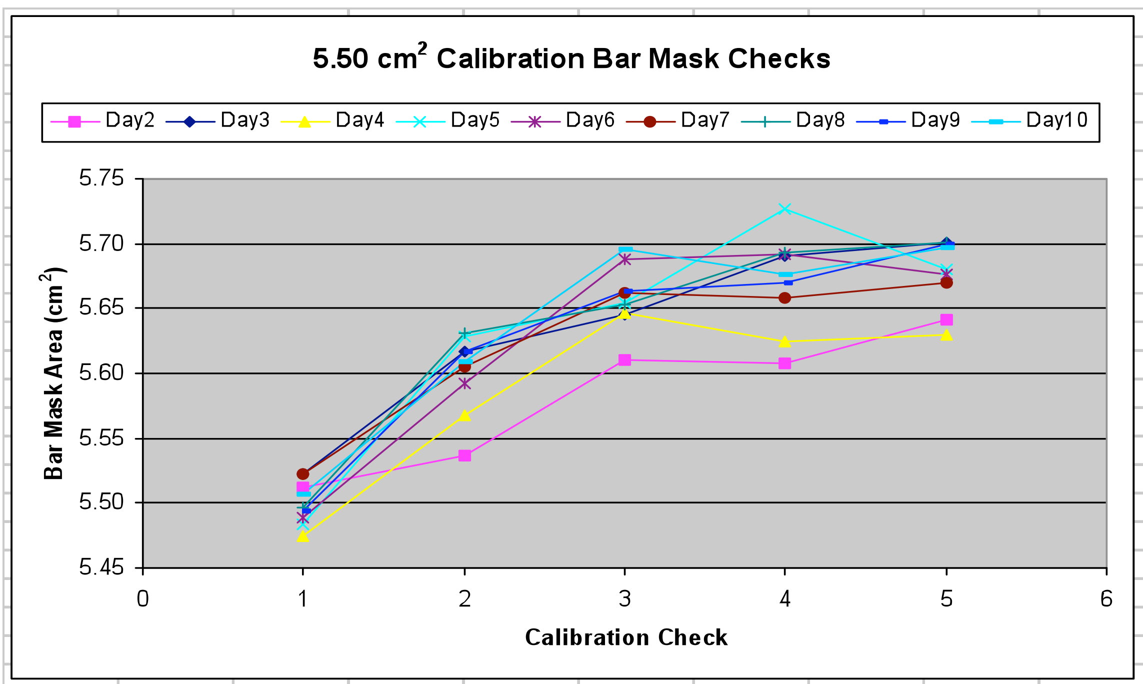

Figure 3-8: Drift observed in the 5.50 cm^2 area calibration bar mask measured with the Li-Cor LI 3100 leaf area meter. Day 1 checks were carried out using a mask with a different area and are not charted.

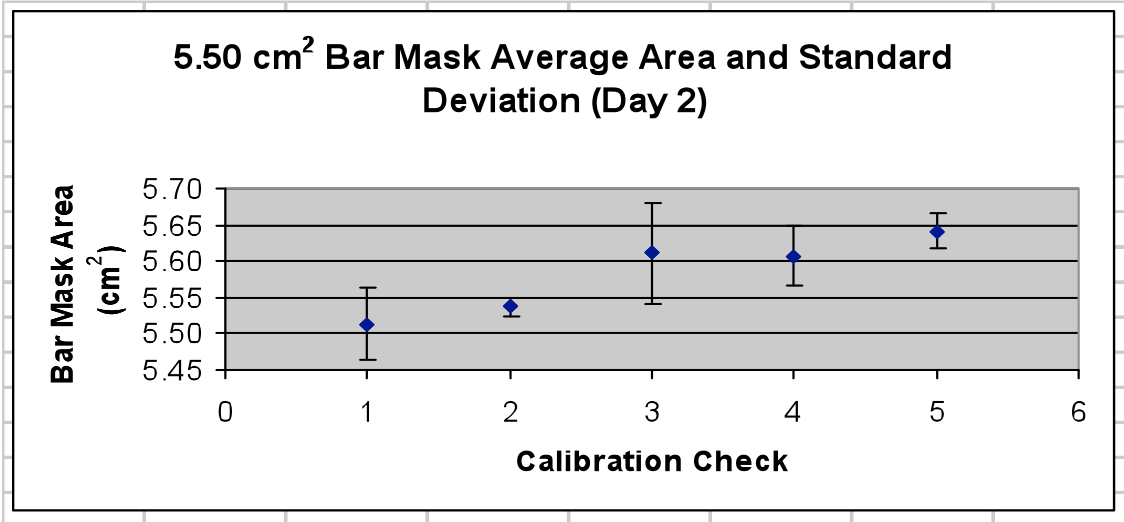

Figure 3-9: Average area and standard deviation of the 5.50 cm^2 calibration bar mask measured on day 2 of the study with the Li-Cor LI 3100 leaf area meter.

3.7 - Dry Weight Measurements

Upon completion of the area measurement, the needles were stored in individual ceramic containers and oven-dried for 24 hours at 80˚ C. Needle dry weight was then acquired by means of the same analytical scale used to measure fresh weight.

3.8 - Quantities Derived from Measurements

For each sample, the following quantities were derived from the aforementioned measurements:

- Water Content (WC) in g;
- Water Content (WC %) as percentage of fresh weight;
- Equivalent Water Thickness (EWT) in g cm^{-2};
- Specific Leaf Weight (SLW) in g cm^{-2};

- Fuel Moisture Content (FMC) as a percentage of dry weight;

These quantities were computed with the following equations:

$$WC = FW - DW \tag{3-1}$$

$$WC\ \% = 100 * (FW - DW) / FW \tag{3-2}$$

$$EWT = (FW - DW) / A \tag{3-3}$$

$$SLW = DW / A \tag{3-4}$$

$$FMC = 100 * (FW - DW) / DW = EWT / SLW \tag{3-5}$$

Where FW is fresh weight, DW is dry weight, and A is leaf area.

In addition, a number of established spectral indices were computed from the needle reflectance spectra. The indices related to water content were:

- Water Index, WI = R900 / R970
- Moisture Stress Index, MSI = R1600 / R820
- Simple Ratio Water Index, SRWI = R860 / R1240
- Normalized Difference Water Index, NDWI = (R860 - R1240) / (R860 + R1240)
- Normalized Difference Infrared Index, NDII = (R820- R1650) / (R820 + R1650)
- Weighted Normalized Difference Infrared Index,

  wNDII = (2 * R820- R1650) / (2 * R820 + R1650)
- Global Vegetation Moisture Index,

  GVMI = ((R820 + 0.1) -(R1600 + 0.2)) / ((R820 + 0.1) + (R1600 + 0.2))
- Ratio of Thematic Mapper 5 to 7, TM5 / TM7 = R1650 / R2218

- Datt 1, Datt 1 = (R850 - R1788) / (R850 - R1928)
- Datt 2, Datt 2 = (R850 - R2218) / (R850 - R1928)
- Moisture Index 1, MI1 = (R880 / R680) * (1 / R1600)
- Moisture Index 2, MI 2 = ((R800 - R680) / (R800 + R680)) * (1 / R1600)
- Normalized Difference Vegetation Index, NDVI = (R800 - R680) / (R800 + R680)
- Photochemical Reflectance Index, PRI = (R531 - R570) / (R531 + R570)

Two known indices that could be related to dry matter content were also computed:

- Cellulose Absorption Index, CAI = 0.5 * (R2000 + R2200) - R2100
- Normalized Difference Lignin Index,

  NDLI = (log (1 / R1754) - log (1 / R1680)) / (log (1 / R1754) + log 1 / R1680))

where, the prefix R in front of the digits means that the index is computed with the value of reflectance at those specific wavelengths.

It is worth noticing that, different from all other considered indices, NDLI is based on pseudo-absorbance values (log 1/R) instead of reflectance ones. Also, NDVI and PRI are indices that were not developed specifically for assessing water content in vegetation, but are still often used as a proxy measure, and were included in this study for comparison. Finally, an effort to derive other spectral indices for retrieving dry matter content were also carried out and it will be fully explained in Chapter 4.

Chapter 4: Results and Discussion

4.1 - Sample Characterization

A comprehensive characterization of the samples used for the study is essential to understand the merits and limitations of the adopted methodology, as well as to provide some of the keys for the correct interpretation of the study results. In the following paragraphs some relevant descriptive statistics for the foliage samples investigated in this study are introduced along with statistical tests to better understand the inherent sample characteristics and the validity of the sampling strategy. The sample main spectral reflectance features and peculiarities are also discussed.

4.1.1 - Descriptive Statistics and Correlations

Summary statistics for the main needles' variables used in this study are presented in Table 4-1 for day 1 of the study (N = 40), and in Table 4-2 for the entire dataset (N = 400).

Table 4-1: Needle samples summary statistics for day 1 (N = 40)

	Fresh Weight (g)	Dry Weight (g)	Leaf Area (cm^2)	Water Content (%)	SLW (g/cm^2)	EWT (g/cm^2)	FMC (%)
Min	0.2059	0.0788	5.184	51.26	0.0131	0.0209	105.17
Max	0.4477	0.1816	9.173	64.75	0.0212	0.0311	183.66
Mean	0.2954	0.1155	7.115	60.79	0.0162	0.0252	156.33
St. Dev.	0.0582	0.0225	1.103	2.92	0.0019	0.0027	17.43
Coeff. Var.	0.1971	0.1949	0.1550	0.0481	0.1157	0.1068	0.1115

Table 4-2: Needle samples summary statistics for entire dataset (N = 400)

	Fresh Weight (g)	Dry Weight (g)	Leaf Area (cm^2)	Water Content (%)	SLW (g/cm^2)	EWT (g/cm^2)	FMC (%)
Min	0.1394	0.0667	4.917	16.8	0.0117	0.0038	20.20
Max	0.4479	0.1961	13.009	64.7	0.0219	0.0311	183.66
Mean	0.2656	0.1201	7.876	54.0	0.0152	0.0186	121.92
St. Dev.	0.0609	0.0243	1.312	7.2	0.0018	0.0052	30.43
Coeff. Var.	0.2294	0.2025	0.1666	0.1326	0.1175	0.2793	0.2496

While the values in Table 4-1 give an indication of how homogeneous the samples were at the beginning of the study period, those in Table 4-2 reflect the range of variation attained by several variables within the entire 10 days of the study. This is particularly apparent for the variables related to water content, namely Water Content (%), EWT, and FMC. The de-hydration procedure clearly created a range of values of FMC that run across most established thresholds of crown fire risk and down to very high fire risk. An increase in the range of values for Leaf Area was also observed, in particular with a trend toward needles with bigger area. It can also be noticed that the range of variation in dry matter content, represented by SLW, is rather limited despite the effort put forward during sample collection. This can be due to the specific physiology of this species, whereas the criteria of selecting a healthy looking tree could have, to some degree, offset the range of growing conditions in terms of exposure, soil, and light competition. Additional evidence will be presented that supports the selected sampling strategy.

The trends of variation of SLW, Leaf Area, EWT, and FMC with time are displayed in Figure 4-1 to 4-4, allowing for additional comments to be made.

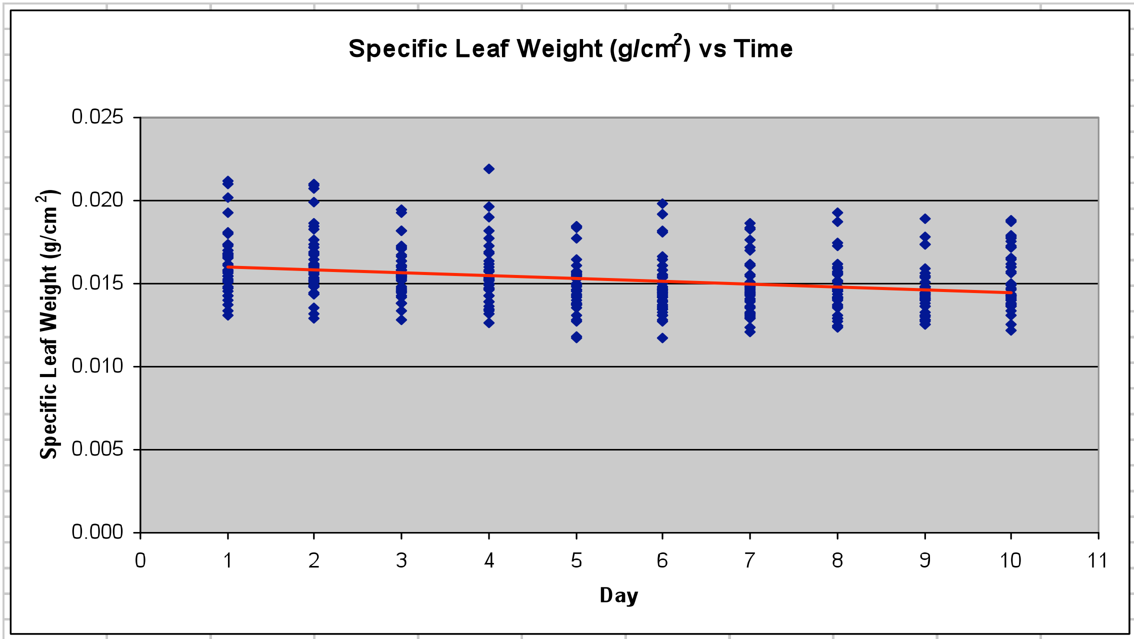

Figure 4-1: Sample Specific Leaf Weight (SLW) variation over the 10 day study period (N = 400).

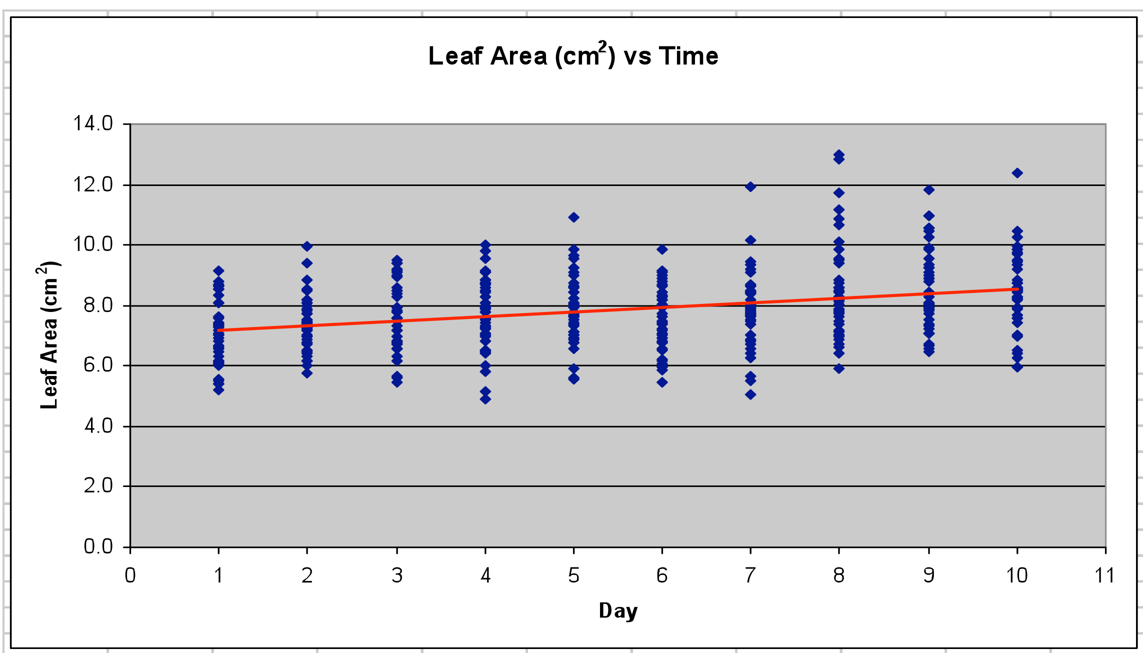

Figure 4-2: Sample Leaf Area (cm^2) variation over the 10 day study period (N = 400).

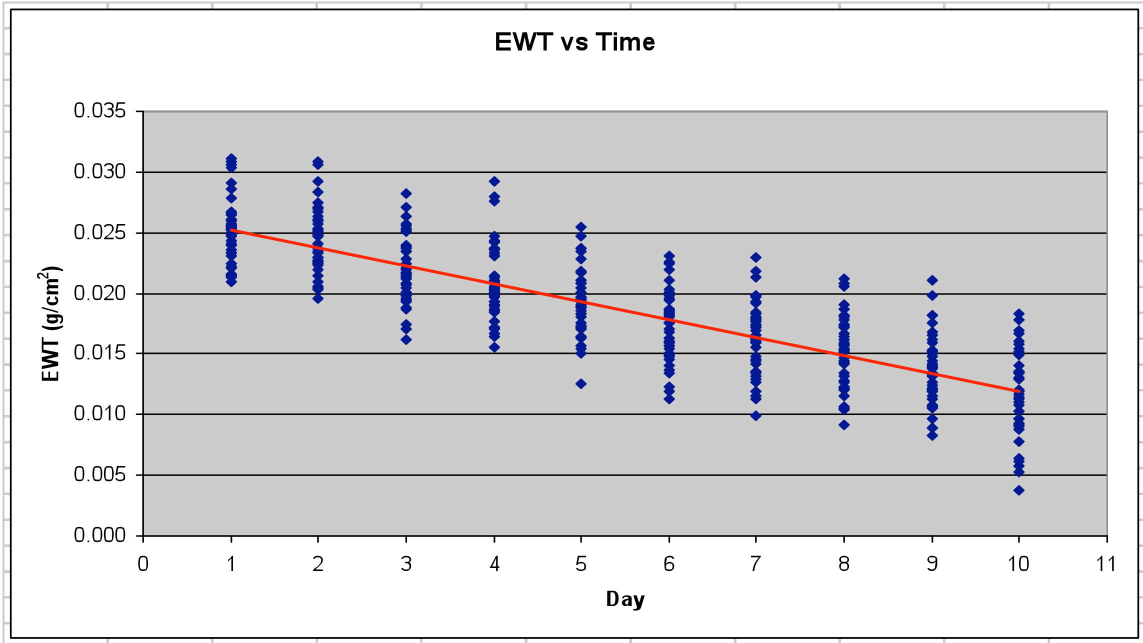

Figure 4-3: Sample Equivalent Water Thickness (EWT) variation over the 10 day study period (N = 400).

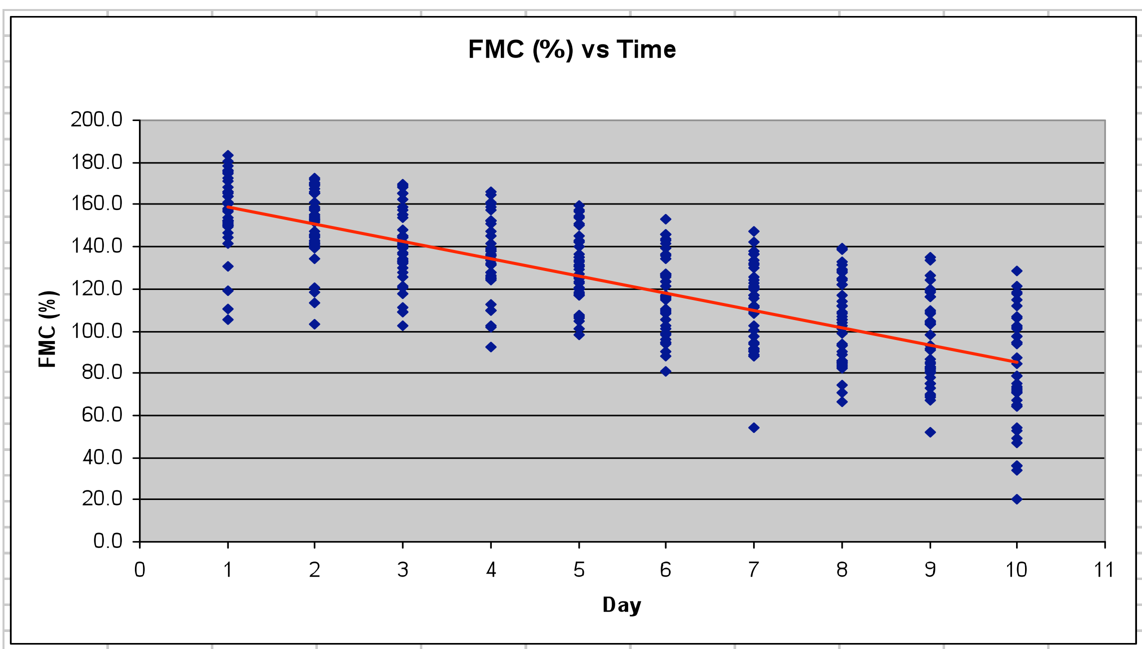

Figure 4-4 : Sample Fuel Moisture Content (FMC) variation over the 10 day study period (N = 400).

