REMOTE RETRIEVAL OF ECOLOGICAL INDICATORS FOR DETECTING FOREST DROUGHT AND WILDFIRE

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THESIS

REMOTE RETRIEVAL OF ECOLOGICAL INDICATORS FOR DETECTING FOREST DROUGHT AND WILDFIRE

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森林の干魃と火災を検知する指標のリモート抽出に関する研究

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Abstract

Events of drought-induced forest mortality and forest fire have been occurred all over the world and will be exacerbated in the future due to rising temperature. Both forest disturbances have substantial influence on the global hydrological and carbon cycle. How to remotely and quantitatively monitor and assess both disturbances have not been effectively addressed until now. Remote sensing provides a reliable and practical means to assess forest disturbances by the retrieval of related indicators. In this study, four indicators, relative water content (RWC), equivalent water thickness (EWT), fluorescence–based quantum yield of PSII (ΔF/F'm) and fuel moisture content (FMC) were retrieved with hyperspectral indices for detecting forest drought and fire, respectively.

Leaf water status information is highly needed for monitoring plant physiological processes and assessing drought stress. In **Chapter 2**, a leaf dehydration experiment was designed to obtain a relatively comprehensive dataset with ranges that were difficult to obtain in field measurements. RWC and EWT were chosen as the surrogates of leaf water status. Moreover, five common types of hyperspectral indices including: single reflectance (R), wavelength difference (D), simple ratio (SR), normalized ratio (ND) and double difference (DDn) were applied to determine the best indices. The results indicated that values of original reflectance, reflectance difference and reflectance sensitivity increased significantly, particularly within the 350-700 nm and 1300-2500 nm domains, with a decrease in leaf water. The identified best indices for RWC and EWT, when all the species were considered together, were the first derivative reflectance based ND type index of dND (1415, 1530) and SR type index of dSR (1530, 1895), with R^2 values of 0.95 ($p<0.001$) and 0.97 ($p<0.001$), respectively, better than previously published indices. Even so, different best indices for different species were identified, most probably due to the differences in leaf

anatomy and physiological processes during leaf dehydration. Although more plant species and field-measured datasets are still needed in future studies, the recommend indices based on derivative spectra provide a means to monitor drought-induced plant mortality in temperate climate regions.

The information of photosynthetic status is greatly required for better understanding forest drought stress. ΔF/F'm is a commonly used indicator of photosynthetic status. In **chapter 3**, ΔF/F'm was retrieved with leaf origin reflectance and first derivative reflectance ranging from 400 nm to 800 nm because leaf water content and dry mater content had minimal impact on these bands. Results showed that the changes of ΔF/F'm could not be traced by the published indices of NDVI and PRI. There were no significant correlations between ΔF/F'm and between ΔF/F'm and NDVI when all species were considered. The identified best indices for estimating ΔF/F'm was dND (533, 686) across different type of indices, with an R^2 of 0.88 and an RMSE of 0.11. The wavelength of 533 nm which is near xanthophyll-cycle-related 531 nm and 686 nm is near one of the emission peak of chlorophyll fluorescence, 690 nm. dND (533, 686) may incorporates the information of both chlorophyll fluorescence and xanthophyll cycle, and therefore it is suitable for the estimation of ΔF/F'm under water stress.

FMC, the water content either in dead or live fuels, is a critical parameter in fire behavior prediction. Although remote sensing is an efficient way to estimate the spatial and temporal variations of FMC, most of the existing spectral indices are oriented to live fuels, while estimation of FMC in dead fuels is commonly done using weather indices instead, and is therefore severely limited by the availability of meteorological stations. In **chapter 4**, dehydration experiments were designed for both live and dead fallen leaves in order to determine the best hyperspectral indices for different fuel types by tracking the time-varying water contents of both fuel materials. Meanwhile, PROSPECT model was used to simulate a dataset with a wide range of input parameters. The results showed that the reflected spectra from 400 to