First of all, it can be observed that the trends of variation with time of the considered variables are well represented by linear relationships. This is particularly valid for EWT. However, a non-linear curve traced across the FMC data only slightly improved the fitting of the displayed linear relationship. SLW displayed a small negative trend with time, while Leaf Area increased with time. SLW is the leaf dry weight ratioed by the leaf area, thus the exhibited trend is consistent with the variation of Leaf Area. However, it is also appropriate considering what type of variation, if any, occurred in the sample dry weight. The trend of Leaf Dry Weight (g) with time is charted in Figure 4-5.

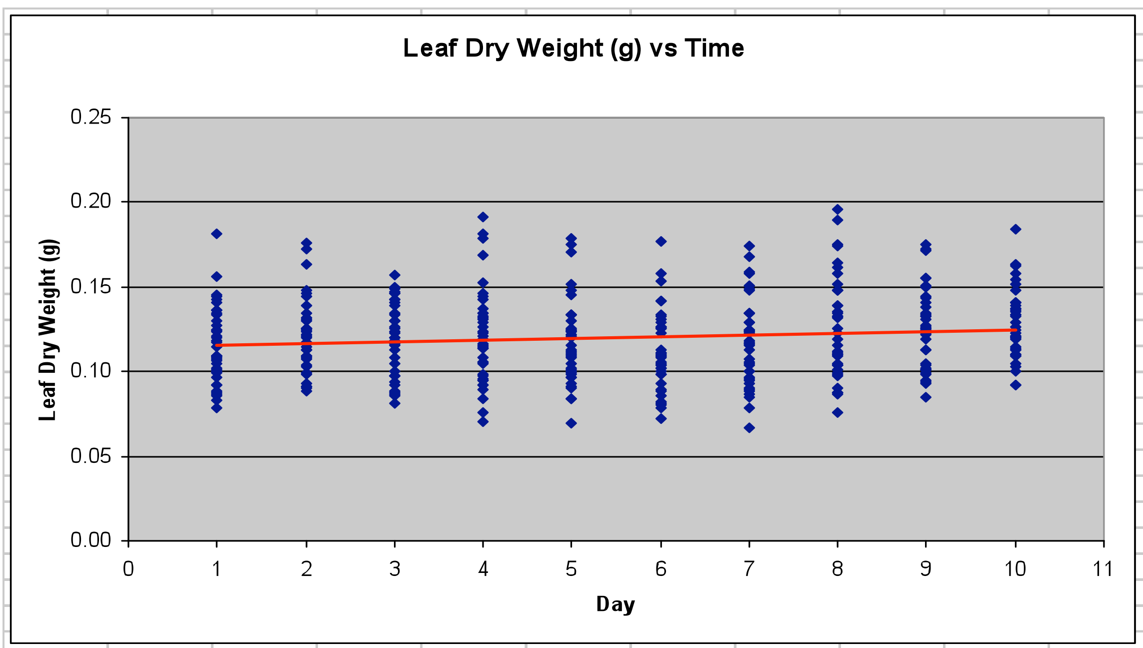

Figure 4-5: Sample Dry Weight (g) variation over the 10 day study period (N = 400).

It is apparent from Figure 4-5 that Leaf Dry Weight did not change significantly during the 10 days duration of the study. Therefore, it can be concluded that the trend in SLW values was indeed caused by Leaf Area variability. To explain it, it is suggested that, as the twig sampling progressed over time from the area around the tip of the branch toward its base, more and more needles were encountered that developed under some degree of shadowing by adjacent and over-standing branches and twigs on the tree. In other words, these needles grew larger to compensate for the loss of exposure to full sun light conditions.

Looking back at Figure 4-3 it is also apparent that while several samples displayed values of FMC below the threshold of 100 % after 6 - 7 days of complete de-hydration, it is only at day 8 that the average FMC of all the 40 samples/day reached the same threshold. Moreover, even after 10 days of de-hydration, several samples still had a FMC value above the threshold, although they were all in the ranges of high to moderate crown fire potential. Finally, very few outliers can be singled out in the FMC dataset.

Pearson's r among SLW, EWT, and FMC are reported in Table 4-3 for the first day of the study (N = 40) and for the entire dataset (N = 400).

Table 4-3: Intercorrelation among SLW, EWT, and FMC for N = 40 and N = 400

	N = 40 (day 1)				**N = 400 (day 1 to 10)**		
	SLW	**EWT**	**FMC**		**SLW**	**EWT**	**FMC**
SLW	**1.00**	0.40*	-0.60**		**1.00**	0.39**	-0.01
EWT		**1.00**	0.49**			**1.00**	0.91**
FMC			**1.00**				**1.00**

* * Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

The correlation values for day 1 of the study were strongly affected by tree n. 5, which did not fully re-hydrate. For instance, after removing the samples of this tree, the correlation between SLW and EWT increased to 0.77 (sig. at 0.01 level) while that with FMC decreased to -0.40 (sig. at 0.05 level). In addition, the correlation between EWT and FMC became not significant. According to Datt (1999), who found similar results with *Eucalyptus* leaves, the positive and negative correlations of SLW with EWT and FMC can be explained by the sclerophyllic nature of the leaves. This would imply that SLW increases more than water content expressed as the difference between the foliage fresh and dry weight. However, this relationship was not found in this study, and actually fresh weight and dry weight were very highly positively correlated (r = 0.94).

As for the correlation values for the whole duration of the study, the trends between SLW, EWT, and FMC became more complicated, but other interesting aspects emerged. With the samples from tree n. 5 included in the analysis, the correlation between SLW and EWT did not change much (0.39 versus 0.40), but declined sharply from the value of 0.77 for day 1 without tree n. 5. In addition, SLW lost any significant correlation with FMC, while EWT became very highly correlated with FMC. The charts in Figures 4.6 to 4.8 help understanding of some of these changes and highlight patterns that are hidden within the correlation values. It is, for instance, apparent that the day-to day- correlations between the variables were not consistent, but displayed specific trends . The correlation between EWT and SLW gradually decreased with increasing de-hydration and quite abruptly changed from positive to negative for samples collected the last day of the study (Figure 4-6). This is an indication that for the Douglas-fir needles studied other factors may have contributed to the observed relationships. Alternatively, the decreasing correlation between SLW and EWT as the samples dried out may be explained considering that the difference between fresh and dried weight (the numerator in equation 2-5 for EWT), became progressively smaller and. Once EWT reached an average value between 0.015 and 0.010 g/cm^2, there was no longer enough water to maintain a positive correlation between the variables.

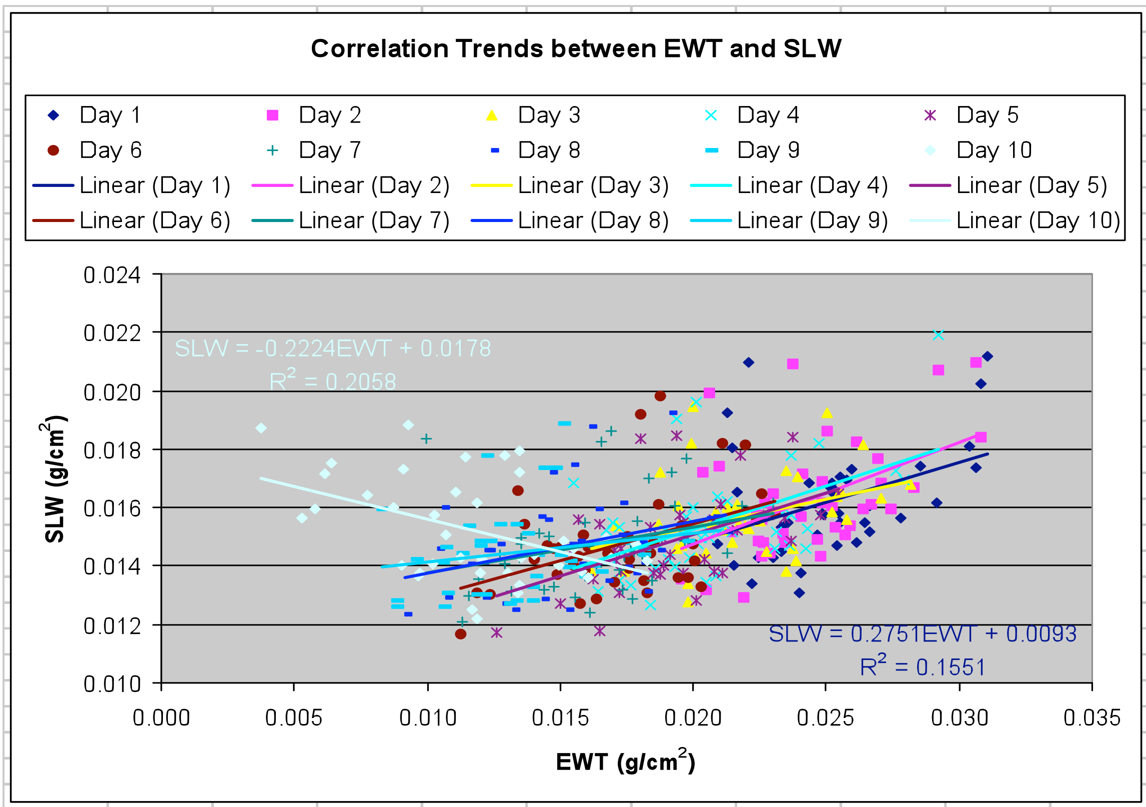

Figure 4-6: Variations in correlation trends between EWT and SLW during the 10-day de-hydration period. Equations and R^2 values for the first and last day are also reported.

The correlation between SLW and FMC (Figure 4-7) also changed on a day-by-day basis but did not reverse for the last day of the study. This appeared to be at odds with what has been said about the correlation of SLW with EWT because the difference between fresh and dry weight is also the numerator in equation 2-1 for FMC. Definitely, then, other factors intervened in the relationship between the water content and dry matter of the

Douglas-fir needles used in this study. It is clear, however, why the correlation between SLW and FMC was lost over the duration of the study. In fact, as FMC decreased because of the foliage de-hydration, SLW remained relatively unchanged resulting in a constant intercept for the relationship.

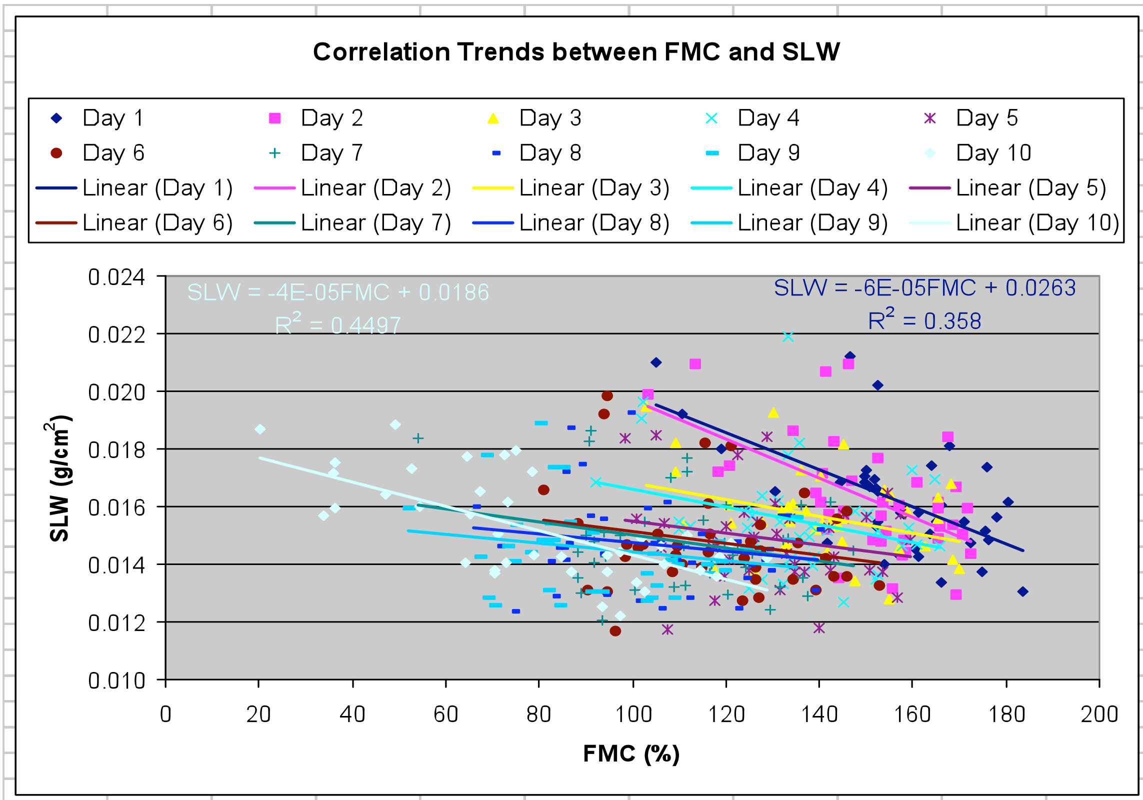

Figure 4-7: Variations in correlation trends between FMC and SLW during the 10-day de-hydration period. Equations and R^2 values for the first and last day are also reported.

The chart in Fig 4-8 illustrates another interesting behaviour in the correlation between FMC and EWT. While this correlation was moderately strong for the samples of the first day of the study (or even not significant if tree n. 5 was excluded), it became very high at the end. The variation of the Pearson's r value with increasing de-hydration is reported in Table 4.4.

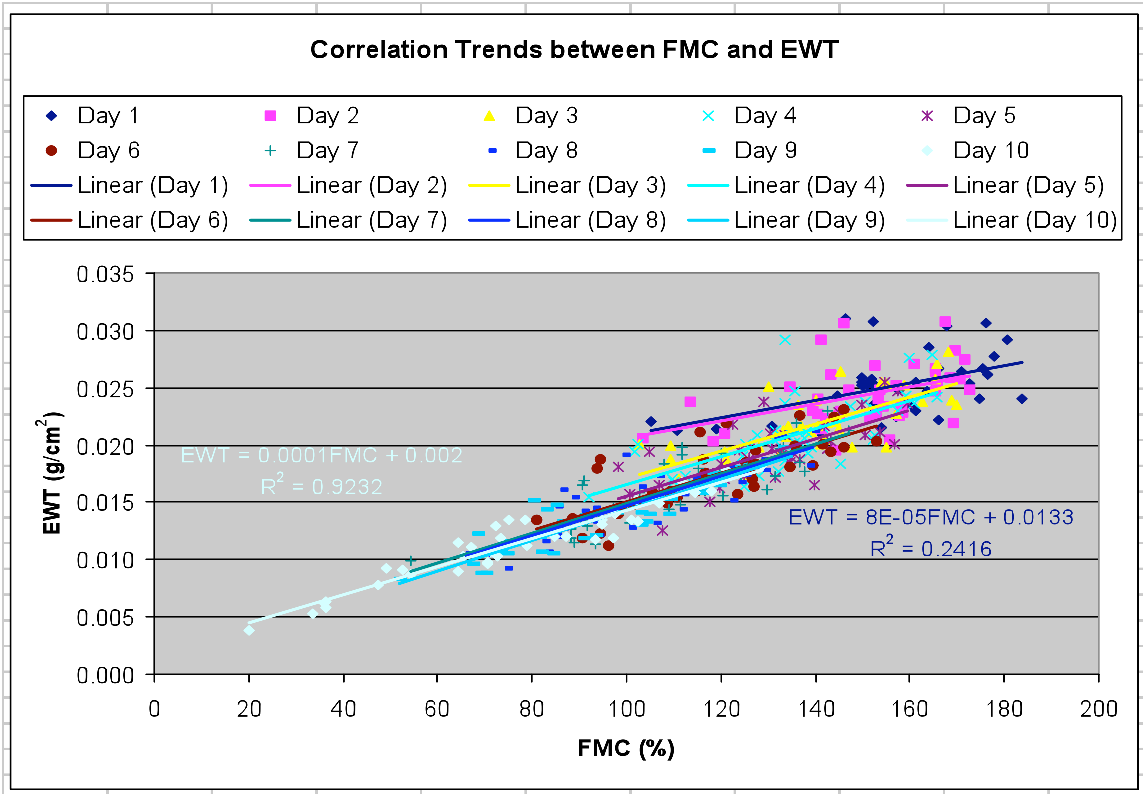

Figure 4-8: Variations in correlation trends between FMC and EWT during the 10-day de-hydration period. Equations and R^2 values for the first and last day are also reported.

Table 4-4: Pearson's r between FMC and EWT for the study duration

Day	Pearson's r
1	0.49
2	0.45
3	0.74
4	0.68
5	0.73
6	0.78
7	0.84
8	0.86
9	0.91
10	0.96

FMC and EWT are both measures of water content, thus they will both tend to zero as the leaf water dries out. In other words, these two quantities must co-vary with changing water content. It is not readily apparent, though, why the relationship was stronger for smaller amounts of water content in the examined needles. Leaf area is the only variable that differentiates FMC from EWT as a measure of water content in plants, thus it can be argued that while fresh weight and dry weight varied exactly in the same fashion in both quantities, variations in leaf area during de-hydration caused EWT to be progressively more positively correlated with FMC. If this is the case there may be significant implications for the retrieval of water content in Douglas-fir leaves as the amount of water changes with time.

Examination of the correlation values indicated that the relationships between SLW, EWT and FMC were rather complex for the studied Douglas-fir needles. Further research will be needed to explain the exact reasons for the observed behaviours.

To have a full characterization of the needle foliage sampled in the field, four statistical tests were carried out:

- One sample Kolmogorov-Smirnov test to verify normality of variables
- Paired T-test on trees' upper and lower canopy foliage
- One-way ANOVA among trees
- One-way ANOVA among the four canopy sampled locations

All tests were performed using SPSS Release 11.0.0 software.

4.1.2 - One sample Kolmogorov-Smirnov test on Leaf Area, SLW, and EWT

A Kolmogorov-Smirnov test was carried out on the samples of the first day of the study to verify that Leaf Area, SLW, and EWT are normally distributed. The results of the test, reported in Table 4.5, indicated that all three variables follow a normal distribution, thus not violating the main assumption for further carrying out a number of parametric tests.

Table 4-5: One-sample Kolmogorov-Smirnov test results.

		Leaf Area	SLW	EWT
N		40	40	40
Normal Parameters	**Mean**	7.11473	0.016237	0.025192
	Std. Deviation	1.102850	0.0018712	0.0026841
	Absolute	0.099	0.117	0.121
	Positive	0.080	0.117	0.121
	Negative	-0.099	-0.058	-0.074
K-S Z		0.623	0.741	0.766
Asymp. Sig.		0.829	0.642	0.601

4.1.3 - Paired T-Test on Trees' Upper and Lower Canopy Foliage

A paired T-test was conducted to infer if there are statistically significant differences between the upper and the lower part of the canopy in terms of Leaf Area, EWT, and SLW for the 40 needle samples of day 1 of the study. More formally, for either Leaf Area, SLW, and EWT, the null and alternate hypotheses were:

H_0: there is no significant difference in the mean values of Leaf Area, SLW, and EWT, between the lower and the upper crown of the sampled trees;

H_1: there is a significant difference in the mean values of Leaf Area, SLW, and EWT, between the lower and the upper crown of the sampled trees;

The results of the test indicated that while Leaf Area was not different between the upper and lower crown, both EWT and SLW were statistically significantly different at 0.01 significance level. Because Leaf Area did not vary, these results may be explained by needles with different thicknesses between the upper and lower crown. In particular, upper crown needles would be thicker than the lower crown ones, based on the average values of SLW. However, needle thickness was not measured, thus the aforementioned statement cannot be confirmed.