1200 nm were quite different between green live leaves and fallen litters with decreasing FMC, while the changes of reflected spectra in the domain of 1200 to2500 nm were similar, with dry matter bands gradually appearing. The identified best index for FMC including both fuel types was a derivative spectra-based index of dND(1900, 2095) with an R^2 of 0.85 and an RMSE of 32%, although it was failed in simulated dataset by PROSPECT. Two fuel types were well separated by normalizing dND (1900, 2095) with a combination of NDVI ((dND-NDVI)/(dND+NDVI)), which had an R^2 of 0.85 and an RMSE of 21% for FMC in green live leaf fuels and a lower R^2 of 0.45 and RMSE of 69% for FMC in dead fallen leaf fuels. The decreased R^2 for FMC in dead fallen leaf fuels was primarily caused by the different NDVI values of different species, suggesting that the recommend indices should be validated with more plant species in the future.

Chapter 1 General introduction

1.1 Background

1.1.1 Forest disturbances

Forest ecosystems play a critical role in the climate regulation and global carbon cycle (IPCC 2007). A large and persistent carbon sink in forests has been found and may annually sequester about 25% anthropogenic carbon emissions to atmosphere (Bonan 2008; Pan et al. 2011). However, a growing number of evidences show that ongoing global warming and extreme climate events are closely linked to vegetation disturbances which will have a positive feedback to global warming. These disturbances include drought stress, forest fire risk, wind throw and pest and pathogen outbreaks caused by heatwave, heavy storms, and floods etc. (Anderegg et al. 2013; Reichstein et al. 2013). Among all the disturbances, forest wildfire and drought- and heat-induced forest mortality are particularly of research interest because they have occurred all over the world (Anderegg et al. 2013; Flannigan et al. 2013; Goto and Suzuki 2013; Reichstein et al. 2013; van der Werf et al. 2004). Figure 1-1 shows some of the examples of widespread drought induced-tree mortality in many forest biomes globally. Predicted-results show that both forest disturbance events will be expected to exacerbate and co-occurred in the future (Adams et al. 2009; Allen 2009; Allen et al. 2010; Liu et al. 2012; Mantgem et al. 2013; Moritz et al. 2012; Williams et al. 2014). Drought stress will increase forest fire severity and fire can destroy plant xylem conductivity, these interactions are not varying substantially across geographical regions (Mantgem et al. 2013). Hence, accurate quantitatively estimation of forest drought and fire is an urgent task, although there are abundant annual rainfall (1000-4000mm) (Forestry Agency Japan 1990) and few drought-induced forest mortality events are observed in Japan, future threaten by rising temperature and high rate of forest fire events, about 3000 times per year (Satoh et al. 2004) and large annual forest area burnt (Figure 1-2) make it still necessity.