4.1.4 - One-Way ANOVA Among Trees

A one-way ANOVA test was also carried out to determine if the variances of Leaf Area, EWT, and SLW between trees are greater than those within trees. Formally, the null and alternate hypotheses were:

H_0: Leaf Area, SLW, and EWT, do not vary more between the sampled trees than within the trees;

H_1: Leaf Area, SLW, and EWT, are more variable between the sampled trees than within the trees;

The ANOVA test results (Appendix A) indicated that Leaf Area was statistically significantly different among trees. As for EWT and SLW, the Levene statistic suggested that the variances of these two variables were not equal. Consequently, a Kruskal-Wallis test (Appendix B) was run for the two variables. The test provided evidence supporting the conclusion that both EWT and SLW may have been more statistically different among the sampled trees than within the trees. The statistical evidence was particularly strong for EWT, and this is consistent with the fact that one tree did not completely re-hydrate during the first 24 hours after sample collection.

4.1.5 - One-Way ANOVA Among the Four Sampled Canopy Locations

A second one-way ANOVA test was performed to investigate if Leaf Area, EWT, and SLW varied among the four sampled crown locations. A two-way ANOVA was not performed because possible interaction effects were considered minimal. The null and alternate hypotheses were:

H_0: Leaf Area, SLW, and EWT, are not statistically different among the four sampled locations within the tree canopy;

H_1: Leaf Area, SLW, and EWT, are statistically different among the four sampled locations within the tree canopy;

SLW was found to be statistically different, while Leaf Area was not (Appendix C). The Tukey HSD post hoc tests indicated that SLW was statistically different either between the upper and lower crowns or between the lower crown with North exposure and the rest of the sampled canopy locations There was also some degree of evidence to support EWT being statistically different, although no more confirming data emerged from the post hoc Tukey tests. These results are consistent with the findings based on the paired t-test. All ANOVA tests were carried out at 0.05 significance level.

Overall, it can therefore be concluded that the results of the statistical tests conducted on the sampled foliage confirm the validity of the sampling strategy. Moreover, they indicated that Douglas-fir foliage from the upper crown may be different from that of the lower crown at least in terms of SLW and EWT. This could have implications when comparing tree canopy water content directly measured from field sampling (usually based on low crown foliage samples) with water content retrieved with remote sensing (biased toward top of the canopy foliage).

4.1.6 - Samples Spectral Reflectance Characteristics

The average reflectance spectra of all samples followed the expected trend, displaying increasing values of reflectance with decreasing water content across the 350 - 2500 nm range (Figure 4-9). The variations were more noticeable from day 5 of the study. Prominent changes in spectral shape occurred in the visible region between 450 and 650 nm, and in the SWIR between 2000 and 2500 nm. A shift of the red edge toward shorter wavelengths was also observed, but more subtle variations occurred in correspondence of the two water absorption features in the NIR and in the 1650 - 1850 nm spectral region as well.

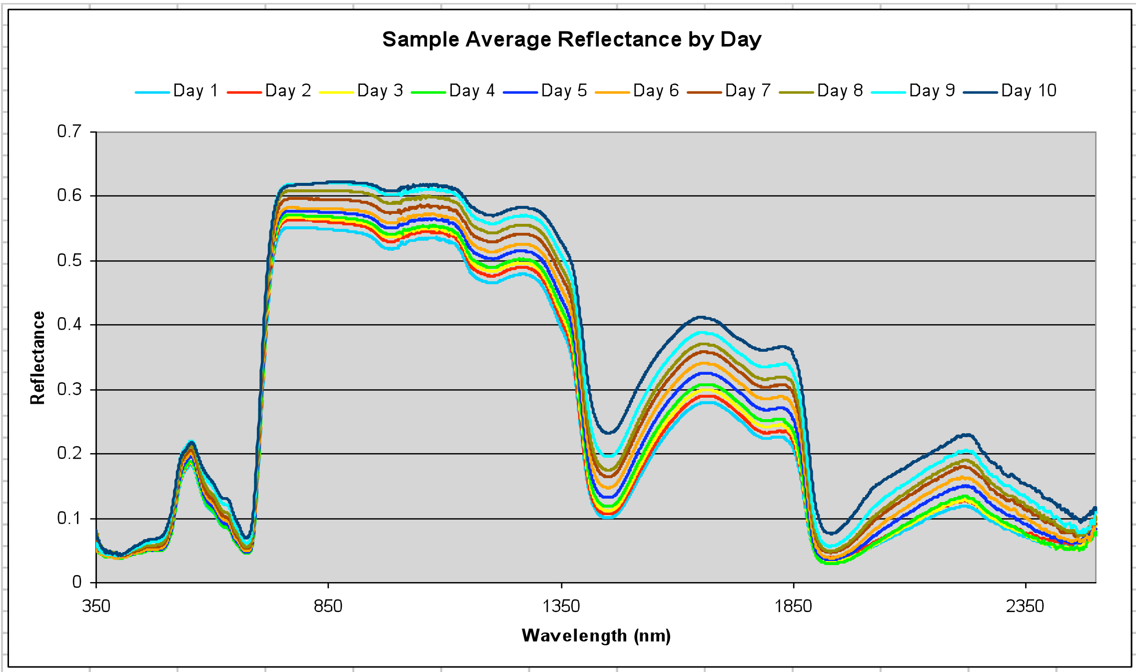

Figure 4-9: Sample average reflectance spectra variation during the 10-day dehydration period (N = 40/day).

More dramatic variations have been observed in the spectra of individual samples during day 9 and 10 of the study. An example is illustrated in Figure 4-10, which displays the spectra of lower crown needles with North exposure of the fifth sampled tree (sample "639"). A prominent and broad absorption feature associated with cellulose developed during day 9 and 10 at about 2100 nm. Noticeable changes in the spectra shapes also occurred at about 2300 nm and in the spectral range between 1650 nm and 1850 nm. In addition, the water absorption features at about 970 nm almost disappeared at day 10, and very relevant changes occurred in the visible portion of the spectrum as well.

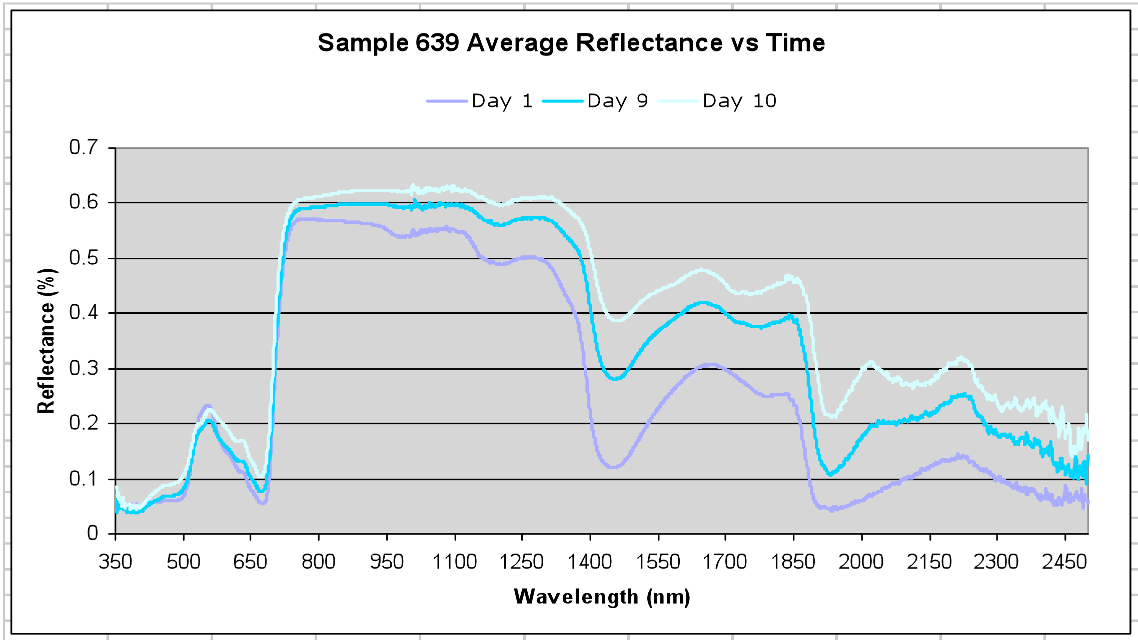

Figure 4-10: Spectral variations observed at three different times of the de-hydration period for sample "639", belonging to needles from low crown with North exposure from sampled tree n.5.

Similar variations were also observed at day 10 for samples belonging to three crown locations (out of four) of the fourth sampled tree, and for one crown location sample of the third tree.

4.2 - Water Content Retrieval

4.2.1 - Spectral Index Approach

The spectral indices listed at the end of Chapter 3 were correlated to foliar water content expressed both in terms of EWT and FMC. All indices were computed as narrow band indices even if some of them, like for instance the ratio TM5/TM7, were originally based on wide multispectral reflectance data. The correlation of the spectral indices with water content in grams, EWT and FMC, and SLW are listed in Table 4-6 for the first day of the study, and in Table 4-7 for the whole dataset.

Table 4-6: Correlations between water content (g), SLW, EWT, FMC, and selected spectral indices used in remote sensing of vegetation water status (N = 40).

	Water Cont. (g)	SLW	EWT	FMC
Water Cont. (g)	**1.00**	0.23	0.68**	0.37*
SLW	0.23	**1.00**	0.40*	-0.60**
EWT	0.68**	0.40*	**1.00**	0.49**
FMC	0.37*	-0.60**	0.49**	**1.00**
WI	0.63**	0.47**	0.84**	0.28
MSI	-0.54**	-0.67**	-0.76**	-0.03
SRWI	0.48**	0.57**	0.71**	0.08
NDWI	0.48**	0.57**	0.71**	0.08
NDII	0.56**	0.65**	0.76**	0.04
WNDII	0.55**	0.66**	0.77**	0.04
GVMI	0.42**	0.75**	0.64**	-0.15
TM5 / TM7	0.53**	0.40*	0.68**	0.19
DATT 1	0.63**	0.58**	0.82**	0.17
DATT 2	0.61**	0.45**	0.80**	0.28
MI 1	0.54**	0.13	0.47**	0.27
MI 2	0.21	0.07	0.25	0.12
PRI	0.40*	-0.47**	0.20	0.60**
NDVI	0.50**	0.07	0.38*	0.24

* * Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
All other correlations are not significant.

For the first day of the study, EWT had a stronger correlation with water content than FMC (0.68 vs. 0.37). More importantly, EWT had strong correlations with all spectral indices except MI 2, PRI and NDVI. The lack of correlation with PRI and NDVI, in particular, indicated that these indices were not suited to retrieve leaf water content, and therefore should not be used as a proxy measure except in well documented instances where vegetation water content has an established and consistent relationship with plant chlorophyll status, as reported by Ceccato (2001). The strongest correlation of EWT was with the Water Index, WI (0.84), which is based on the ratio of reflectance of 900 to 970 nm wavelengths in one of the two NIR water absorption features in the solar spectrum range. In contrast, FMC did not have any significant correlation with any of the spectral indices listed in Table 4-5 except PRI. Based on these results, it should be concluded that, for the Douglas-fir needles considered in this study, FMC was not retrievable with spectral indices, and with spectral reflectance measurements in general. It is also worth noting that this conclusion is consistent with the low correlation between FMC and EWT as has already been discussed, and with the findings of Datt (1999) and, in particular, with Ceccato (2001), who stated that FMC does not respond to changes in spectral reflectance of vegetation based on selected data from the Leaf Optical Properties EXperiment (LOPEX).

When the entire dataset was considered, two main changes were observed (Table 4-7). First, all correlations of EWT with water content and the spectral indices increased. The best correlation of EWT with a spectral index was again with WI (0.98). Second, FMC had significantly strong correlations with the spectral indices and, above all, with WI (0.891). This is in agreement with the results of Danson and Bowyer (2004), who also found a strong correlation between FMC and WI using a simulated database created with the PROSPECT leaf radiative transfer model and the LOPEX data as a reference.
On the other hand, it is also likely that the high correlations between FMC and the indices reported in Table 4-7 were simply the result of the strong co variation between FMC and EWT as the needle samples dried up. The evidence produced through this study, although

partial, suggests that Douglas-fir needle FMC cannot be directly measured with spectral reflectance.

Table 4-7: Correlations between water content (g), SLW, EWT, FMC, and selected spectral indices used in remote sensing of vegetation water status (N = 400).

	Water Cont. (g)	SLW	EWT	FMC
Water Cont. (g)	**1.00**	0.36**	0.84**	0.75**
SLW	0.36**	**1.00**	0.39**	-0.01
EWT	0.84**	0.39**	**1.00**	0.91**
FMC	0.75**	-0.01	0.91**	**1.00**
WI	0.80**	0.35**	0.97**	0.89**
MSI	-0.81**	-0.42**	-0.94**	-0.84**
SRWI	0.78**	0.39**	0.92**	0.82**
NDWI	0.78**	0.38**	0.92**	0.82**
NDII	0.81**	0.45**	0.95**	0.83**
WNDII	0.81**	0.45**	0.95**	0.83**
GVMI	0.82**	0.48**	0.92**	0.79**
TM5 / TM7	0.73**	0.38**	0.86**	0.77**
DATT 1	0.82**	0.45**	0.96**	0.85**
DATT 2	0.79**	0.46**	0.94**	0.83**
MI 1	0.77**	0.21**	0.84**	0.82**
MI 2	0.64**	0.20**	0.83**	0.81**
PRI	0.32**	-0.45**	0.24**	0.45**
NDVI	0.64**	-0.04	0.60**	0.66**

* * Correlation is significant at the 0.01 level (2-tailed).

Consequently, an effort was made to unravel how well water content, in terms of EWT, could be retrieved with WI, which was the index with the highest correlation value. A cross validation methodology was adopted; namely, the whole dataset was randomly split in two parts using half of the data as a calibration set to derive a regression equation to be tested on the remaining half of the data, which represented the validation set.

The results of the linear regression between EWT and WI for the calibration set are presented in Figure 4-11.

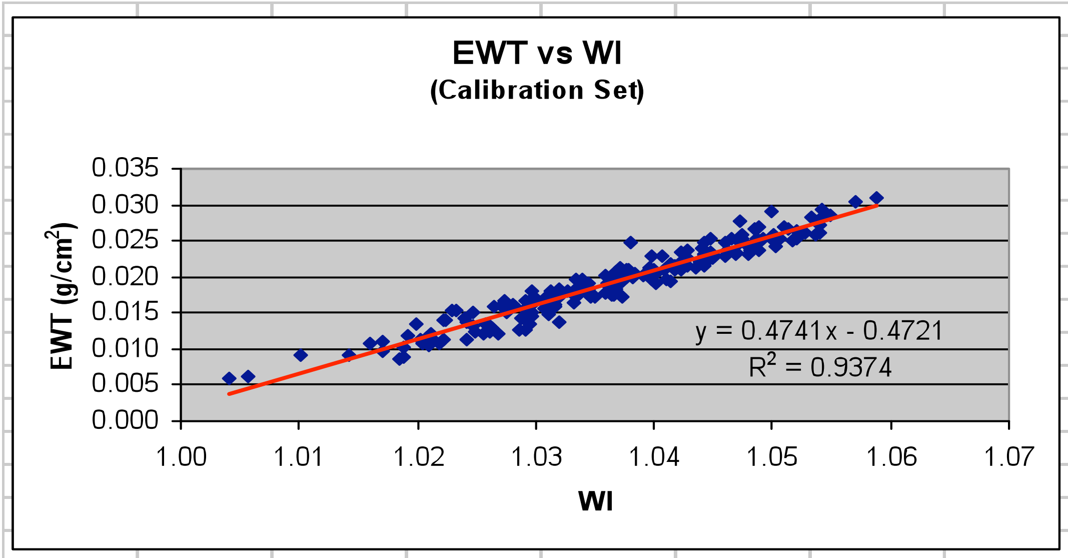

Figure 4-11: Regression of EWT with WI for the calibration set.

The regression equation for the calibration set was:

$$EWT = 0.474 * WI - 0.472 \tag{4-1}$$

With an adjusted R^2 = 0.937 and a standard error of the estimates = 0.001289. The results were significant at the 0.05 significance level.

Both the histogram and the probability plot of the residuals indicated that normality was not violated, but the plot of the residuals versus the predicted value suggested the presence of at least one or two outliers, but no heteroscedasticity.

The regression equation was tested on the validation set. The results are displayed in Figure 4-12. The regression equation for the validation set was:

$$EWT_{(predicted)} = 0.943 * EWT_{(measured)} + 1.4 * 10^{-3} \tag{4-2}$$

with an adjusted R^2 = 0.930 and a standard error of the estimates = 0.001338. The results were significant at the 0.05 significance level.

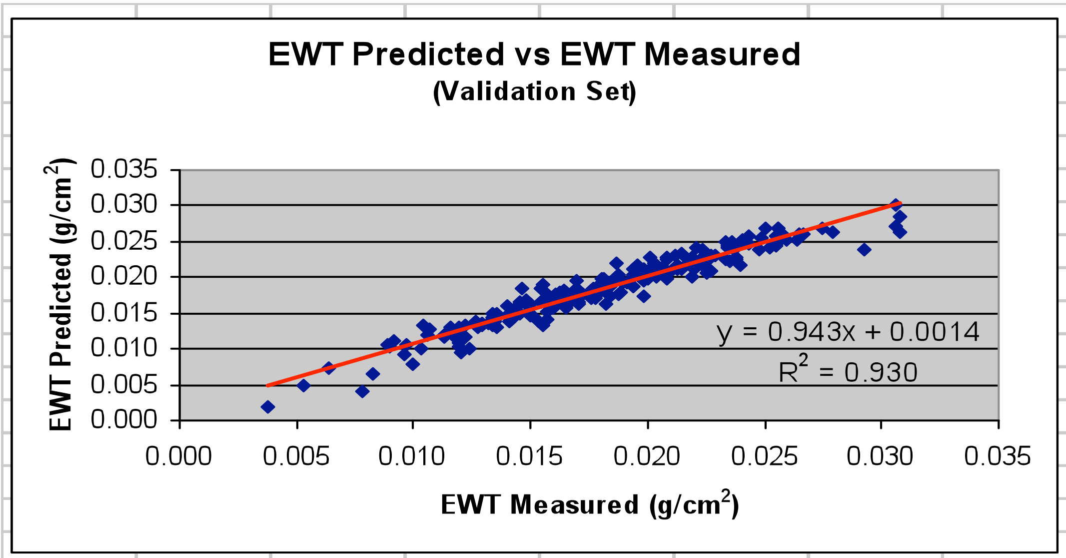

Figure 4-12: Regression of EWTpredicted with EWTmeasured for the validation set.

Also in this case, both the histogram and the probability plot of the residuals indicated that normality was not violated, but the plot of the residuals versus the predicted value suggested the presence of at least three outliers, but no heteroscedasticity.

4.2.2 - Continuum Removal Approach

In both Figures 4.9 and 4.10 is possible to notice a series of changes in the shapes of the spectra of the de-hydrating Douglas-fir foliage. Continuum removal is a mathematical procedure that may help in the analysis and interpretation of some of those changes through the emphasis it places on the location and depth of absorbing features (Schmidt and Skidmore, 2003). Extensively used in terrestrial and planetary geology remote sensing for the quantitative analysis of reflectance spectral of particulate surfaces of mineralogical nature, continuum removal is useful for (Clark and Roush, 1984):

- isolating a given absorption feature for detailed spectral analysis,
- correcting a band minimum to its true centre for shifts caused by a sloping continuum,
- providing a consistent definition of band depth, which is directly related to the amount of absorbed radiation.

Just in connection with this last statement, continuum removal is often referred to as a normalization technique. The main assumption of continuum removal is that a spectrum has two components: a) an apparent continuum, and b) one or more individual absorption features (van der Meer, 2004). The continuum is the general albedo of the reflectance spectrum, often called the convex hull. It may be caused by non-isotropic scattering and/or absorptions from processes different from the one under investigation. The hull can also be thought as the overall absorption from compounds other than those under investigation. Thus, the apparent continuum contribution to the spectrum can be mathematically derived and "removed" based on a reflectance equation that mirrors the Beer's Law equation for absorbance, leaving the selected absorption feature as a normalized curve.

In this study, continuum removal was performed on specific spectral features of the needles' reflectance spectra according to the following procedure:

1. For each absorption feature to be investigated, starting and an ending points are selected at convenient points at or close to the feature's shoulders;
2. A line is traced connecting these two points;
3. The apparent continuum is derived for each wavelength within the spectral range identified by the starting and ending points, by means of the following equation:

   $$R' = R / R_l \quad (4\text{-}3)$$

   where R' is the continuum-removed spectrum, R is the value of reflectance on the original spectrum, and R_l is the corresponding value of reflectance on the line representing the continuum.
4. For each wavelength within the selected spectral range, the band depth is obtained from the continuum-removed curve as:

   $$\text{Band Depth} = 1 - R' \quad (4\text{-}4)$$

5. A normalized band depth ratio is also computed as follows:

   $$\text{Normalized Band Depth} = \text{Band Depth} / \text{Maximum Band Depth} \quad (4\text{-}5)$$

   The resulting curve is normalized, having all values in the range between 0 and 1. The wavelength of Maximum Band Depth is a reference point separating the absorption feature in two sections: a left section for the part of the feature located at the left of the wavelength of Maximum Band Depth, and a corresponding right section. Often, the wavelength of Maximum Band Depth occurs around the midpoint of the range of an absorption feature, and it is thus called the feature Band Centre.
6. The total area under the continuum-removed curve was also computed, as well as the portion of the area on the left of the Band Centre and that one the right of it.
7. A second form of band depth normalization by area was computed as:

Normalized Band Depth_by_Area = Band Depth / Area (4-6)

8. Finally, the ratio between the left and the right area represents the symmetry of the continuum-removed absorption feature:

   Symmetry = Area Left / Area Right (4-7)

Continuum Removal was applied to three spectral regions: 925 - 1025 nm, 1120 - 1250 nm, and 1690 - 1830 nm. The first two ranges pertained to the two NIR water absorption features, while the third one is located in the SWIR and was not a water feature. However, because of it location in the SWIR, water absorption was expected to affect the spectrum in the selected range.

The results in the 925 - 1025 nm range were negatively affected by a spectrometer manufacturing issue. The overlapping between the VNIR and first SWIR units occurs exactly over this range, and the difference in the units' response is clearly affecting the acquired spectrum, in spite of the instrument control software that is supposed to create a seamless switch between the units. An example is presented in Figure 4-13, where the noise caused by the overlapping units is well apparent over 1000 nm. As a consequence, the normalization of the band depth of two spectra is based on maxima displaced from their respective correct locations.

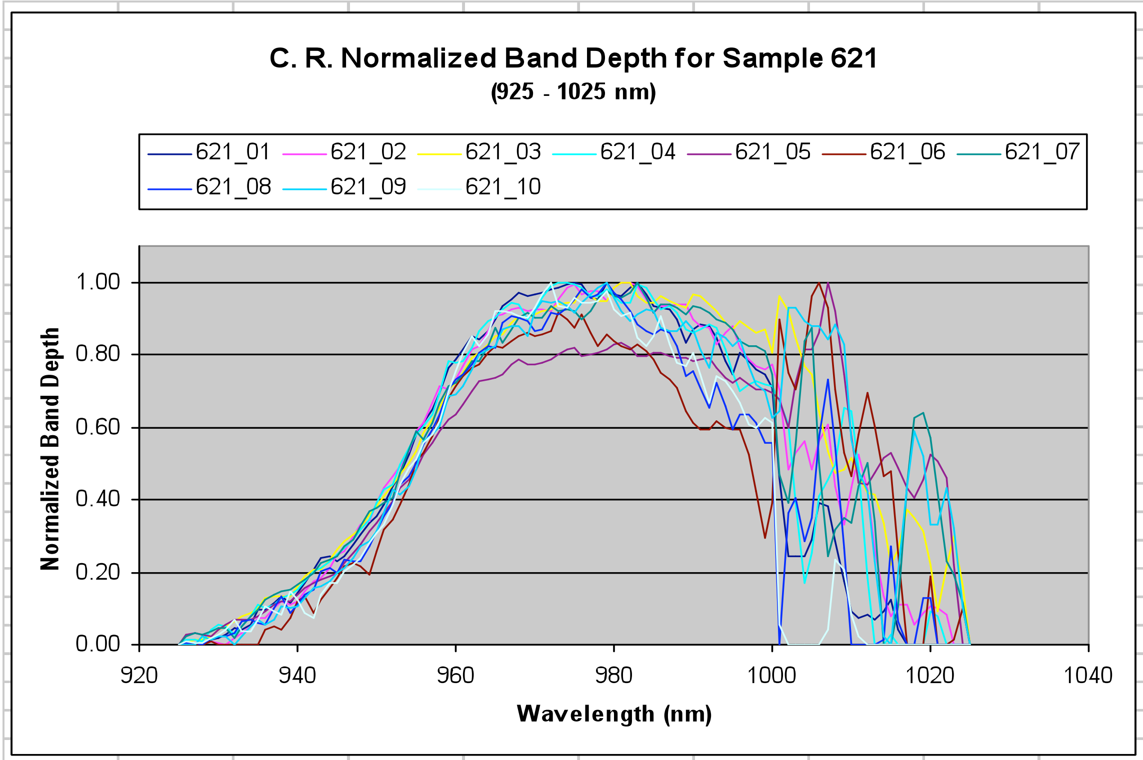

Figure 4-13: Continuum removed Normalized Band Depth over the 925 - 1025 nm spectral range for sample "621". The noise in the spectrum over 1000 nm is due to the overlapping of the VNIR and SWIR spectrometers.

In the 1120 - 1205 nm range, EWT was highly correlated with Maximum Band Depth, with a Pearson's r = 0.95 at the 0.01 significant level (N = 400). The second strongest correlation was with Total Area (r = 0.54).

As for the spectral indices, a calibration regression was carried out between EWT and Maximum Band Depth. The results are displayed in Figure 4-14. The regression equation for the calibration set was:

$$EWT = 0.416 * \text{Maximum Band Depth} - 5.28*10^{-3} \qquad (4\text{-}8)$$

with an adjusted $R^2 = 0.919$ and a standard error of the estimates = 0.00146. The results were significant at the 0.05 significance level.

No violation of normality was found, as well as no heteroscedasticity of the residuals. However, the plot of the residuals versus the predicted value suggested the presence of at least two outliers.

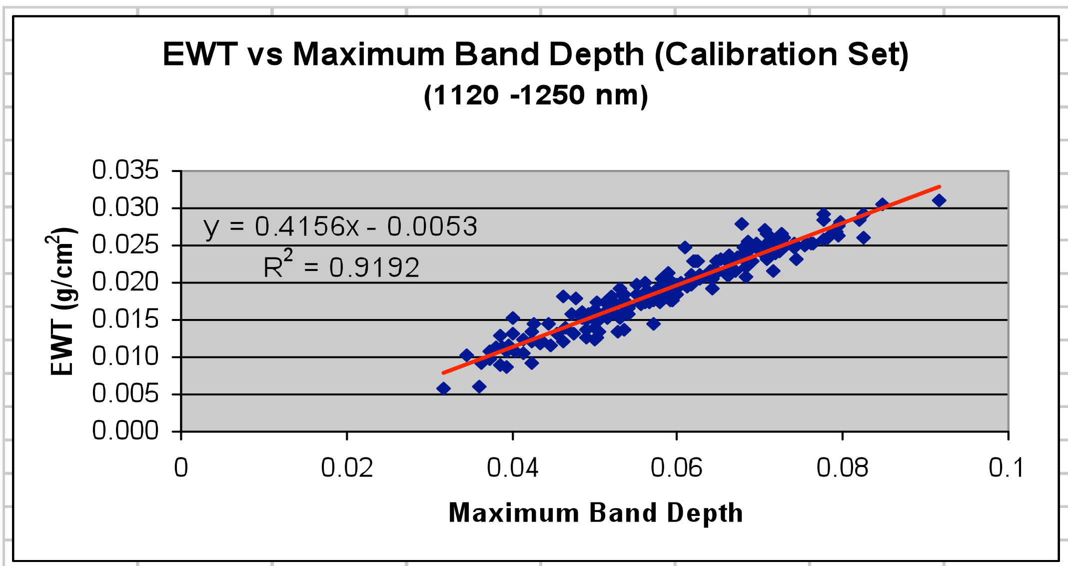

Figure 4-14: Regression of EWT with Maximum Band Depth for the calibration set.

The regression equation was tested with the validation set and the results are illustrated in Figure 4-15. The regression equation for the validation set was:

$$EWT_{(predicted)} = 0.911 * EWT_{(measured)} - 4.412 * 10^{-4} \qquad (4\text{-}9)$$

with an adjusted $R^2 = 0.900$ and a standard error of the estimates = 0.001579. The results were significant at the 0.05 significance level. No violation of normality and heteroscedasticity were found. As in the previous regression, one or two outliers were identified.

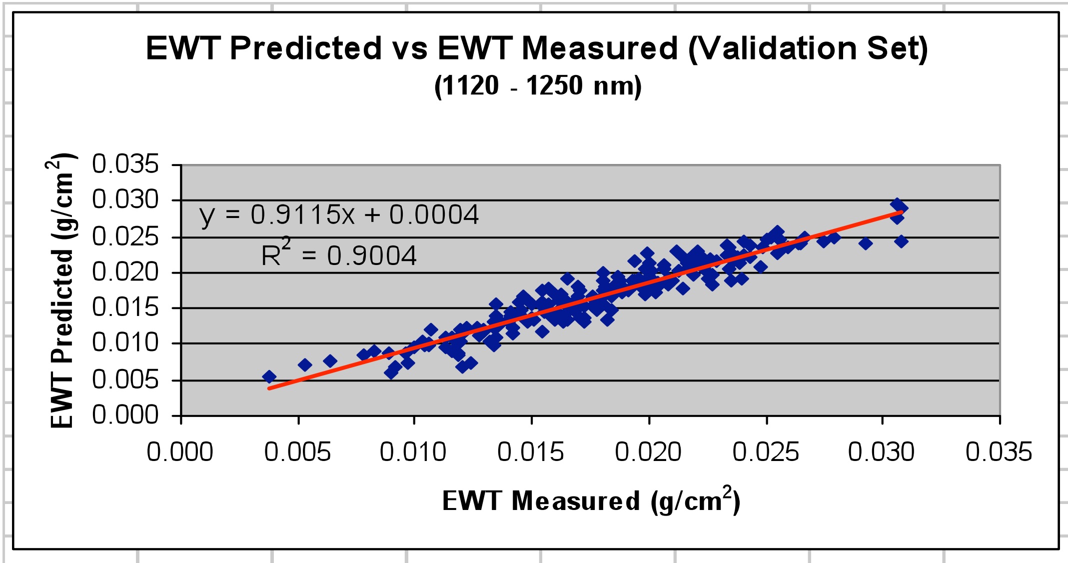

Figure 4-15: Regression of EWTpredicted with EWTmeasured for the validation set.

The continuum removal analysis over the range 1690 - 1830 nm produced very similar results. EWT was highly correlated with Maximum Band Depth, with a Pearson's r = 0.90 at the 0.01 significant level (N = 400). The second strongest correlation was with Total Area (r = -0.82).

The Calibration equation was:

$$EWT = 0.466 * \text{Maximum Band Depth} - 1.21*10^{-2} \quad (4\text{-}10)$$

The associated R^2 was 0.849 with a standard error for the estimates = 0.0019966.

The equation obtained for the validation set was:

$$EWT_{(predicted)} = 0.797 * EWT_{(measured)} + 4.409*10^{-3} \quad (4\text{-}11)$$

The relationship had an R^2 = 0.849 and a standard error of the estimates = 0.0022694.

The results of this analysis indicated that the Douglas-fir needle water content could be retrieved in terms of EWT either with a spectral index or with continuum removal. The most effective index resulted to be WI, while the best spectral region for continuum removal was 1120 - 1250 nm. The range 1690 - 1830 nm was also effective for EWT measurement, but was less accurate than the previous one. This is not surprising considering that there is no water absorption feature in this SWIR range. Several relevant evidence were found to conclude that FMC could not be directly retrieved with spectral reflectance. However, more research should be carried out to arrive at a more definitive conclusion on this issue.

4.3 - Dry Matter Content Retrieval

The detection of the biochemical composition of vegetation is among the most important goals in remote sensing. Although there is a large body of literature on the remote estimation of several plant biochemicals, much less is devoted to the retrieval of dry matter content as a whole. There are two main reasons for this. First of all, there is the inherent challenge of defining dry matter as a specific substance with a well defined chemical fingerprint associated with spectral reflectance. Secondly, the fingerprint signal must be strong enough to be unambiguously detectable, particularly when there may be other concomitant substances, such as water, that have a rather strong absorption across the solar spectral range. Perhaps because of this, there is no spectral index specifically developed to retrieve vegetation dry matter content yet. However, there are two known indices that may be associated, to a certain degree, with it. The Cellulose Absorption

Index, CAI, was introduced by Daughtry et al., (1996) to separate the signal of crop residue and plant litter from the soil signal, and the Normalized Difference Lignin index, NDLI, was proposed by Serrano et al., (2002) to detect canopy lignin. A subtle difference that may be pointed out is that CAI is supposed to work with dry vegetation residue, while NDLI was designed for fresh vegetation. Furthermore, in the spectra of dry vegetation, a number of wavelengths and bands corresponding to absorption by a variety of biochemicals have been identified during the past forty years (Curran, 1989).

Because FMC can be derived indirectly from separate estimates, or measurements, of EWT and SLW, this study explored the opportunity to determine the needle dry matter content in terms of SLW. Both CAI and NDLI were tested to verify the strength of their association to SLW, along with a series of wavelengths derived from the literature, and mainly related to vegetation Nitrogen, lignin, and cellulose content. Water content, expressed as EWT, was also included in the analysis in order to gain an appreciation of the possible interfering effects that plant moisture could have on the estimation of dry matter with spectral reflectance. Correlations of EWT and SLW with CAI, NDLI, and various SWIR wavelengths are reported in Table 4-8 for the first day of the study (N = 40) and for the entire dataset (N = 400). Few patterns emerged. First of all, SLW was better correlated with both CAI and NDLI than EWT for the first day of the study. When the whole dataset was considered, the strength of the correlation of SLW with CAI and NDLI decreased, while a strong positive correlation developed between EWT and NDLI. The correlation of EWT with CAI also slightly increased. All single wavelengths were found consistently negatively correlated with both EWT and SLW. This was expected for

EWT, because as water content decreases in plants, reflectance tends to increase. Less obvious were the connections with SLW. For the first day of the study, in particular, almost all the selected wavelengths did not have any significant correlation with SLW. It is possible that the observed behaviour depended on the strength of the absorption by needle water content that masked the much weaker absorption associated with dry matter compounds.

Table 4-8: Correlation of EWT, SLW with CAI, NDLI, and wavelengths associated to absorptions by biochemical compounds in vegetation.

	N = 40			N = 400	
	EWT	SLW		EWT	SLW
CAI	0.34**	0.56**		0.36**	0.49**
NDLI	0.35**	0.56**		0.66**	0.47**
R1500	-0.66**	-0.13		-0.93**	-0.26**
R1690	-0.51**	-0.08		-0.93**	-0.33**
R1730	-0.54**	-0.13		-0.93**	-0.34**
R1754	-0.57**	-0.14		-0.94**	-0.34**
R2060	-0.52**	-0.17		-0.89**	-0.24**
R2130	-0.62**	-0.32*		-0.91**	-0.33**
R2180	-0.63**	-0.28		-0.91**	-0.32**
R2240	-0.64**	-0.22		-0.92**	-0.32**
R2262	-0.59**	-0.29		-0.91**	-0.34**
R2300	-0.56**	-0.28		-0.89**	-0.34**
R2380	-0.48**	-0.28		-0.84**	-0.26**

* * Correlation is significant at the 0.01 level (2-tailed)
*   Correlation is significant at the 0.05 level (2-tailed)
The prefix R in front of the number indicate reflectance at that wavelength

Two aspects may have contributed to the observed Pearson's r values. First, it was noticed that the acquired reflectance spectra were characterized by a rather poor Signal-to Noise ratio, SNR, in the range between 2000 and 2500 nm. Besides the lower sensitivity of the spectroradiometer sensors in the extreme SWIR, it is believed that the major cause of this problem was the lack of a suitable level of artificial illumination during spectral data acquisition. Because the Cellulose Absorption Index is computed from three narrow bands at 2000, 2100, and 2200 nm, a smoothing was performed between 1900 and 2500 nm of all spectra using a moving average with a kernel of 15. An example of an original and a smoothed spectrum from a needle sample investigated in this study is displayed in Figure 4-16.

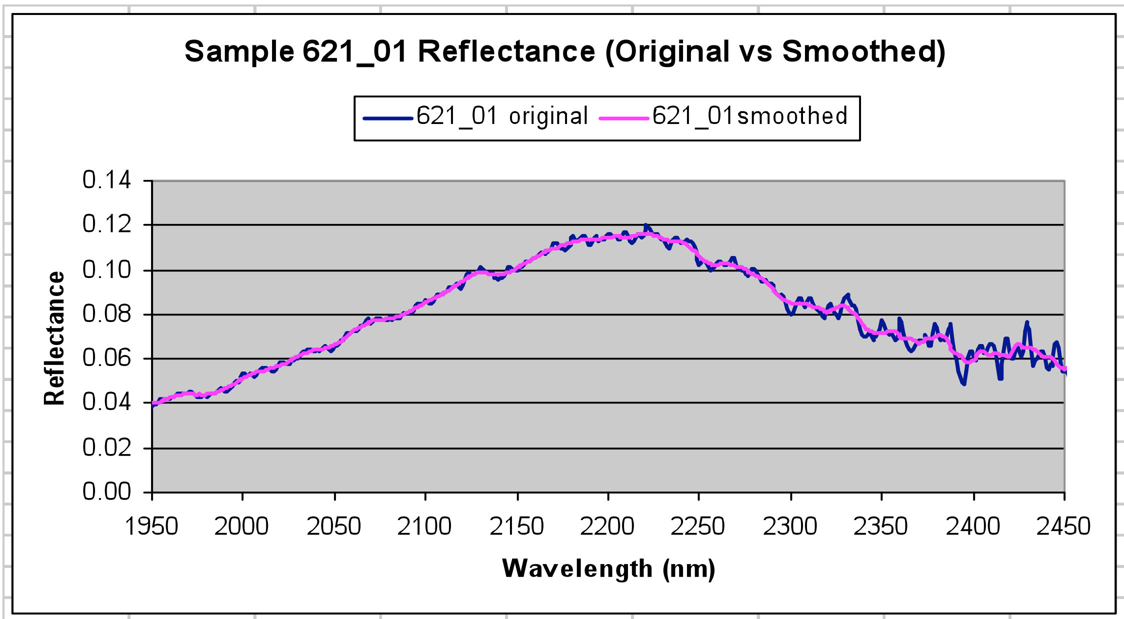

Figure 4-16: Example of an original versus a smoothed reflectance spectrum of a needle sample in the range 1950 - 2450 nm from day 1 of the study.

Although a kernel of 15 may appear as excessive, it must be remembered that the cellulose absorption features in this particular spectral range are quite broad. CAI values were re-calculated from the smoothed spectra, and new correlations were derived for EWT and SLW. For the 40 samples of the first day of the study the correlation of CAI from smoothed spectra with EWT and SLW became 0.40 and 0.48 respectively, while for the entire dataset the new values of the Pearson's r became 0.94 (EWT) and 0.34 (SLW). Therefore, the smoothing of the spectra, did not improve the strength of the relationship between CAI and SLW, and actually degraded the effectiveness of the spectral index. The second aspect that may have had a negative effect on the relationship between SLW and reflectance is directly related to the physiology of the Douglas-fir needless and the conifers in general. In Chapter 2 it was pointed out that in the search for robust functional leaf traits Garnier et al., (2001b) had developed a relationship between DMC and SLA, which is the reciprocal of SLW. The pattern of SLA against DMC for the Douglas-fir needles of this study is displayed in Figure 4-17, along with the relationship established by the cited authors.