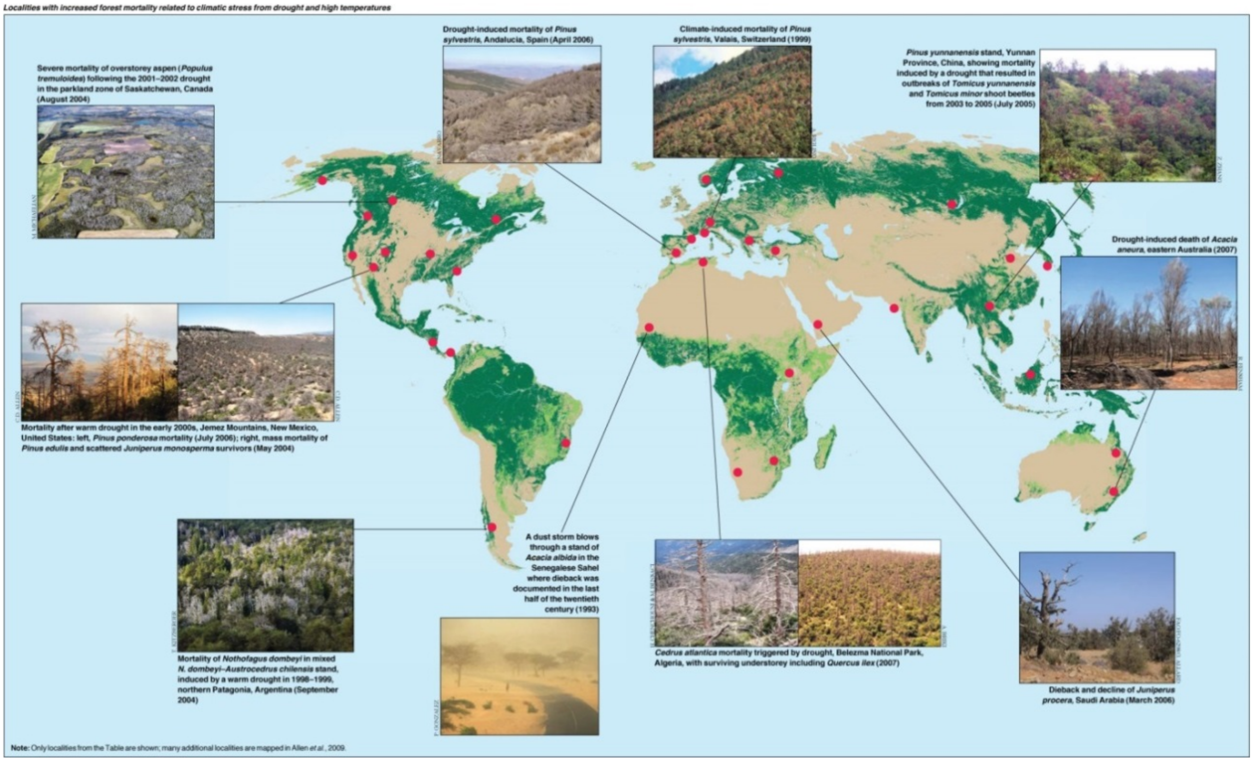

Figure 1-1 Examples of increased tree mortality caused by drought and high temperatures during the last two decades all over the world (Allen 2009).

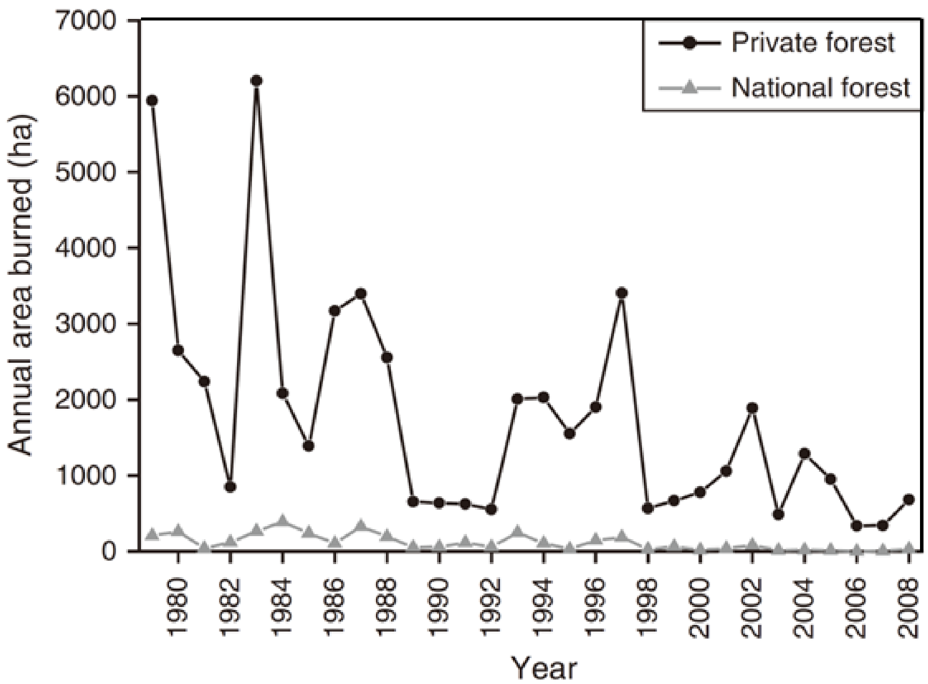

Figure 1-2 Annual area burnt in national and private forests of Japan during the period 1979 through 2008 (Goto and Suzuki 2013).

However, direct measurement of these disturbances is time or labor-intensive and costly, and usually limited by the lack of a complete monitoring system which extremely rely on meteorological data (Mu et al. 2013), while remote sensing provides a practical means to assess forest disturbances across a range of scales and its rapid advances substantially improve the understanding of disturbances (McDowell et al. 2014).

1.1.2 Indicators of plant drought stress and wildfire

The basic principle for monitoring plant drought stress and wildland fire by remote sensing is based on potential link between vegetation spectral characteristic and disturbance information which is often obtained from plant biochemical and biophysical parameters (Carter 1994; Carter and McCain 1993; Garbulsky et al. 2011; Jackson et al. 1983; Yebra et al. 2013). Theoretically, the retrieval of these parameters can offer the possibilities to assess forest drought and fire.

Recently, more efforts have been focused on the physiological mechanisms of drought-induced tree mortality, two hypotheses, hydraulic failure and carbon starvation are proposed to explain tree death (McDowell et al. 2008; McDowell et al. 2013). Meanwhile, lab-controled experimental observations also have been carried out to test both hypotheses (Hartmann et al. 2013a; Hartmann et al. 2013b; Sevanto et al. 2014; Zhao et al. 2013). Although assessments of the individual contributions of two interdependent mechanisms are difficult, the common observed results demestrate that hydraulic failure is closely related to leaf water status and carbon starvation is fairly regulated by the process of photosynthesis (McDowell et al. 2008; McDowell et al. 2013; Way et al. 2013). The estimations of both leaf water status (Bowman 1989; Cheng et al. 2011; Clevers et al. 2010; Colombo et al. 2008; De Jong et al. 2014; Gao 1996; Hunt Jr et al. 1987; Jacquemoud et al. 2009; Peñuelas et al. 1993; Pu et al. 2003; Sims and Gamon 2003; Tucker 1980; Zarco-Tejada et al. 2003) and photosynthesis status (Barton and North 2001; Gamon et al. 1992; Gamon et al. 1997; Gamon et al.

1993; Gamon et al. 2005; Garbulsky et al. 2011; Wong and Gamon 2015a,b) from remote sensing data have been tentatively implemented across a range of spatial and temporal scales. Available leaf water status related water stress include water potential, relative water content (RWC, %) and equivalent water thickness (EWT, g/cm^2). Gas exchanges and chlorophyll fluorescence are two commonly available photosynthesis statuses.

Among all leaf water status, the most used indicator is EWT, the amount of water content per unit leaf area, because it is an input parameter for PROSPECT model (Jacquemoud and Baret 1990; Jacquemoud et al. 1996; Jacquemoud et al. 2009). RWC, the ratio of the leaf water content at full turgor, is another popular leaf water indicator and draw more attention due to its direct relationship with drought stress (Carter 1994; Peñuelas et al. 1993). Chlorophyll fluorescence parameters are often regarded as indicator of photosynthesis status for remote sensing since it can trace variation of photosynthesis yield (Garbulsky et al. 2011; Wong and Gamon. 2015a,b).

Similarly, the indicator fuel moisture content (FMC), the mass of leaf water in relation to leaf dry mass, has also been widely retrieved by remote sensing in the past several decades (Wang et al. 2013; Yebra and Chuvieco 2009; Yebra et al. 2008; Yebra et al. 2013) as it is a critical variable for fire behavior prediction models and affects combustion, fire severity and spread, fire propagation(Viegas et al. 1992). In this study, leaf EWT, RWC, chlorophyll fluorescence and FMC were used as the remotely estimation indicators.