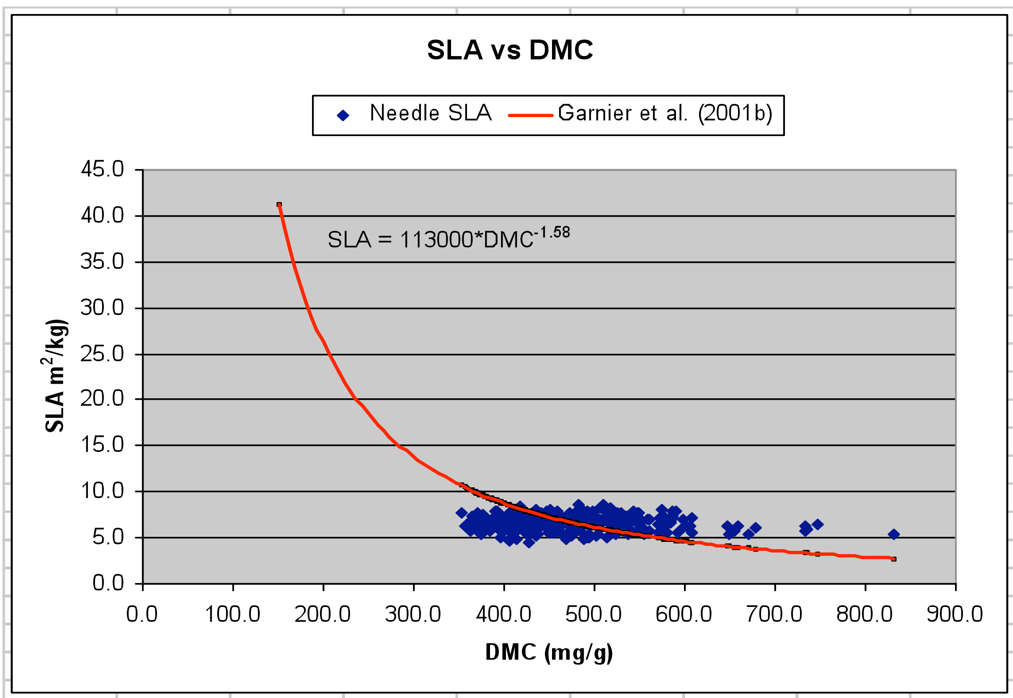

Figure 4-17: The Douglas-fir needles SLA vs. DMC charted along with the relationship developed by Garnier et al. (2001b).

It is apparent from the chart that the Douglas-fir needles had physiological characteristics such as SLA, and thus SLW, that did not perform well as a surrogate of dry matter content, because they all had a SLA value below the threshold of 10 to 15 m^2 / kg.

An extra effort was made, however, to test if other band combinations could have been found that were more effective to detect the Douglas-fir needle SLW. In Figure 4-18, the typical spectrum of a needle sample after 10 days of de-hydration is compared with three spectra of dry needles. Dry_N 1 spectrum was measured on a needle sample from the same Douglas-fir foliage used in this study, while Dry_N 2 and Dry_N 3 were measured on two other unrelated Douglas-fir samples.

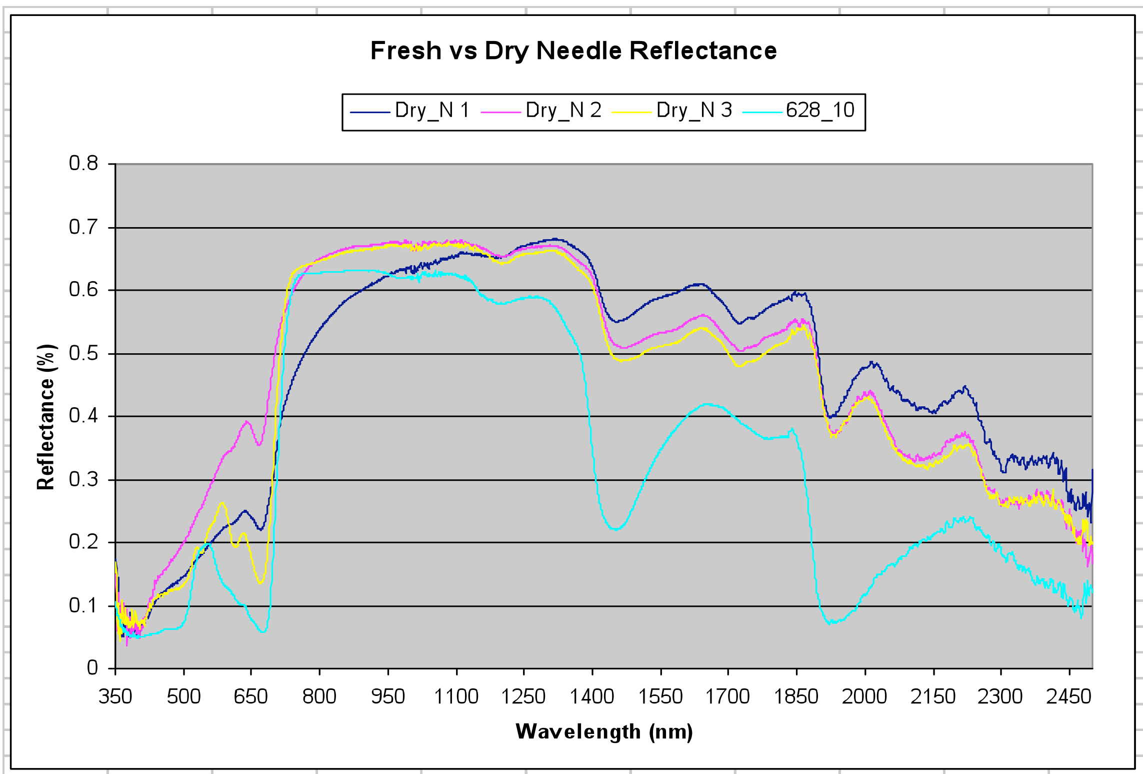

Figure 4-18: Comparison of fresh vs. dry Douglas-fir needle reflectance.

All dry needle samples dried up in natural conditions and were then carefully placed between two glass plates and warmed up in an oven at low temperature for 24 hours to eliminate any excess surface water. Two prominent absorption feature associated with dry matter compounds, namely lignin and cellulose, are visible in all three dry needle spectra between 1650 and 1830 nm and between 2000 and 2220 nm. A third less defined feature is present around 2300 nm and is also related to cellulose and other dry matter compounds.

A dry matter index was developed following the semi-empirical procedure reported in Datt (1999). The physical aspect of the index development was based on the assumption that a leaf reflectance spectrum may be approximated with the following equation:

$$R = Rs + S * \exp(-\Sigma\ ki * Ci) \qquad (4\text{-}12)$$

where R is the leaf reflectance, Rs is the value of reflectance from the leaf surface, S is the leaf reflectance from the leaf interior in case of no absorption, and ki and Ci are the specific absorption coefficient and content of compound I, respectively. The total absorption within the leaf is modelled by the exponential of the sum within curved brackets in equation (4-12).

Carefully selecting three proper wavelengths to compute three equations based on (4-12) allows the mathematical elimination of both the additive term, Rs, and the multiplicative term, S, and to obtain an index that is related to the absorption caused by a given biochemical content. The proper wavelengths must be:

- a reference to compute the term (Rs + S), and
- two other wavelengths corresponding to strong absorption by the selected compound, for which the term S is negligible.

Based on the dry needle data charted in Figure 4-18, the selected reference wavelength was 850 nm because there is no absorption by dry matter content, while the two remaining wavelength were 1730 nm and 2130 nm, at which there was strong absorption by dry matter. An alternative chosen absorbing wavelength was 2310 nm.

The equations constructed with these wavelengths were:

$$R850 = Rs + S \quad (4\text{-}13)$$

$$R1730 = Rs + S * \exp(-\Sigma\, ki_{(1730)} * SLW) \quad (4\text{-}14)$$

$$R2130 = Rs + S * \exp(-\Sigma\, ki_{(2130)} * SLW) \quad (4\text{-}15)$$

$$R2310 = Rs + S * \exp(-\Sigma\, ki_{(2310)} * SLW) \quad (4\text{-}16)$$

Computing the differences between Equation (4-13) and (4-14), and between (4-13) and (4-15), and dividing the results gave:

$$DM\_1 = (R850 - R1730) / (R850 - R2130) \quad (4\text{-}17)$$

and

$$DM\_2 = (R850 - R2130) / (R850 - R2310) \quad (4\text{-}18)$$

The indices were linearly correlated to both EWT and SLW and the results are reported in Table 4-9.

Table 4-9: Correlations of indices DM_1 and DM_2 with EWT and SLW.

	DM_1	**DM_2**
EWT (g/cm^2)	0.52	0.93
SLW (g/cm^2)	0.30	0.46

DM_2 was better correlated to SLW than DM_1. Both indices, however, were even more correlated to EWT. These results are an indication that in the de-hydrating, but still fresh, Douglas-fir needles, water content was the main control over the sample reflectance spectra even at wavelengths of maximum absorption by important dry matter compounds. It is also argued that because DM_2 was based on two wavelengths in the farther part of the SWIR, where water is a less effective absorber, its correlation with SLW was greater than DM_1.

A simpler approach was applied over the 1650 - 1830 nm range. Considering the absorption feature in the spectra of dry needles, a simple ratio index was computed dividing the reflectance at the wavelength of maximum absorption with all wavelengths within the feature and up to the feature shoulders, at intervals of 5 nm. The goal was to test if the concept of a simple ratio index, namely dividing the wavelength of maximum absorption by a reference one at, or near, a feature shoulders, would have been more effective in detecting dry matter content in fresh needles. The correlations between SLW, EWT, and all indices in the form R1725 / Rxxxx, are displayed in Figure 4-19. All simple ratio indices between 1685 nm and 1830 nm, had a stronger correlation with EWT rather than SLW, but between 1650 nm and 1685 nm, the pattern reversed and the indices were more strongly correlated to SLW. The strength of the correlations with SLW, however, were never higher than -0.68 (R1725 / R1680), confirming that the concept worked, but also that the masking effect of water absorption could not be overcome. This result is consistent with the findings of Kokaly and Clark, (1999) who, based on inversions of the Hapke radiative transfer modeling, concluded that leaf water should be less than 10 % in

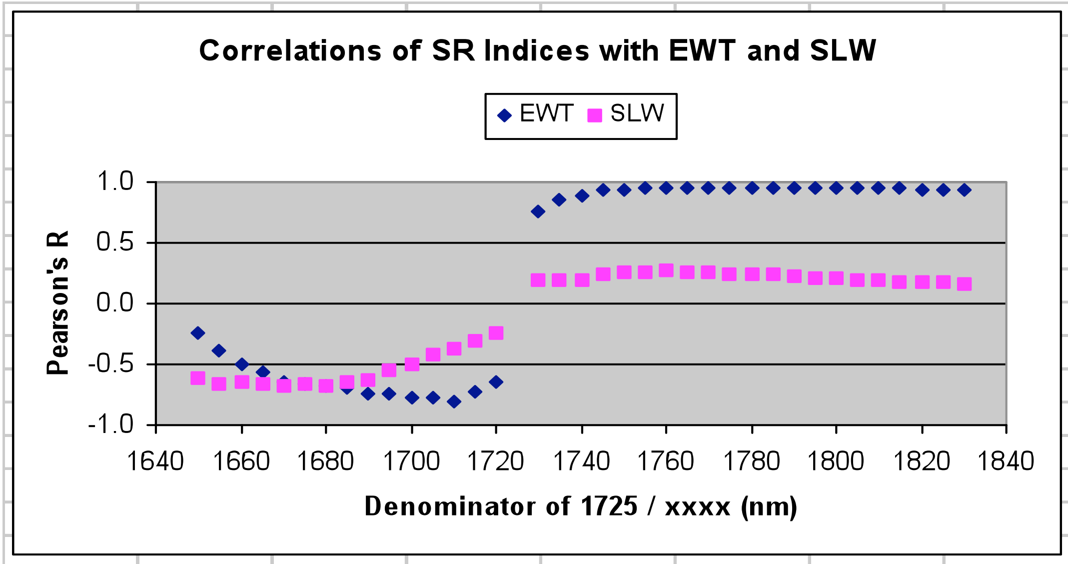

Figure 4-19: Correlations between EWT, SLW, and simple ratio indices as R1725 / Rxxx.

order to be able to derive and apply regression equations for the retrieval of Nitrogen, lignin, and cellulose in vegetation samples.

Overall, the results of the test conducted in this study suggested that the detection of dry matter content in fresh foliage of Douglas-fir needles is very challenging, hampering the opportunity to retrieve FMC ratioing corresponding to remote estimates of EWT and SLW.

Chapter 5: Conclusion

5.1 - Research Outcomes

This study examined the effectiveness of spectral reflectance for estimating water and dry matter in samples of Douglas-fir needles that were subjected to full hydration before a ten-day period of progressive de-hydration. Two techniques were considered and compared: spectral indices and continuum removal. Also two very different measures of water content were selected: Fuel Moisture Content (FMC) and Equivalent Water Thickness (EWT). Specific Leaf Weight (SLW) was chosen as surrogate measure of leaf dry matter content in consideration of the fact that it can be combined with EWT to indirectly derive FMC. The emphasis of the study was on the estimation of FMC because it is a fundamental variable in determining forest fire risk and modeling fire behaviour. The decision to select the spectral index and the continuum removal approaches was also based on the fact that, if an operational system to produce information on FMC from spectral reflectance may be developed, it must be simple and work in near real time.

The study was carried out at the leaf level on samples of Douglas-fir foliage collected in the Rithet Creek Valley within the Greater Victoria Sooke Lake Watershed on Vancouver Island, British Columbia, during the summer of 2005.

It was assumed that focusing on the leaf level in a laboratory environment, it would allow for a greater control of the variables involved, and in the elimination of the confounding factors arising from observations taken at the canopy level.

Four research questions were formulated. With reference to the first research question:

- *Can FMC be estimated with spectral reflectance measurements using the spectral index and the continuum removal approaches?*

this study produced evidence, based on correlation between variables of foliage water and dry matter content, as well as with spectral indices, suggesting that the task may be very problematic. At the beginning of the 10-day dehydration period the correlation between FMC and EWT was very weak, or even not significant, if few samples were considered outliers. However, the correlation consistently increased and became very high at the end. A similar pattern was observed when FMC was correlated to a series of spectral indices. Therefore, it was speculated that the observed high correlations were the results of a co-variation of FMC with EWT as the samples dried out. On the other hand, an in-depth examination of the correlations of SLW with FMC and EWT respectively suggested that the relationships among these variables were not straightforward and that, perhaps, leaf area could have been more a confounding factor than expected.
Douglas-fir needle water content was, however, retrievable in terms of EWT, either with the spectral index or the continuum removal approach.

With reference to the second research question:

- *Is continuum removal more effective than a spectral index for estimating leaf water content?*

this study clearly indicated that the spectral index and the continuum removal approach were equally effective in estimating EWT. The best index was the Water Index, based on the ratio of reflectance 900 / 970 nm, but several other established vegetation moisture indices performed quite well. Cross validation was used to verify the robustness of the developed regression equation. Continuum removal worked best on the range 1120 - 1250 nm, followed by the range 1690 -1830 nm. It was not possible to proficiently carry out the continuum removal over the range 925 - 1025 nm because of an adverse instrument manufacturing characteristic.

With reference to the third research question:

- *Is it possible to obtain estimates of FMC by combining spectral indices for EWT and DMC?*

this study indicated that combinations of spectral indices for EWT and dry matter content in terms of SLW are potentially possible, but not effective. The measurement of dry matter content from spectral reflectance of fresh needles appeared to be very challenging. The dominance of leaf water absorption over much part of the infrared spectral range was likely responsible for the observed outcomes, but the fact that SLW is less than an ideal measure of dry matter content for Douglas-fir needles may also have been a contributing factor.

As for the final question:

- *How does the remote sensing approach to FMC estimation compare to the field observations?*

two simple answers emerged from this study. The first is that FMC appears to be not directly detectable with reflectance measurements. The second answer is that an indirect estimation of FMC is potentially feasible combining estimates of EWT and SLW from spectral indices. However, the accuracy of the indirect approach will be not comparable to field observation due to the inadequacy of the retrieval of SLW.

5.2 - Suggestions for further research

Although enough evidence was produced to highlight a critical difficulty in detecting FMC with remote sensing, the expansion of the study to at least another tree species is highly recommended. Adopting a rigorous experimental design is also recommended in order to exercise a greater control on the measured variables. In addition, the measure of leaf thickness should be valuable to complement the measure of leaf area, helping in the interpretation of the relationships between water content and dry matter content.

Further research should be devoted to develop a methodology to disentangle the contributions of water and dry matter on the reflectance spectrum of fresh leaves.
This methodology would represent a critical improvement toward the estimation of dry matter in fresh foliage.

Finally, it is also suggested to acquire dry leaf spectra for the same foliage for which water content need to be estimated, with the goal of further developing and testing the semi-empirical methodology used in this study to compute dry matter indices.

Bibliography

Agee, J. K., and Skinner, C. N. (2005). Basic principles of forest fuel reduction treatments. *Forest Ecology and Management* **211,** 83-96.

Agee, J. K., Wright, C. S., Williamson, N., and Huff, M. H. (2002). Foliar moisture content of Pacific Northwest vegetation and its relation to wildland fire behavior. *Forest Ecology and Management* **167,** 57-66.

Alessio, G. A., Peñuelas, J., De Lillis, M., and Llusiá, J. (2008). Implications of foliar terpene content and hydration on leaf flammability of *Quercus ilex* and *Pinus halepensis*. *Plant Biology* **10,** 123-128.

Alexander, M. E. (1988). Help with making crown fire hazard assessment *In* "Proceedings of the Symposium and Workshop in Protecting People and Homes from Wildfire in the Interior West" USDA Forest Service General Technical Report INT-251, pp. 147-156.

Allen, W. A., Gausman, H. W., Richardson, A. J., and Thomas, J. R. (1969). Interaction of Isotropic Light with a Compact Plant Leaf. *Journal of the Optical Society of America* **59**(10)**,** 1376-1379.

Almeida, T. I. R., and De Souza Filho, C. R. (2004). Principal component analysis applied to feature-oriented band ratios of hyperspectral data: a tool for vegetation studies. *International Journal of Remote Sensing* **25**(22)**,** 5005-5023.

Anderson, H. E. (1970). Forest Fuel Ignitibility. *Fire Technology* **6,** 312-319.

Arora, V. K., and Boer, G. J. (2005). Fire as an interactive component of dynamic vegetation models. *Journal of Geophysical Research* **110**(G02008)**,** doi:10.1029/2005JG000042.

Arroyo, L. A., Pascual, C., and Manzanera, J. A. (2008). Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management* **256,** 1239-1252.

Babrauskas, V. (2006). Effective heat of combustion for flaming combustion of conifers. *Canadian Journal of Forest Research* **36,** 659-663.

Benito, M. T. J., Ojeda, C. B., and Rojas, F. S. (2008). Process Analytical Chemistry: Applications of Near Infrared Spectrometry in Environmental and Food Analysis: An Overview. *Applied Spectroscopy Reviews* **43,** 452-484.

Boerjan, W., Ralph, J., and Baucher, M. (2003). Lignin Biosynthesis. *Annual Review of Plant Biology* **54,** 519-546.

Bolster, K. L., Martin, M. E., and Aber, J. D. (1996). Determination of carbon fraction and nitrogen concentration in tree foliage by near infrared reflectance: a comparison of statistical methods. *Canadian Journal of Forest Research* **26,** 590-600.

Boschetti, L., Roy, D., Barbosa, P., Boca, R., and Justice, C. (2008). A MODIS assessment of the summer 2007 extent burned in Greece. *International Journal of Remote Sensing* **29**(8)**,** 2433-2436.

Boudet, A. M., Lapierre, C., and Grima-Pettenati, J. (1995). Biochemistry and molecular biology of lignification. *New Phytologist* **129,** 203-236.

Bowman, D. M. J. S., and Bogss, G. S. (2006). Fire ecology. *Progress in Physical Geography* **30**(2)**,** 245-257.

Bowyer, P., and Danson, F. M. (2004). Sensitivity of spectral reflectance to variation in live fuel moisture content at leaf and canopy level. *Remote Sensing of Environment* **92,** 297-308.

Butler, B. W., Finney, M. A., Andrews, P. L., and Albini, F. A. (2004). A radiation-driven model for crown fire spread. *Canadian Journal of Forest Research* **34,** 1588-1599.

Card, D. H., Peterson, D. L., Matson, P. A., and Aber, J. D. (1988). Prediction of Leaf Chemistry by the Use of Visible and Near Infrared Reflectance Spectroscopy. *Remote Sensing of Environment* **26**(2)**,** 123-147.

Castro, F. X., Tudela, A., and Sebastià, M. T. (2003). Modeling moisture content in shrubs to predict fire risk in Catalonia (Spain). *Agricultural and Forest Meteorology* **116,** 49-59.