1.1.3 Remote sensing approach

Remote sensing has been proved as a reliable and rapid method to estimate various biophysical and biochemical variables across different spatial and temporal scales, particularly hyperspectral remote sensing which can provide more detail spectral information than traditional broad-band remote sensing (see section 1.2). Recently, the commonly retrieved indicators by remote sensing can be categorized into two different types, physical-related change detection and functional-related change detection. Leaf water status of EWT and FMC can be estimated by physical radiative transfer model (see 1.2.1), and chlorophyll fluorescence parameters such as quantum yield of PSII can be estimated based on functional-related mechanism (see 1.2.2).

1.2 State of the art

Hyperspectral remote sensing has advantages of hundreds of narrow contiguous bands from 400 to 2500 nm, which can avoid the loss of crucial information available in specific narrow bands. Currently, two common remote sensing approaches, physical model inversion (Jacquemoud and Baret 1990; Jacquemoud et al. 1996) and spectral indices(Ceccato et al. 2001; Ceccato et al. 2002b; le Maire et al. 2008; Le Maire et al. 2004), have been successfully used to estimate vegetation biochemical and biophysical parameters. And the applications of hyperspectral remote sensing at large scales will move a substantial stage duo to the continuing improvements in spectral resolution of the optical sensors.

1.2.1 Radiative transfer model

Different leaf-radiative transfer models have been developed for broadleaves (Jacquemoud and Baret 1990) and needle-shaped leaves(Dawson et al. 1998) to interpret the interactions between electromagnetic radiation and vegetation leaves. The widespread model in remote sensing for broadleaves, PROSPECT, is used in this study, which is firstly proposed by Jacquemoud and Baret in 1990. Briefly, PROSPECT is a simple plate model assuming leaf as a succession of absorbing layers. Leaf reflectance and transmittance from 400 to 2500 nm with a step of 5 nm can be calculated by four input parameters: leaf structure index (N), leaf chlorophyll content (Cab, μg/cm^2), leaf water content (Cw or EWT, g/cm^2), and leaf mass area (Cm or LMA, g/m^2). The leaf reflectance and total absorption coefficient k for one layer is calculated by specific absorption coefficients K of each component. More details are as follows:

$$k(\lambda) = k_e(\lambda) + \frac{C_{ab}}{N} K_{ab}(\lambda) + \frac{C_m}{N} K_m(\lambda) + \frac{C_w}{N} K_w(\lambda) \qquad (1)$$

where k is the wavelength, k_e (λ) is the absorption of an "albinos" leaf, and K_{ab}, K_m, and K_w are the specific absorption coefficients of chlorophyll a+b, leaf dry matter and leaf water content, respectively. After then, several improved versions have been released, including the introduction of absorption properties from individual dry mater components such as cellulose and lignin (Baret and Fourty 1997; Jacquemoud et al. 1996), the improvement of spectral resolution from 5 nm to 1 nm (Feret et al. 2008; Le Maire et al. 2004), combination of chlorophyll a fluorescence emission (Pedrós et al. 2010), separation of individual photosynthetic pigment(Feret et al. 2008) and up-scaled PROSAIL model (Jacquemoud et al. 2009). Recently, the most used version only takes N, Cab, Cw and Cm into account with a 1 nm step (Feret et al. 2008). PROSPECT can simulate thousands of reflectance that are hardly obtained from the field based on a series of combinations of input parameters to determine the universal indices which are applicable to a wide range of species and leaf structure(le Maire et al. 2008; Le Maire et al. 2004). However, model inversion faces a serious ill-posed inverse problem, meaning that various combinations of input parameters might yield similar spectra (Li and Wang 2011; Yebra and Chuvieco 2009). Moreover, there are many other parameters which are not as inputs in the PROSPECT still need to be estimated. Thus, in this study, spectral indices, an important statistical method, were used to determine the best indices for leaf photosynthesis status and RWC, only retrieval of FMC was based on measured jointly with simulated datasets which are generating from PROSPECT-4 developed by Feret et al. (2008).