Ceccato, P., Flasse, S., and Grégoire, J.-M. (2002). Designing a spectral index to estimate vegetation water content from remote sensing data Part 2. Validation and applications. *Remote Sensing of Environment* **82,** 198-207.

Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S., and Grégoire, J.-M. (2001). Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sensing of Environment* **77,** 22-33.

Chrosciewicz, Z. (1986). Foliar moisture content variations in four coniferous tree species of central Alberta. *Canadian Journal of Forest Research* **16,** 157-162.

Chuvieco, E., Aguado, I., Cocero, D., and Riaño, D. (2003). Design of an empirical index to estimate fuel moisture content from NOAA-AVHRR images in forest fire danger studies. *International Journal of Remote Sensing* **24**(8)**,** 1621-1637.

Chuvieco, E., Aguado, I., and Dimitrakopoulos, A. P. (2004). Conversion of fuel moisture content values to ignition potential for integrated fire danger assessment. *Canadian Journal of Forest Research* **34,** 2284-2293.

Chuvieco, E., and Kasischke, E. S. (2007). Remote sensing information for fire management and fire effects assessment. *Journal of Geophysical Research* **112,** G01S90, doi:10.1029/2006JG000230.

Chuvieco, E., Riaño, D., Aguado, I., and Cocero, D. (2002). Estimation of fuel moisture content from multitemporal analysis of Landsat Thematic Mapper reflectance data: applications in fire danger assessment. *International Journal of Remote Sensing* **23**(11)**,** 2145-2162.

Clark, R. N., and Roush, T. L. (1984). Reflectance Spectroscopy: Quantitative Analysis Techniques for Remote Sensing Applications. *Journal of Geophysical Research* **89**(B7)**,** 6329-6340.

Cornelissen, J. H. C., Lavorel, S., Garnier, E., Díaz, S., Buchmann, N., Gurvich, D. E., Reich, P. B., ter Steege, H., Morgan, H. D., van der Heijden, M. G. A., Pausas, J. G., and Poorter, H. (2003). A handbook of protocols for standardised and easy measurement of plant functional traits worldwide. *Australian Journal of Botany* **51,** 335-380.

Cruz, M. G., Alexander, M. E., and Wakimoto, R. H. (2004). Modeling the Likelihood of Crown Fire Occurrence in Conifer Forest Stands. *Forest Science* **50**(5)**,** 640-658.

Cruz, M. G., Alexander, M. E., and Wakimoto, R. H. (2005). Development and testing of models for predicting crown fire rate of spread in conifer forest stands. *Canadian Journal of Forest Research* **35,** 1626-1639.

Curran, P. J. (1989). Remote Sensing of Foliar Chemistry. *Remote Sensing of Environment* **30,** 271-278.

Curran, P. J., Dungan, J. L., Macler, B. A., Plummer, S. E., and Peterson, D. L. (1992). Reflectance Spectroscopy of Fresh Whole Leaves for the Estimation of Chemical Concentration. *Remote Sensing of Environment* **39,** 153-166.

Curran, P. J., Dungan, J. L., and Peterson, D. L. (2001). Estimating the foliar biochemical concentration of leaves with reflectance spectrometry. Testing the Kokaly and Clark methodologies. *Remote Sensing of Environment* **76,** 349-359.

Danson, F. M., and Bowyer, P. (2004). Estimating live fuel moisture content from remotely sensed reflectance. *Remote Sensing of Environment* **92,** 309-321.

Datt, B. (1999). Remote Sensing of Water Content in *Eucalyptus* Leaves. *Australian Journal of Botany* **47,** 909-923.

Daughtry, C. S. T., Hunt Jr., E. R., Doraiswamy, P. C., and McMurtrey III, J. E. (2005). Remote Sensing the Spatial Distribution of Crop Residues. *Agronomy Journal* **97,** 864-871.

Daughtry, C. S. T., Nagler, P. L., Kim, M. S., McMurtrey III, J. E., and Chappelle, E. W. (1996). Spectral reflectance of soils and crop residues. *In* "Near infrared spectroscopy: The future waves" (A. M. C. Davies and P. Williams, eds.), pp. 505-510. NIR Publications, Chichester, UK.

Dawson, T. P., Curran, P. J., North, P. R. J., and Plummer, S. E. (1999). The Propagation of Foliar Biochemical Absorption Features in Forest Canopy Reflectance: A Theoretical Analysis. *Remote Sensing of Environment* **67,** 147-159.

Dawson, T. P., Curran, P. J., and Plummer, S. E. (1998). LIBERTY -- Modeling the Effects of Leaf Biochemical Concentration on Reflectance Spectra. *Remote Sensing of Environment* **65,** 50-60.

DeBano, L. F., Neary, D. G., and Ffolliot, P. F. (1998). "Fire's Effects on Ecosystems." John Wiley & Sons, Inc., New York, USA. pp. 333.

DellaSala, D. A., Williams, J. E., Williams, C. D., and Franklin, J. F. (2004). Beyond Smoke and Mirrors: a Synthesis of Fire Policy and Science. *Conservation Biology* **18**(4)**,** 976-986.

Demetriades-Shah, T. H., Steven, M. D., and Clark, J. A. (1990). High Resolution Derivative Spectra in Remote Sensing. *Remote Sensing of Environment* **33,** 55-64.

Dennison, P. E., Roberts, D. A., Peterson, S. H., and Rechel, J. (2005). Use of Normalized Difference Water Index for monitoring live fuel moisture. *International Journal of Remote Sensing* **26**(5)**,** 1035-1042.

Dimitrakopoulos, A. P., and Papaioannou, K. K. (2001). Flammability Assessment of Mediterranean Forest Fuels. *Fire Technology* **37,** 143-152.

Downing, H. G., Carter, G. A., Holladay, K. W., and Cibula, W. G. (1993). The Radiative-Equivalent Water Thickness of Leaves. *Remote Sensing of Environment* **46**(1)**,** 103-107.

Elvidge, C. D., and Lyon, R. J. P. (1985). Estimation of the vegetation contribution to the 1.65/2.22 μm ratio in airborne thematic-mapper imagery of the Virginia Range, Nevada. *International Journal of Remote Sensing* **6,** 75-88.

Epting, J., Verbyla, D., and Sorbel, B. (2005). Evaluation of remotely sensed indices for assessing burn severity in interior Alaska using Landsat TM and ETM+. *Remote Sensing of Environment* **96,** 328-339.

Estienne, F., Pasti, L., Centner, V., Walczak, B., Despagne, F., Jouan Rimbaud, D., de Noord, O. E., and Massart, D. L. (2001). A comparison of multivariate calibration techniques applied to experimental NIR data sets Part II. Predictive ability under extrapolation conditions. *Chemometrics and Intelligent Laboratory Systems* **58,** 195-211.

FAO (2007). "Fire management - global assessment 2006." FAO Forestry Paper, 151. Food and Agriculture Organization of the United Nations, Rome, pp.121.

Feret, J.-B., Françoise, C., Asner, G. P., Gitelson, A. A., Martin, R. E., Bidel, L. P. R., Ustin, S. L., le Maire, G., and Jacquemoud, S. (2008). PROSPECT-4 and 5: Advances in the leaf optical properties model separating photosynthetic pigments. *Remote Sensing of Environment* **112**(6)**,** 3030-3043.

Ferwerda, J. G., Skidmore, A. K., and Stein, A. (2006). A bootstrap procedure to select hyperspectral wavebands related to tannin content. *International Journal of Remote Sensing* **27**(7)**,** 1413-1424.

Foley, S., Rivard, B., Sanchez-Azofeifa, G. A., and Calvo, J. (2006). Foliar spectral properties following leaf clipping and implications for handling techniques. *Remote Sensing of Environment* **103**(3)**,** 265-275.

Fonda, R. W. (2001). Burning Characteristics of Needles from Eight Pine Species. *Forest Science* **47**(3)**,** 390-396.

Fonda, R. W., Belanger, L. A., and Burley, L. L. (1998). Burning Characteristics of Western Conifer Needles. *Northwest Science* **72**(1)**,** 1-9.

Fourty, T., and Baret, F. (1997). Vegetation Water and Dry Matter Contents Estimated from Top-of-the-Atmosphere Reflectance Data: A Simulation Study. *Remote Sensing of Environment* **61,** 34-45.

Fourty, T., and Baret, F. (1998). On spectral estimates of fresh leaf biochemistry. *International Journal of Remote Sensing* **19**(7)**,** 1283-1297.

Fourty, T., Baret, F., Jacquemoud, S., Schmuck, G., and Verdebout, J. (1996). Leaf Optical Properties with Explicit Description of Its Biochemical Composition: Direct and Inverse Problems. *Remote Sensing of Environment* **56,** 104-117.

Gamon, J. A., Peñuelas, J., and Field, C. B. (1992). A Narrow-Waveband Spectral Index That Tracks Diurnal Changes in Photosynthetic Efficiency. *Remote Sensing of Environment* **41**(1)**,** 35-44.

Gao, B.-C. (1996). NDWI - A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water From Space. *Remote Sensing of Environment* **58,** 257-266.

Gao, B.-C., and Goetz, A. F. H. (1994). Extraction of Dry Leaf Spectral Features from Reflectance Spectra of Green Vegetation. *Remote Sensing of Environment* **47,** 369-374.

Gao, B.-C., and Goetz, A. F. H. (1995). Retrieval of Equivalent Water Thickness and Information Related to Biochemical Components of Vegetation Canopies from AVIRIS Data. *Remote Sensing of Environment* **52,** 155-162.

Garnier, E., Laurent, G., Bellmann, A., Debain, S., Berthelier, P., Ducout, B., Roumet, C., and Navas, M.-L. (2001a). Consistency of species ranking based on functional leaf traits. *New Phytologist* **152,** 69-83.

Garnier, E., Shipley, B., Roumet, C., and Laurent, G. (2001b). A standardized protocol for the determination of specific leaf area and leaf dry matter content. *Functional Ecology* **15,** 688-695.

Gary, H. L. (1971). Seasonal and Diurnal Changes in Moisture Contents and Water Deficits of Engelmann Spruce Needles. *Botanical Gazette* **132**(4)**,** 327-332.

Gastellu-Etchegorry, J. P., Zagolski, F., Mougin, E., Marty, G., and Giordano, G. (1995). An assessment of canopy chemistry with AVIRIS -- a case study in the Landes Forest, South-west France. *International Journal of Remote Sensing* **16**(3)**,** 487-501.

Gates, D. M., Keegan, H. J., Schleter, J. C., and Weidner, V. R. (1965). Spectral Properties of Plants. *Applied Optics* **4**(1)**,** 11-20.

Gausman, H. W. (1974). Leaf Reflectance of Near-lnfrared. *Photogrammetric Engineering* **40,** 183-191.

Gill, A. M., and Moore, P. H. R. (1996). "Ignitibility of leaves of Australian plants, a contract report to the Australian Flora Foundation." Centre for Plant Biodiversity Research, CSIRO Plant Industry, Canberra, pp. 34.

Goetz, A. F. H., Gao, B.-C., Wessman, C. A., and Bowman, W. D. (1990). Estimation of biochemical constituents from fresh, green leaves by spectrum matching techniques. *Proceedings IGARSS 1990 - International Geoscience and Remote Sensing Seminar***,** 971-974.

Grossman, Y. L., Ustin, S. L., Jacquemoud, S., Sanderson, E. W., Schmuck, G., and Verdebout, J. (1996). Critique of Stepwise Multiple Linear Regression for the Extraction of Leaf Biochemistry Information from Leaf Reflectance Data. *Remote Sensing of Environment* **56,** 182-193.

Hall, S. A., and Burke, I. C. (2006). Considerations for characterizing fuels as inputs for fire behavior models. *Forest Ecology and Management* **227,** 102-114.

Hao, X., and Qu, J. J. (2007). Retrieval of real-time live fuel moisture content using MODIS measurements. *Remote Sensing of Environment* **108**(2)**,** 130-137.

Hardisky, M. A., Klemas, V., and Smart, R. M. (1983). The Influence of Soil Salinity, Growth Form, and Leaf Moisture on the Spectral Radiance of *Spartina alterniflora* Canopies. *Photogrammetric Engineering & Remote Sensing* **49**(1)**,** 77-83.

Hardy, C. C., and Burgan, R. E. (1999). Evaluation of NDVI for Monitoring Live Moisture in Three Vegetation Types of the Western U.S. *Photogrammetric Engineering & Remote Sensing* **65**(5)**,** 603-610.

Hessburg, P. F., and Agee, J. K. (2003). An environmental narrative of Inland Northwest United States forests, 1800–2000. *Forest Ecology and Management* **178,** 23-59.

Hoch, G. (2007). Cell wall hemicelluloses as mobile carbon stores in non-reproductive plant tissues. *Functional Ecology* **21,** 823-834.

Holben, B. N., Schutt, J. B., and McMurtrey III, J. E. (1983). Leaf water stress detection utilizing thematic mapper bands 3, 4, and 5 in soybean plants. *International Journal of Remote Sensing* **7,** 289-297.

Hosoya, T., Kawamoto, H., and Saka, S. (2007). Cellulose–hemicellulose and cellulose–lignin interactions in wood pyrolysis at gasification temperature. *Journal of Analytical and Applied Pyrolysis* **80,** 118-125.

Hunt Jr., E. R., and Rock, B. N. (1989). Detection of Changes in Leaf Water Content Using Near- and Middle-Infrared Reflectances. *Remote Sensing of Environment* **30,** 43-54.

Jacquemoud, S., and Baret, F. (1990). PROSPECT: A Model of Leaf Optical Properties Spectra. *Remote Sensing of Environment* **34,** 75-91.

Jacquemoud, S., Verdebout, J., Schmuck, G., Andreoli, G., and Hosgood, B. (1995). Investigation of Leaf Biochemistry by Statistics. *Remote Sensing of Environment* **54,** 180-188.

Jia, G. J., Burke, I. C., Goetz, A. F. H., Kaufmann, M. R., and Kindel, B. C. (2006a). Assessing spatial patterns of forest fuel using AVIRIS data. *Remote Sensing of Environment* **102**(3-4)**,** 318-327.

Jia, G. J., Burke, I. C., Kaufmann, M. R., Goetz, A. F. H., Kindel, B. C., and Pu, Y. (2006b). Estimates of forest canopy fuel attributes using hyperspectral data. *Forest Ecology and Management* **229,** 27-38.

Johnson, E. A., and Miyanishi, K. (2001). Strenghtening Fire Ecolgy's Roots. *In* "Forest Fires: Behavior and Ecological Effects" (E. A. Johnson and K. Miyanishi, eds.), pp. 1-9. Academic Press, San Diego, USA.

Joshi, C. P., and Mansfield, S. D. (2007). The cellulose paradox — simple molecule, complex biosynthesis. *Current Opinion in Plant Biology* **10,** 220-226.

Keyes, C. R. (2006). Foliar Moisture Contents of North American Conifers *In* "Fuels Management-How to Measure Success. Conference Proceedings. 28-30 March 2006; Portland, OR." (P. L. Andrews and B. W. Butler, eds.) *Proceedings RMRS-P-41*. U.S. Department of Agricolture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO. p.395-399.

Kokaly, R. F. (2001). Investigating a Physical Basis for Spectroscopic Estimates of Leaf Nitrogen Concentration. *Remote Sensing of Environment* **75,** 153-161.

Kokaly, R. F., and Clark, R. N. (1999). Spectroscopic Determination of Leaf Biochemistry Using Band-Depth Analysis of Absorption Features and Stepwise Multiple Linear Regression. *Remote Sensing of Environment* **67,** 267-287.

Kokaly, R. F., Rockwell, B. W., Haire, S. L., and King, T. V. V. (2007). Characterization of post-fire surface cover, soils, and burn severity at the Cerro Grande Fire, New Mexico, using hyperspectral and multispectral remote sensing. *Remote Sensing of Environment* **106**(3)**,** 305-325.

Kötz, B., Schaepman, M., Morsdorf, F., Bowyer, P., Itten, K., and Allgöwer, B. (2004). Radiative transfer modeling within a heterogeneous canopy for estimation of forest fire fuel properties. *Remote Sensing of Environment* **92,** 332-344.

Krasnow, K., Schoennagel, T., and Veblen, T. T. (2009). Forest fuel mapping and evaluation of LANDFIRE fuel maps in Boulder County, Colorado, USA. *Forest Ecology and Management* **257,** 1603-1612.

Kumar, L., Schmidt, K. S., Dury, S., and Skidmore, A. K. (2001). Imaging spectrometry and vegetation science. *In* "Imaging spectrometry: basic principles and prospective applications" (F. D. van der Meer and S. M. de Jong, eds.), pp. 111-155.

Kupiec, J. A., and Curran, P. J. (1995). Decoupling effects of the canopy and foliar biochemicals in AVIRIS spectra. *International Journal of Remote Sensing* **16**(9)**,** 1731-1739.

le Maire, G., Françoise, C., and Dufrêne, E. (2004). Towards universal broad leaf chlorophyll indices using PROSPECT simulated database and hyperspectral reflectance measurements. *Remote Sensing of Environment* **89,** 1-28.

Leone, V., and Lovreglio, R. (2003). Human fire causes: a challenge for modeling. *In* "Proceedings of the 4th International Workshop on Remote Sensing and GIS applications to Forest Fire Management: Innovative Concepts and Methods in Fire Danger Estimation", pp. 233. EARSeL, Ghent University, Ghent, Belgium.

Li, L., Ustin, S. L., and Riaño, D. (2007). Retrieval of Fresh Leaf Fuel Moisture Content Using Genetic Algorithm Partial Least Squares (GA-PLS) Modeling. *IEEE Geoscience and Remote Sensing Letters* **4**(2)**,** 216-220.

Little, C. H. A. (1970). Seasonal changes in carbohydrate and moisture content in needles of balsam fir (*Abies balsamea*). *Canadian Journal of Botany* **48,** 2021-2028.

Mak, E. H. T. (1988). Measuring Foliar Flammability with the Limiting Oxygen Index Method. *Forest Science* **34**(2)**,** 523-529.

Mamleev, V., Bourbigot, S., and Yvon, J. (2007a). Kinetic analysis of the thermal decomposition of cellulose: The change of the rate limitation. *Journal of Analytical and Applied Pyrolysis* **80,** 141-150.

Mamleev, V., Bourbigot, S., and Yvon, J. (2007b). Kinetic analysis of the thermal decomposition of cellulose: The main step of mass loss. *Journal of Analytical and Applied Pyrolysis* **80,** 151-165.

Martin, M. E., and Aber, J. D. (1997). High spectral resolution remote sensing of forest canopy lignin, nitrogen, and ecosystem processes. *Ecological Applications* **7**(2)**,** 431-443.

Nelson Jr, R. M. (2001). Water Relations of Forest Fuels. *In* "Forest Fires: Behavior and Ecological Effects" (E. A. Johnson and K. Miyanishi, eds.), pp. 79-149. Academic Press, San Diego, USA.

Palacio, S., Milla, R., Albuixech, J., Peréz-Rontomé, C., Camarero, J. J., Maestro, M., and Montserrat-Martì, G. (2008). Seasonal variability of dry matter content and its relationship with shoot growth and nonstructural carbohydrates. *New Phytologist* **180,** 133-142.

Paltridge, G. W., and Barber, J. (1988). Monitoring Grassland Dryness and Fire Potential in Australia with NOAA/AVHRR Data. *Remote Sensing of Environment* **25**(3)**,** 381-394.

Peñuelas, J., Piñol, J., Ogaya, R., and Filella, I. (1997). Estimation of plant water concentration by the reflectance Water Index WI (R900/R970). *International Journal of Remote Sensing* **18**(13)**,** 2869-2875.

Perry, G. L. W. (1998). Current approaches to modelling the spread of wildland fire: a review. *Progress in Physical Geography* **22**(2)**,** 222-245.

Peterson, D. L., Aber, J. D., Matson, P. A., Card, D. H., Swanberg, N., Wessman, C., and Spanner, M. (1988). Remote Sensing of Forest Canopy and Leaf Biochemical Contents. *Remote Sensing of Environment* **24**(1)**,** 85-108.

Peterson, S. H., Roberts, D. A., and Dennison, P. E. (2008). Mapping live fuel moisture with MODIS data: A multiple regression approach. *Remote Sensing of Environment* **112**(12)**,** 4272-4284.

Petisco, C., García-Criado, B., Mediavilla, S., Vázquez de Aldana, B. R., Zabalgogeazcoa, I., and García-Ciudad, A. (2006). Near-infrared reflectance spectroscopy as a fast and non-destructive tool to predict foliar organic constituents of several woody species. *Analytical and Bioanalytical Chemistry* **386**(6)**,** 1823-1833.

Philpot, C. W. (1970). Influence of Mineral Content on the Pyrolysis of Plant Material. *Forest Science* **16**(4)**,** 461-471.

Ralph, J., Lundquist, K., Brunow, G., Lu, F., Kim, H., Schatz, P. F., Marita, J. M., Hatfield, R. D., Ralph, S. A., Christensen, J. H., and Boerjan, W. (2004). Lignins: Natural polymers from oxidative coupling of 4-hydroxyphenylpropanoids. *Phytochemistry Reviews* **3,** 29-60.

Riaño, D., Vaughan, P., Chuvieco, E., Zarco-Tejada, P. J., and Ustin, S. L. (2005). Estimation of Fuel Moisture Content by Inversion of Radiative Transfer Models to Simulate Equivalent Water Thickness and Dry Matter Content: Analysis at Leaf and Canopy Level. *IEEE Transactions on Geoscience and Remote Sensing* **43**(4)**,** 819-826.

Robichaud, P. R., Lewis, S. A., Laes, D. Y. M., Hudak, A. T., Kokaly, R. F., and Zamudio, J. A. (2007). Postfire soil burn severity mapping with hyperspectral image unmixing. *Remote Sensing of Environment* **108**(4)**,** 467-480.

Roderick, M. L. (2000). On the measurement of growth with applications to the modelling and analysis of plant growth. *Functional Ecology* **14,** 244-251.

Roderick, M. L., Berry, S. L., Noble, I. R., and Farquhar, G. D. (1999). A theoretical approach to linking the composition and morphology with the function of leaves. *Functional Ecology* **13,** 683-695.

Rollins, M. G., Keane, R. E., and Parsons, R. A. (2004). Mapping Fuels and Fire Regimes Using Remote Sensing, Ecosystem Simulation, and Gradient Modeling. *Ecological Applications* **14**(1)**,** 75-95.

Rouse, J. W., Haas, R. H., Schell, J. A., and Deering, D. W. (1974). Monitoring Vegetation Systems in the Great Plains with ERTS. *Proceedings of the 3rd Earth Resource Technology Satellite (ERTS) Symposium* **1,** 48-62.

Ryser, P. (1996). The Importance of Tissue Density for Growth and Life Span of Leaves and Roots: A Comparison of Five Ecologically Contrasting Grasses. *Functional Ecology* **10**(6)**,** 717-723.

Schmidt, K. S., and Skidmore, A. K. (2003). Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment* **85,** 92-108.

Scott, J. H., and Reinhardt, E. D. (2001). Assessing Crown Fire Potential by Linking Models of Surface and Crown Fire Behavior. *Res. Pap. RMRS-RP-29*. U.S. Department of Agricolture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO. pp.59.

Seelig, H.-D., Hoehn, A., Stodieck, L. S., Klaus, D. M., Adams III, W. W., and Emery, W. J. (2008). Relations of remote sensing leaf water indices to leaf water thickness in cowpea, bean, and sugarbeet plants. *Remote Sensing of Environment* **112**(2)**,** 445-455.

Serrano, L., Peñuelas, J., and Ustin, S. L. (2002). Remote sensing of nitrogen and lignin in Mediterranean vegetation from AVIRIS data: Decomposing biochemical from structural signals. *Remote Sensing of Environment* **81,** 355-364.

Shipley, B., and Vu, T.-T. (2002). Dry matter content as a measure of dry matter concentration in plants and their parts. *New Phytologist* **153,** 359-364.

Sims, D. A., and Gamon, J. A. (2003). Estimation of vegetation water content and photosynthetic tissue area from spectral reflectance: a comparison of indices based on liquid water and chlorophyll absorption features. *Remote Sensing of Environment* **84,** 526-537.

Smith, G. M., and Curran, P. J. (1996). The signal-to-noise ratio (SNR) required for the estimation of foliar biochemical concentrations. *International Journal of Remote Sensing* **17**(5)**,** 1031-1058.

Soukupová, J., Rock, B. N., and Albrechtová, J. (2002). Spectral characteristics of lignin and soluble phenolics in the near infrared - a comparative study. *International Journal of Remote Sensing* **23**(15)**,** 3039-3055.

Stchur, P., Cleveland, D., Zhou, J., and Michel, R. G. (2002). A Review of Recent Applications of Near Infrared Spectroscopy, and of the Characteristics of a Novel PbS CCD Array-based Near-Infrared Spectrometer. *Applied Spectroscopy Reviews* **37,** 383-428.

Stimson, H. C., Breshears, D. D., Ustin, S. L., and Kefauver, S. C. (2005). Spectral sensing of foliar water conditions in two co-occurring conifer species: *Pinus edulis* and *Juniperus monosperma*. *Remote Sensing of Environment* **96,** 108-118.

Stocks, B. J., Alexander, M. E., Wotton, B. M., Stefner, C. N., Flannigan, M. D., Taylor, S. W., Lavoie, N., Mason, J. A., Hartley, G. R., Maffey, M. E., Dalrymple, G. N., Blake, T. W., Cruz, M. G., and Lanoville, R. A. (2004). Crown fire behaviour in a northern jack pine – black spruce forest. *Canadian Journal of Forest Research* **34,** 1548-1560.

Stocks, B. J., Lawson, B. D., Alexander, M. E., Van Wagner, C. E., McAlpine, R. S., Lynham, T. J., and Dubé, D. E. (1989). The Canadian Forest Fire Danger Rating System: An overview. *The Forestry Chronicle* **65,** 450-457.

Stow, D., and Niphadkar, M. (2007). Stability, normalization and accuracy of MODIS-derived estimates of live fuel moisture for southern California chaparral. *International Journal of Remote Sensing* **28**(22)**,** 5175-5182.

Stow, D., Niphadkar, M., and Kaiser, J. (2005). MODIS-derived visible atmospherically resistant index for monitoring chaparral moisture content. *International Journal of Remote Sensing* **26**(17)**,** 3867-3873.

Taylor, N. G. (2008). Cellulose biosynthesis and deposition in higher plants. *New Phytologist* **178,** 239-252.

Taylor, S. W., and Alexander, M. E. (2006). Science, technology, and human factors in fire danger rating: the Canadian experience. *International Journal of Wildland Fire* **15,** 121-135.

Tian, Q., Tong, Q., Pu, R., Guo, X., and Zhao, C. (2001). Spectroscopic determination of wheat water status using 1650-1850 nm spectral absorption features. *International Journal of Remote Sensing* **22**(12)**,** 2329-2338.

Toomey, M., and Vierling, L. A. (2005). Multispectral remote sensing of landscape level foliar moisture: techniques and applications for forest ecosystem monitoring. *Canadian Journal of Forest Research* **35,** 1087-1097.

Trombetti, M., Riaño, D., Rubio, M. A., Cheng, Y. B., and Ustin, S. L. (2008). Multi-temporal vegetation canopy water content retrieval and interpretation using artificial neural networks for the continental USA. *Remote Sensing of Environment* **112**(1)**,** 203-215.

Tucker, C. J. (1980). Remote Sensing of Leaf Water Content in the Near Infrared. *Remote Sensing of Environment* **10**(1)**,** 23-32.

Úbeda, X., and Mataix-Solera, J. (2008). Fire effects on soil properties: A key issue in forest ecosystems. *Catena* **74,** 175-176.

Ustin, S. L., Roberts, D. A., Pinzón, J. E., Jacquemoud, S., Gardner, M., Scheer, G., Castañeda, C. M., and Palacios-Orueta, A. (1998). Estimating Canopy Water Content of Chaparral Shrubs Using Optical Methods. *Remote Sensing of Environment* **65,** 280-291.

Vaieretti, M. V., Díaz, S., Vile, D., and Garnier, E. (2007). Two Measurement Methods of Leaf Dry Matter Content Produce Similar Results in a Broad Range of Species. *Annals of Botany* **99,** 955-958.

van der Meer, F. (2004). Analysis of spectral absorption features in hyperspectral imagery. *International Journal of Applied Earth Observation and Geoinformation* **5,** 55-68.

Viegas, D. X. (1998). Forest Fire Propagation. *Philosophical Transactions: Mathematical, Physical and Engineering Sciences* **356**(1748)**,** 2907-2928.

Vile, D., Garnier, E., Shipley, B., Laurent, G., Navas, M.-L., Roumet, C., Lavorel, S., Díaz, S., Hodgson, J. G., Lloret, F., Midgley, G. F., Poorter, H., Rutherford, M. C., Wilson, P. J., and Wright, I. J. (2005). Specific Leaf Area and Dry Matter Content Estimate Thickness in Laminar Leaves. *Annals of Botany* **96,** 1129-1136.

Weise, D. R., Hartford, R. A., and Mahaffey, L. (1998). Assessing live fuel moisture for fire management applications. *In* "Fire in ecosystem management: shifting the paradigm from suppression to prescription. Tall Timbers Fire Ecology Conference Proceedings, No. 20." (T. L. Pruden and L. A. Brennan, eds.), pp. 49-55. Tall Timbers Research Station, Tallahassee, FL. USA.

Wessman, C. A., Aber, J. D., Peterson, D. L., and Melillo, J. M. (1988). Foliar analysis using near infrared reflectance spectroscopy. *Canadian Journal of Forest Research* **18,** 6-11.

Wilson, P. J., Thompson, K., and Hodgson, J. G. (1999). Specifc leaf area and leaf dry matter content as alternative predictors of plant strategies. *New Phytologist* **143,** 155-162.

Witkowski, E. T. F., and Lamont, B. B. (1991). Leaf specific mass confounds leaf density and thickness. *Oecologia* **88,** 486-493.

Wold, S., Sjöström, M., and Eriksson, L. (2001). PLS-regression: a basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems* **58,** 109-130.

Xanthopoulos, G., and Wakimoto, R. H. (1993). A time to ignition - temperature - moisture relationship for branches of three western conifers. *Canadian Journal of Forest Research* **23,** 253-258.

Yebra, M., Chuvieco, E., and Riaño, D. (2008). Estimation of live fuel moisture content from MODIS images for fire risk assessment. *Agricultural and Forest Meteorology* **148,** 523-536.

Zagolski, F., Pinel, V., Romier, J., Alcayde, D., Fontanari, J., Gastellu-Etchegorry, J. P., Giordano, G., Marty, G., Mougin, E., and Joffre, R. (1996). Forest canopy chemistry with high spectral resolution remote sensing. *International Journal of Remote Sensing* **17**(6)**,** 1107-1128.

Zarco-Tejada, P. J., Rueda, C. A., and Ustin, S. L. (2003). Water content estimation in vegetation with MODIS reflectance data and model inversion methods. *Remote Sensing of Environment* **85,** 109-124.

Zarco-Tejada, P. J., and Ustin, S. L. (2001). Modeling Canopy Water Content for Carbon Estimates from MODIS data and Land EOS Validation Sites. *Proceedings IGARSS 2001 - International Geoscience and Remote Sensing Seminar* **1,** 342-344.

Appendix A - One-Way ANOVA Among Trees

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
AREA	1.0	4	7.34675	1.091774	.545887	5.60949	9.08401	6.167	8.789
	2.0	4	8.79450	.254242	.127121	8.38994	9.19906	8.642	9.173
	3.0	4	5.60800	.504159	.252080	4.80577	6.41023	5.184	6.335
	4.0	4	7.01900	.683031	.341515	5.93215	8.10585	6.103	7.632
	5.0	4	6.19150	.201621	.100810	5.87068	6.51232	6.054	6.489
	6.0	4	5.92075	.548757	.274379	5.04756	6.79394	5.425	6.650
	7.0	4	7.88575	.700890	.350445	6.77048	9.00102	7.255	8.629
	8.0	4	7.54050	.639290	.319645	6.52325	8.55775	6.836	8.087
	9.0	4	7.32275	.854177	.427088	5.96356	8.68194	6.617	8.566
	10.0	4	7.51775	.802475	.401238	6.24083	8.79467	6.565	8.521
	Total	40	7.11473	1.102850	.174376	6.76202	7.46743	5.184	9.173
SLW	1.0	4	.014650	.0010970	.0005485	.012904	.016396	.0131	.0156
	2.0	4	.015550	.0003317	.0001658	.015022	.016078	.0151	.0158
	3.0	4	.015850	.0012124	.0006062	.013921	.017779	.0143	.0170
	4.0	4	.015625	.0014221	.0007111	.013362	.017888	.0143	.0170
	5.0	4	.018675	.0019033	.0009516	.015646	.021704	.0165	.0210
	6.0	4	.016275	.0008016	.0004008	.015000	.017550	.0155	.0174
	7.0	4	.016025	.0020532	.0010266	.012758	.019292	.0138	.0181
	8.0	4	.015925	.0010308	.0005154	.014285	.017565	.0148	.0168
	9.0	4	.018875	.0021562	.0010781	.015444	.022306	.0168	.0212
	10.0	4	.014925	.0014637	.0007319	.012596	.017254	.0134	.0165
	Total	40	.016237	.0018712	.0002959	.015639	.016836	.0131	.0212
EWT	1.0	4	.025950	.0016279	.0008139	.023360	.028540	.0240	.0278
	2.0	4	.025000	.0004082	.0002041	.024350	.025650	.0247	.0256
	3.0	4	.024425	.0013376	.0006688	.022297	.026553	.0230	.0258
	4.0	4	.024125	.0014569	.0007284	.021807	.026443	.0225	.0255
	5.0	4	.021625	.0003403	.0001702	.021083	.022167	.0213	.0221
	6.0	4	.027700	.0012961	.0006481	.025638	.029762	.0265	.0291
	7.0	4	.027800	.0032239	.0016119	.022670	.032930	.0241	.0306
	8.0	4	.023425	.0018536	.0009268	.020476	.026374	.0209	.0252
	9.0	4	.028250	.0031332	.0015666	.023264	.033236	.0252	.0311
	10.0	4	.023625	.0020106	.0010053	.020426	.026824	.0216	.0255
	Total	40	.025193	.0026841	.0004244	.024334	.026051	.0209	.0311

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
AREA	1.158	9	30	.356
SLW	3.994	9	30	.002
EWT	9.650	9	30	.000

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
AREA	Between Groups	33.657	9	3.740	8.143	.000
	Within Groups	13.778	30	.459		
	Total	47.435	39			
SLW	Between Groups	.000	9	.000	3.844	.003
	Within Groups	.000	30	.000		
	Total	.000	39			
EWT	Between Groups	.000	9	.000	5.288	.000
	Within Groups	.000	30	.000		
	Total	.000	39			

POST HOC TESTS

Multiple Comparisons

Tukey HSD

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
AREA	1.0	2.0	-1.44775	.479199	.117	-3.39823	.50273
		3.0	1.73875	.479199	.030	-.21173	3.68923
		4.0	.32775	.479199	.999	-1.62273	2.27823
		5.0	1.15525	.479199	.355	-.79523	3.10573
		6.0	1.42600	.479199	.129	-.52448	3.37648
		7.0	-.53900	.479199	.978	-2.48948	1.41148
		8.0	-.19375	.479199	1.000	-2.14423	1.75673
		9.0	.02400	.479199	1.000	-1.92648	1.97448
		10.0	-.17100	.479199	1.000	-2.12148	1.77948
	2.0	1.0	1.44775	.479199	.117	-.50273	3.39823
		3.0	3.18650	.479199	.000	1.23602	5.13698
		4.0	1.77550	.479199	.025	-.17498	3.72598
		5.0	2.60300	.479199	.000	.65252	4.55348
		6.0	2.87375	.479199	.000	.92327	4.82423
		7.0	.90875	.479199	.671	-1.04173	2.85923
		8.0	1.25400	.479199	.253	-.69648	3.20448
		9.0	1.47175	.479199	.106	-.47873	3.42223
		10.0	1.27675	.479199	.233	-.67373	3.22723
	3.0	1.0	-1.73875	.479199	.030	-3.68923	.21173
		2.0	-3.18650	.479199	.000	-5.13698	-1.23602
		4.0	-1.41100	.479199	.137	-3.36148	.53948

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		5.0	-.58350	.479199	.964	-2.53398	1.36698
		6.0	-.31275	.479199	1.000	-2.26323	1.63773
		7.0	-2.27775	.479199	.002	-4.22823	-.32727
		8.0	-1.93250	.479199	.011	-3.88298	.01798
		9.0	-1.71475	.479199	.034	-3.66523	.23573
		10.0	-1.90975	.479199	.012	-3.86023	.04073
	4.0	1.0	-.32775	.479199	.999	-2.27823	1.62273
		2.0	-1.77550	.479199	.025	-3.72598	.17498
		3.0	1.41100	.479199	.137	-.53948	3.36148
		5.0	.82750	.479199	.772	-1.12298	2.77798
		6.0	1.09825	.479199	.422	-.85223	3.04873
		7.0	-.86675	.479199	.725	-2.81723	1.08373
		8.0	-.52150	.479199	.982	-2.47198	1.42898
		9.0	-.30375	.479199	1.000	-2.25423	1.64673
		10.0	-.49875	.479199	.987	-2.44923	1.45173
	5.0	1.0	-1.15525	.479199	.355	-3.10573	.79523
		2.0	-2.60300	.479199	.000	-4.55348	-.65252
		3.0	.58350	.479199	.964	-1.36698	2.53398
		4.0	-.82750	.479199	.772	-2.77798	1.12298
		6.0	.27075	.479199	1.000	-1.67973	2.22123
		7.0	-1.69425	.479199	.037	-3.64473	.25623
		8.0	-1.34900	.479199	.177	-3.29948	.60148
		9.0	-1.13125	.479199	.383	-3.08173	.81923
		10.0	-1.32625	.479199	.193	-3.27673	.62423
	6.0	1.0	-1.42600	.479199	.129	-3.37648	.52448
		2.0	-2.87375	.479199	.000	-4.82423	-.92327
		3.0	.31275	.479199	1.000	-1.63773	2.26323
		4.0	-1.09825	.479199	.422	-3.04873	.85223
		5.0	-.27075	.479199	1.000	-2.22123	1.67973
		7.0	-1.96500	.479199	.009	-3.91548	-.01452
		8.0	-1.61975	.479199	.054	-3.57023	.33073
		9.0	-1.40200	.479199	.142	-3.35248	.54848
		10.0	-1.59700	.479199	.060	-3.54748	.35348
	7.0	1.0	.53900	.479199	.978	-1.41148	2.48948
		2.0	-.90875	.479199	.671	-2.85923	1.04173
		3.0	2.27775	.479199	.002	.32727	4.22823
		4.0	.86675	.479199	.725	-1.08373	2.81723
		5.0	1.69425	.479199	.037	-.25623	3.64473
		6.0	1.96500	.479199	.009	.01452	3.91548
		8.0	.34525	.479199	.999	-1.60523	2.29573
		9.0	.56300	.479199	.971	-1.38748	2.51348
		10.0	.36800	.479199	.999	-1.58248	2.31848
	8.0	1.0	.19375	.479199	1.000	-1.75673	2.14423
		2.0	-1.25400	.479199	.253	-3.20448	.69648
		3.0	1.93250	.479199	.011	-.01798	3.88298
		4.0	.52150	.479199	.982	-1.42898	2.47198
		5.0	1.34900	.479199	.177	-.60148	3.29948
		6.0	1.61975	.479199	.054	-.33073	3.57023
		7.0	-.34525	.479199	.999	-2.29573	1.60523