1.2.2 Spectral indices

The ill-posed problem limits the application of radiative transfer model, spectral indices is an alternative approach based on the reflectance combination of different wavelengths computed from various mathematical equation. To data, a large number of spectral indices for target parameters (RWC, EWT and FMC) have been developed and applied to different vegetation types at leaf and canopy scales (Table 1-1), including simple spectral wavelength, spectral ratio, normalized ratio and first derivatives reflectance and its ratios. Most of these indices have been designed generally using the typical absorption bands by water centered at around 970 nm, 1200 nm, 1450 nm, 1940 nm and 2500 nm or by leaf dry mater centered at such as around 1650nm and 2100 nm. For example, R1450, R1950 and R2500 for RWC applied to *Acer platanoides L.* and *var* Emerald Queen (Carter and McCain 1993), WI (Peñuelas et al. 1993) and R1300/R1450 (Seelig et al. 2008b) for RWC, NDWI (Gao 1996) and MSI(Ceccato et al. 2001; Hunt and Rock 1989) for EWT and dSR(2110, 2260) for FMC (Wang and Li 2012b). Although strong correlations have been observed between these indices and target parameters, these indices are usually calibrated based on a specific database, which means these indices may not be suitable for other databases(le Maire et al. 2008). Most importantly, extreme drought stress conditions were not included, which is critical for drought-induced forest mortality. There has been no study examining the relationship between leaf water status and hyperspectral indices of various types as reviewed by le Maire et al (2004, 2008) which are essential for determining universal indices. For example, le Maire et al (2004) attempted to design universal broad leaf chlorophyll indices using PROSPECT simulated and hyperspectral measured database combining index types from simple ratios to more sophisticated indices of first derivatives reflectance. Furthermore, forest fire is significantly affected by fuel types, among all the FMC indices, most of them are specially designed for LMA or EWT of green leaves. Newly FMC indices for different fuel types are needed to be designed for monitoring forest fire risk in the future.

Previous studies have demonstrated that photosynthetic status is greatly affected by drought stress, including stomatal closure, a decrease in photosynthetic efficiency and so on (Sevanto et al. 2014; Souza et al. 2004). How to remotely and dynamically monitor these changes is still a considerable challenge due to the fact that rapid changes in plant photosynthetic status brought by stress are hardly tracked and the link between indices and photosynthetic functioning is uncertain. Even so, a number of attempts have been made to develop the spectral indices for monitoring photosynthetic status, however, most existing vegetation indices only can be used for estimating pigment contents (Feret et al. 2008; Filella and Penuelas 1994; Le Maire et al. 2004; Sims and Gamon 2002), vegetation distribution or net primary productivity (Box et al. 1989; Newnham et al. 2011; RAYMOND HUNT 1994; Schloss et al. 1999). For example, Normalized Difference Vegetation Index (NDVI) can be used as an empirical indicator of spatial and temporal variability of greenness for certain ecosystems(Newnham et al. 2011). But it is a poor indicator for temporal variation in photosynthetic status, particularly for evergreen species (Gamon et al. 1995).

Photochemical Reflectance Index (PRI, [R531−R570]/[R531+R570]) has been developed to remotely assess photosynthetic efficiency or photosynthetic light use efficiency (Gamon et al. 1990; Gamon et al. 1992; Gamon et al. 1997; Garbulsky et al. 2011; Peñuelas et al. 1997a; Peñuelas et al. 1994; Penuelas et al. 1995; Stylinski et al. 2002; Wong and Gamon 2014, 2015) since 531 nm is related to the de-epoxidation state of the xanthophyll cycle which has a link with the photosynthesis protection mechanism from extra light or heat (Demmig-Adams and Adams Iii 1992). However, the relationship between PRI and photosynthetic status under drought is unclear although PRI always is used as water stress indicator. Chlorophyll fluorescence is an alternative mean for the estimation of leaf physiological status bacause it can track the real-time varition of photosynthetic efficiency (Genty et al. 1989; Kooten and Snel 1990; Maxwell and Johnson 2000) and its parameters always are used to test PRI (Garbulsky et al. 2011). These parameters include photochemical quenching (qP), non-photochemical quenching (NPQ) and quantum yield of PSII and so on. Thus, an attempt examining the relationship between chlorophyll fluorescence paremeters and hypespectral reflectance under extreme drought condition was essential.