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		9.0	.21775	.479199	1.000	-1.73273	2.16823
		10.0	.02275	.479199	1.000	-1.92773	1.97323
	9.0	1.0	-.02400	.479199	1.000	-1.97448	1.92648
		2.0	-1.47175	.479199	.106	-3.42223	.47873
		3.0	1.71475	.479199	.034	-.23573	3.66523
		4.0	.30375	.479199	1.000	-1.64673	2.25423
		5.0	1.13125	.479199	.383	-.81923	3.08173
		6.0	1.40200	.479199	.142	-.54848	3.35248
		7.0	-.56300	.479199	.971	-2.51348	1.38748
		8.0	-.21775	.479199	1.000	-2.16823	1.73273
		10.0	-.19500	.479199	1.000	-2.14548	1.75548
	10.0	1.0	.17100	.479199	1.000	-1.77948	2.12148
		2.0	-1.27675	.479199	.233	-3.22723	.67373
		3.0	1.90975	.479199	.012	-.04073	3.86023
		4.0	.49875	.479199	.987	-1.45173	2.44923
		5.0	1.32625	.479199	.193	-.62423	3.27673
		6.0	1.59700	.479199	.060	-.35348	3.54748
		7.0	-.36800	.479199	.999	-2.31848	1.58248
		8.0	-.02275	.479199	1.000	-1.97323	1.92773
		9.0	.19500	.479199	1.000	-1.75548	2.14548
SLW	1.0	2.0	-.000900	.0010281	.996	-.005085	.003285
		3.0	-.001200	.0010281	.972	-.005385	.002985
		4.0	-.000975	.0010281	.993	-.005160	.003210
		5.0	-.004025	.0010281	.015	-.008210	.000160
		6.0	-.001625	.0010281	.847	-.005810	.002560
		7.0	-.001375	.0010281	.936	-.005560	.002810
		8.0	-.001275	.0010281	.959	-.005460	.002910
		9.0	-.004225	.0010281	.009	-.008410	-.000040
		10.0	-.000275	.0010281	1.000	-.004460	.003910
	2.0	1.0	.000900	.0010281	.996	-.003285	.005085
		3.0	-.000300	.0010281	1.000	-.004485	.003885
		4.0	-.000075	.0010281	1.000	-.004260	.004110
		5.0	-.003125	.0010281	.113	-.007310	.001060
		6.0	-.000725	.0010281	.999	-.004910	.003460
		7.0	-.000475	.0010281	1.000	-.004660	.003710
		8.0	-.000375	.0010281	1.000	-.004560	.003810
		9.0	-.003325	.0010281	.074	-.007510	.000860
		10.0	.000625	.0010281	1.000	-.003560	.004810
	3.0	1.0	.001200	.0010281	.972	-.002985	.005385
		2.0	.000300	.0010281	1.000	-.003885	.004485
		4.0	.000225	.0010281	1.000	-.003960	.004410
		5.0	-.002825	.0010281	.200	-.007010	.001360
		6.0	-.000425	.0010281	1.000	-.004610	.003760
		7.0	-.000175	.0010281	1.000	-.004360	.004010
		8.0	-.000075	.0010281	1.000	-.004260	.004110
		9.0	-.003025	.0010281	.138	-.007210	.001160
		10.0	.000925	.0010281	.995	-.003260	.005110
	4.0	1.0	.000975	.0010281	.993	-.003210	.005160
		2.0	.000075	.0010281	1.000	-.004110	.004260

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		3.0	-.000225	.0010281	1.000	-.004410	.003960
		5.0	-.003050	.0010281	.131	-.007235	.001135
		6.0	-.000650	.0010281	1.000	-.004835	.003535
		7.0	-.000400	.0010281	1.000	-.004585	.003785
		8.0	-.000300	.0010281	1.000	-.004485	.003885
		9.0	-.003250	.0010281	.087	-.007435	.000935
		10.0	.000700	.0010281	.999	-.003485	.004885
	5.0	1.0	.004025	.0010281	.015	-.000160	.008210
		2.0	.003125	.0010281	.113	-.001060	.007310
		3.0	.002825	.0010281	.200	-.001360	.007010
		4.0	.003050	.0010281	.131	-.001135	.007235
		6.0	.002400	.0010281	.398	-.001785	.006585
		7.0	.002650	.0010281	.271	-.001535	.006835
		8.0	.002750	.0010281	.229	-.001435	.006935
		9.0	-.000200	.0010281	1.000	-.004385	.003985
		10.0	.003750	.0010281	.029	-.000435	.007935
	6.0	1.0	.001625	.0010281	.847	-.002560	.005810
		2.0	.000725	.0010281	.999	-.003460	.004910
		3.0	.000425	.0010281	1.000	-.003760	.004610
		4.0	.000650	.0010281	1.000	-.003535	.004835
		5.0	-.002400	.0010281	.398	-.006585	.001785
		7.0	.000250	.0010281	1.000	-.003935	.004435
		8.0	.000350	.0010281	1.000	-.003835	.004535
		9.0	-.002600	.0010281	.294	-.006785	.001585
		10.0	.001350	.0010281	.943	-.002835	.005535
	7.0	1.0	.001375	.0010281	.936	-.002810	.005560
		2.0	.000475	.0010281	1.000	-.003710	.004660
		3.0	.000175	.0010281	1.000	-.004010	.004360
		4.0	.000400	.0010281	1.000	-.003785	.004585
		5.0	-.002650	.0010281	.271	-.006835	.001535
		6.0	-.000250	.0010281	1.000	-.004435	.003935
		8.0	.000100	.0010281	1.000	-.004085	.004285
		9.0	-.002850	.0010281	.192	-.007035	.001335
		10.0	.001100	.0010281	.984	-.003085	.005285
	8.0	1.0	.001275	.0010281	.959	-.002910	.005460
		2.0	.000375	.0010281	1.000	-.003810	.004560
		3.0	.000075	.0010281	1.000	-.004110	.004260
		4.0	.000300	.0010281	1.000	-.003885	.004485
		5.0	-.002750	.0010281	.229	-.006935	.001435
		6.0	-.000350	.0010281	1.000	-.004535	.003835
		7.0	-.000100	.0010281	1.000	-.004285	.004085
		9.0	-.002950	.0010281	.159	-.007135	.001235
		10.0	.001000	.0010281	.992	-.003185	.005185
	9.0	1.0	.004225	.0010281	.009	.000040	.008410
		2.0	.003325	.0010281	.074	-.000860	.007510
		3.0	.003025	.0010281	.138	-.001160	.007210
		4.0	.003250	.0010281	.087	-.000935	.007435
		5.0	.000200	.0010281	1.000	-.003985	.004385
		6.0	.002600	.0010281	.294	-.001585	.006785

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		7.0	.002850	.0010281	.192	-.001335	.007035
		8.0	.002950	.0010281	.159	-.001235	.007135
		10.0	.003950	.0010281	.018	-.000235	.008135
	10.0	1.0	.000275	.0010281	1.000	-.003910	.004460
		2.0	-.000625	.0010281	1.000	-.004810	.003560
		3.0	-.000925	.0010281	.995	-.005110	.003260
		4.0	-.000700	.0010281	.999	-.004885	.003485
		5.0	-.003750	.0010281	.029	-.007935	.000435
		6.0	-.001350	.0010281	.943	-.005535	.002835
		7.0	-.001100	.0010281	.984	-.005285	.003085
		8.0	-.001000	.0010281	.992	-.005185	.003185
		9.0	-.003950	.0010281	.018	-.008135	.000235
EWT	1.0	2.0	.000950	.0013456	.999	-.004527	.006427
		3.0	.001525	.0013456	.977	-.003952	.007002
		4.0	.001825	.0013456	.931	-.003652	.007302
		5.0	.004325	.0013456	.078	-.001152	.009802
		6.0	-.001750	.0013456	.946	-.007227	.003727
		7.0	-.001850	.0013456	.926	-.007327	.003627
		8.0	.002525	.0013456	.684	-.002952	.008002
		9.0	-.002300	.0013456	.782	-.007777	.003177
		10.0	.002325	.0013456	.772	-.003152	.007802
	2.0	1.0	-.000950	.0013456	.999	-.006427	.004527
		3.0	.000575	.0013456	1.000	-.004902	.006052
		4.0	.000875	.0013456	1.000	-.004602	.006352
		5.0	.003375	.0013456	.304	-.002102	.008852
		6.0	-.002700	.0013456	.601	-.008177	.002777
		7.0	-.002800	.0013456	.554	-.008277	.002677
		8.0	.001575	.0013456	.972	-.003902	.007052
		9.0	-.003250	.0013456	.352	-.008727	.002227
		10.0	.001375	.0013456	.988	-.004102	.006852
	3.0	1.0	-.001525	.0013456	.977	-.007002	.003952
		2.0	-.000575	.0013456	1.000	-.006052	.004902
		4.0	.000300	.0013456	1.000	-.005177	.005777
		5.0	.002800	.0013456	.554	-.002677	.008277
		6.0	-.003275	.0013456	.342	-.008752	.002202
		7.0	-.003375	.0013456	.304	-.008852	.002102
		8.0	.001000	.0013456	.999	-.004477	.006477
		9.0	-.003825	.0013456	.168	-.009302	.001652
		10.0	.000800	.0013456	1.000	-.004677	.006277
	4.0	1.0	-.001825	.0013456	.931	-.007302	.003652
		2.0	-.000875	.0013456	1.000	-.006352	.004602
		3.0	-.000300	.0013456	1.000	-.005777	.005177
		5.0	.002500	.0013456	.695	-.002977	.007977
		6.0	-.003575	.0013456	.236	-.009052	.001902
		7.0	-.003675	.0013456	.207	-.009152	.001802
		8.0	.000700	.0013456	1.000	-.004777	.006177
		9.0	-.004125	.0013456	.107	-.009602	.001352
		10.0	.000500	.0013456	1.000	-.004977	.005977
	5.0	1.0	-.004325	.0013456	.078	-.009802	.001152

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		2.0	-.003375	.0013456	.304	-.008852	.002102
		3.0	-.002800	.0013456	.554	-.008277	.002677
		4.0	-.002500	.0013456	.695	-.007977	.002977
		6.0	-.006075	.0013456	.003	-.011552	-.000598
		7.0	-.006175	.0013456	.003	-.011652	-.000698
		8.0	-.001800	.0013456	.936	-.007277	.003677
		9.0	-.006625	.0013456	.001	-.012102	-.001148
		10.0	-.002000	.0013456	.887	-.007477	.003477
	6.0	1.0	.001750	.0013456	.946	-.003727	.007227
		2.0	.002700	.0013456	.601	-.002777	.008177
		3.0	.003275	.0013456	.342	-.002202	.008752
		4.0	.003575	.0013456	.236	-.001902	.009052
		5.0	.006075	.0013456	.003	.000598	.011552
		7.0	-.000100	.0013456	1.000	-.005577	.005377
		8.0	.004275	.0013456	.084	-.001202	.009752
		9.0	-.000550	.0013456	1.000	-.006027	.004927
		10.0	.004075	.0013456	.116	-.001402	.009552
	7.0	1.0	.001850	.0013456	.926	-.003627	.007327
		2.0	.002800	.0013456	.554	-.002677	.008277
		3.0	.003375	.0013456	.304	-.002102	.008852
		4.0	.003675	.0013456	.207	-.001802	.009152
		5.0	.006175	.0013456	.003	.000698	.011652
		6.0	.000100	.0013456	1.000	-.005377	.005577
		8.0	.004375	.0013456	.072	-.001102	.009852
		9.0	-.000450	.0013456	1.000	-.005927	.005027
		10.0	.004175	.0013456	.099	-.001302	.009652
	8.0	1.0	-.002525	.0013456	.684	-.008002	.002952
		2.0	-.001575	.0013456	.972	-.007052	.003902
		3.0	-.001000	.0013456	.999	-.006477	.004477
		4.0	-.000700	.0013456	1.000	-.006177	.004777
		5.0	.001800	.0013456	.936	-.003677	.007277
		6.0	-.004275	.0013456	.084	-.009752	.001202
		7.0	-.004375	.0013456	.072	-.009852	.001102
		9.0	-.004825	.0013456	.033	-.010302	.000652
		10.0	-.000200	.0013456	1.000	-.005677	.005277
	9.0	1.0	.002300	.0013456	.782	-.003177	.007777
		2.0	.003250	.0013456	.352	-.002227	.008727
		3.0	.003825	.0013456	.168	-.001652	.009302
		4.0	.004125	.0013456	.107	-.001352	.009602
		5.0	.006625	.0013456	.001	.001148	.012102
		6.0	.000550	.0013456	1.000	-.004927	.006027
		7.0	.000450	.0013456	1.000	-.005027	.005927
		8.0	.004825	.0013456	.033	-.000652	.010302
		10.0	.004625	.0013456	.047	-.000852	.010102
	10.0	1.0	-.002325	.0013456	.772	-.007802	.003152
		2.0	-.001375	.0013456	.988	-.006852	.004102
		3.0	-.000800	.0013456	1.000	-.006277	.004677
		4.0	-.000500	.0013456	1.000	-.005977	.004977
		5.0	.002000	.0013456	.887	-.003477	.007477

			Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval	
Dependent Variable	(I) TREE	(J) TREE				Lower Bound	Upper Bound
		6.0	-.004075	.0013456	.116	-.009552	.001402
		7.0	-.004175	.0013456	.099	-.009652	.001302
		8.0	.000200	.0013456	1.000	-.005277	.005677
		9.0	-.004625	.0013456	.047	-.010102	.000852

- The mean difference is significant at the .01 level.

HOMOGENEOUS SUBSETS

AREA
Tukey HSD

	N	Subset for alpha = .01		
TREE		1	2	3
3.0	4	5.60800		
6.0	4	5.92075		
5.0	4	6.19150	6.19150	
4.0	4	7.01900	7.01900	7.01900
9.0	4	7.32275	7.32275	7.32275
1.0	4	7.34675	7.34675	7.34675
10.0	4	7.51775	7.51775	7.51775
8.0	4	7.54050	7.54050	7.54050
7.0	4		7.88575	7.88575
2.0	4			8.79450
Sig.		.011	.037	.025

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 4.000.

SLW
Tukey HSD

	N	Subset for alpha = .01	
TREE		1	2
1.0	4	.014650	
10.0	4	.014925	.014925
2.0	4	.015550	.015550
4.0	4	.015625	.015625
3.0	4	.015850	.015850
8.0	4	.015925	.015925
7.0	4	.016025	.016025
6.0	4	.016275	.016275
5.0	4	.018675	.018675
9.0	4		.018875
Sig.		.015	.018

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 4.000.

EWT

Tukey HSD

	N	Subset for alpha = .01	
TREE		1	2
5.0	4	.021625	
8.0	4	.023425	.023425
10.0	4	.023625	.023625
4.0	4	.024125	.024125
3.0	4	.024425	.024425
2.0	4	.025000	.025000
1.0	4	.025950	.025950
6.0	4		.027700
7.0	4		.027800
9.0	4		.028250
Sig.		.078	.033

Means for groups in homogeneous subsets are displayed.

a Uses Harmonic Mean Sample Size = 4.000.

Appendix B - Kruskal-Wallis Test for EWT and SLW

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
SLW	40	.016237	.0018712	.0131	.0212
EWT	40	.025193	.0026841	.0209	.0311
TREE	40	5.500	2.9089	1.0	10.0

Kruskal-Wallis Test

Ranks

	TREE	N	Mean Rank
SLW	1.0	4	9.50
	2.0	4	16.00
	3.0	4	19.00
	4.0	4	17.25
	5.0	4	33.63
	6.0	4	22.88
	7.0	4	20.50
	8.0	4	19.63
	9.0	4	34.50
	10.0	4	12.13
	Total	40	
EWT	1.0	4	25.75
	2.0	4	19.50
	3.0	4	18.00
	4.0	4	16.13
	5.0	4	3.88
	6.0	4	33.75
	7.0	4	29.75
	8.0	4	11.75
	9.0	4	32.13
	10.0	4	14.38
	Total	40	

Test Statistics

	SLW	EWT
Chi-Square	17.558	24.636
df	9	9
Asymp. Sig.	.041	.003

a Kruskal Wallis Test
b Grouping Variable: TREE

Appendix C - One-Way ANOVA Among the Four Sampled Canopy Locations

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
AREA	1	10	7.39770	1.260664	.398657	6.49588	8.29952	5.184	8.789
	2	10	7.27910	1.220715	.386024	6.40585	8.15235	5.582	9.173
	3	10	6.86850	.873442	.276207	6.24368	7.49332	5.521	8.712
	4	10	6.91360	1.094038	.345965	6.13097	7.69623	5.392	8.651
	Total	40	7.11473	1.102850	.174376	6.76202	7.46743	5.184	9.173
SLW	1	10	.017240	.0018787	.0005941	.015896	.018584	.0151	.0212
	2	10	.017250	.0018799	.0005945	.015905	.018595	.0155	.0210
	3	10	.014880	.0012994	.0004109	.013950	.015810	.0131	.0168
	4	10	.015580	.0012796	.0004046	.014665	.016495	.0140	.0180
	Total	40	.016237	.0018712	.0002959	.015639	.016836	.0131	.0212
EWT	1	10	.026410	.0029004	.0009172	.024335	.028485	.0213	.0311
	2	10	.026320	.0027345	.0008647	.024364	.028276	.0221	.0308
	3	10	.023660	.0018332	.0005797	.022349	.024971	.0209	.0267
	4	10	.024380	.0023593	.0007461	.022692	.026068	.0215	.0291
	Total	40	.025193	.0026841	.0004244	.024334	.026051	.0209	.0311

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
AREA	1.191	3	36	.327
SLW	.453	3	36	.717
EWT	.500	3	36	.685

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
AREA	Between Groups	2.082	3	.694	.551	.651
	Within Groups	45.353	36	1.260		
	Total	47.435	39			
SLW	Between Groups	.000	3	.000	5.525	.003
	Within Groups	.000	36	.000		
	Total	.000	39			
EWT	Between Groups	.000	3	.000	3.096	.039
	Within Groups	.000	36	.000		
	Total	.000	39			

POST HOC TESTS

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) CROWN_B	(J) CROWN_B	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
AREA	1	2	.11860	.501958	.995	-1.23329	1.47049
		3	.52920	.501958	.719	-.82269	1.88109
		4	.48410	.501958	.770	-.86779	1.83599
	2	1	-.11860	.501958	.995	-1.47049	1.23329
		3	.41060	.501958	.846	-.94129	1.76249
		4	.36550	.501958	.885	-.98639	1.71739
	3	1	-.52920	.501958	.719	-1.88109	.82269
		2	-.41060	.501958	.846	-1.76249	.94129
		4	-.04510	.501958	1.000	-1.39699	1.30679
	4	1	-.48410	.501958	.770	-1.83599	.86779
		2	-.36550	.501958	.885	-1.71739	.98639
		3	.04510	.501958	1.000	-1.30679	1.39699
SLW	1	2	-.000010	.0007207	1.000	-.001951	.001931
		3	.002360	.0007207	.012	.000419	.004301
		4	.001660	.0007207	.116	-.000281	.003601
	2	1	.000010	.0007207	1.000	-.001931	.001951
		3	.002370	.0007207	.012	.000429	.004311
		4	.001670	.0007207	.113	-.000271	.003611
	3	1	-.002360	.0007207	.012	-.004301	-.000419
		2	-.002370	.0007207	.012	-.004311	-.000429
		4	-.000700	.0007207	.767	-.002641	.001241
	4	1	-.001660	.0007207	.116	-.003601	.000281
		2	-.001670	.0007207	.113	-.003611	.000271
		3	.000700	.0007207	.767	-.001241	.002641
EWT	1	2	.000090	.0011139	1.000	-.002910	.003090
		3	.002750	.0011139	.082	-.000250	.005750
		4	.002030	.0011139	.280	-.000970	.005030
	2	1	-.000090	.0011139	1.000	-.003090	.002910
		3	.002660	.0011139	.098	-.000340	.005660
		4	.001940	.0011139	.318	-.001060	.004940
	3	1	-.002750	.0011139	.082	-.005750	.000250
		2	-.002660	.0011139	.098	-.005660	.000340
		4	-.000720	.0011139	.916	-.003720	.002280
	4	1	-.002030	.0011139	.280	-.005030	.000970
		2	-.001940	.0011139	.318	-.004940	.001060
		3	.000720	.0011139	.916	-.002280	.003720

* The mean difference is significant at the .05 level.

HOMOGENEOUS SUBSETS

AREA
Tukey HSD

	N	Subset for alpha = .05
CROWN_B		1
3	10	6.86850
4	10	6.91360
2	10	7.27910
1	10	7.39770
Sig.		.719

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 10.000.

SLW
Tukey HSD

	N	Subset for alpha = .05	
CROWN_B		1	2
3	10	.014880	
4	10	.015580	.015580
1	10		.017240
2	10		.017250
Sig.		.767	.113

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 10.000.

EWT
Tukey HSD

	N	Subset for alpha = .05
CROWN_B		1
3	10	.023660
4	10	.024380
2	10	.026320
1	10	.026410
Sig.		.082

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 10.000.