Table 1-1 published spectral indices for RWC, EWT and FMC

Index	Scale	Related to	Species	Reference
R810, R1665, R2210	Leaf	RWC	*Gossypium hirsutum* cv. Stoneville 825	(Bowman 1989)
R1450, R1950, R2500	Leaf	RWC	*Acer platanoides L.* *var* Emerald Queen	(Carter and McCain 1993)
R695/R420, R605/R760 R695/R760, R710/R760	Leaf	RWC	*Arundinaria gigantea (Walter)* Muhl.	(Carter 1994)
LWCI: $-\log[1-(TM4-TM5)]/$ $-\log[1-(TM4_{full\ turgor}-TM5_{full\ turgor})]$	Leaf	RWC	*Agave deserti Engelm*	(Hunt Jr et al. 1987)
WI: R970/R900	Leaf	RWC	*Gerbera jamesonii; Capsicum annuum; Phaseolus vulgaris*	(Peñuelas et al. 1993)
R1300/R1450	Leaf	RWC	*Spathiphyllum lynise*	(Seelig et al. 2008b)
RRI(1455): $(R1455_{time\ of\ stress}$ $-R1455_{control})/R1455_{control}$	Leaf	RWC	*Olea europaea L.*	(Sun et al. 2008)
$2R_{960-990}/(R_{920-940}+R_{1090-1110})$ $2R_{1180-1220}/(R_{1090-1110}+R_{1265-1285})$	Leaf	RWC	*Quercus agrifolia*	(Pu et al. 2003)
NDVI(895, 675)	Canopy	RWC	*Ceanothus chaparral* *Chamise chaparral* *Coastal sage scrub*	(Serrano et al. 2000)
MDWI: $(R_{max1500-1750}-R_{min1500-1750})/$ $(R_{max1500-1750}+R_{min1500-1750})$	Leaf and Canopy	RWC EWT	*Populus spp.*	(Eitel et al. 2006)
MSI: SR(1600, 820)	Leaf	EWT	LOPEX93 (about 50 species)	(Ceccato et al. 2001; Hunt and Rock 1989)
d940, d1000, d1150, d1240, d1380, d1550, d1920, d2100	Leaf	EWT	26 species	(Danson et al. 1992)
(R850-R2218)/(R850-R1928) (R850-R1788)/(R850-R1928)	Leaf	EWT	*21 Eucalyptus species*	(Datt 1999)
(R970-R1060)/90	Leaf	EWT	*Arbutus unedo* *Quercus ilex* *Quercus pubescens*	(De Jong et al. 2014)
R960/R950	Leaf	EWT	*Citrus Unshiu Marcovitch*	(Dzikiti et al. 2010)
R1070/R1340	Leaf	EWT	*Vitis vinifera* cv. Pinot noir	(Rodríguez-Pérez et al. 2007)
dSR(1510, 1560)	Leaf	EWT	*Fagus crenata* (main species) and other 15 species	(Wang and Li 2012b)
DDn(1530, 525)	Leaf	EWT	*Fagus crenata* (main species) and other 15 species	(Wang and Li 2012a)
SR(2307, 1347)	Leaf	EWT	*Gossypium hirsutum L.*	(Zhang et al. 2012)

ND(1347, 2307)				
NDWI: ND(860,1240)	Canopy	EWT		(Gao 1996)
$R_{1150\text{-}1260}$ $R_{1520\text{-}1540}$	Canopy	EWT	23 species	(Sims and Gamon 2003)
GVMI: ((NIR+0.1)-(SWIR+0.02))/ ((NIR+0.1)+(SWIR+0.02))	Canopy	EWT		(Ceccato et al. 2002a; Ceccato et al. 2002b; Chuvieco et al. 2002)
ND(860, 1200) ND(860, 1450) ND(860, 1940)	Leaf and Canopy	EWT FMC	wheat	(Wu et al. 2009)
SRWI: R858/R1240	Canopy	CWC FMC	7 Chaparral species	(Zarco-Tejada et al. 2003)
(R1050-R1015)/35	Canopy	CWC		(Clevers et al. 2010)
slopes of the 970 and 1200 nm	Canopy	CWC	More than 10 species	(Clevers et al. 2008)
ND(858, 2130) ND(858, 1640)	Canopy	CWC	corn and soybeans	(Chen et al. 2005)
NDII: ND(819,1600)	Canopy	(Fw-Dw)/Fw	*Spartina alterniflora*	(Hardinsky et al,1983)
dSR(2110, 2260)	Leaf	FMC	*Fagus crenata* (main species) and other 15 species	(Wang and Li 2012b)
SR(1801, 1650) ND(1650,1801)	Leaf	FMC	*Gossypium hirsutum L.*	(Zhang et al. 2012)
WI NDWI	Canopy	FMC	*Adenostoma fasciculatuml;* *Ceanothus megacarpus;* *Ceanothus crassifolius;* *Salvia mellifera; Salvia leucophylla;* *Artemisia californica*	(Roberts et al. 2006)
NDWI	Canopy	FMC	*Adenostoma fasciculatum* *Salvia leucophylla, Salvia mellifera* *Ceanothus megacarpus* *Salvia mellifera*	(Dennison et al. 2005)
NDWI	Canopy	FMC	savanna	(Verbesselt et al. 2007)
MSI	Canopy	FMC	*Calluna vulgaris*	(Al-Moustafa et al. 2012)
NDII	Canopy	FMC		(Caccamo et al. 2012)
NDVI	Canopy	FMC	*Agropyron caninum* *Artemisia tridentate* *Pseudotsuga menziesii* *Pinus ponderosa* *Carex geyeri, Berberis repens* *Symphoricorpos albus*	(Hardy and Burgan 1999)
NDII/NDMI: ND(860,1650)/ND(1649, 1722)	Leaf Canopy	FMC	*Quercus alba L* *Acer rubrum L. Zea mays L.*	(Wang et al. 2013)

RWC: relative water content; EWT: equivalent water thickness; FMC: fuel moisture content; CWC: canopy water content; Fw: leaf fresh weight; Dw: leaf dry weight

1.3 Objectives of this study

This study aims to investigate the hyperspectral indices for estimating the forest drought stress- and wildfire- related indicators, both physical and physiological, including leaf RWC, EWT, FMC, and quantum yield of PSII. Two experiments were designed to understand the physiological characteristic and variation of reflectance for different type fuels during gradually dehydration of green leaf and fallen litter. In the green leaf dehydration experiment, leaf reflectance, chlorophyll fluorescence, leaf water content and leaf weight were measured. In the fallen litter refreshing, leaf reflectance, leaf water content and weight were measured. The main objectives are to: (1) provide leaf reflectance, leaf RWC and EWT variations of different broadleaved species in the temperate climate zone during dehydration processes to compose a comprehensive dataset within biological realities and identify the best hyperspectral indices for estimating leaf RWC and EWT based on different types and different treatments of reflected spectra; (2) investigate the response of chlorophyll fluorescence and leaf reflectance ranging from 400-800 nm to drought stress; examine whether PRI can be used to trace the variation of quantum yield of PSII and attempt to identify best hyperspectral indices for quantum yield of PSII; (3) compare the variations of leaf reflectance and first derivative spectra in two different fuel types during dehydration processes and determine the best hyperspectral indices for FMC based on PROSPECT simulated and measured datasets with an attempt to separate FMC estimation in the two fuel materials.

Chapter 2 Best hyperspectral indices for tracing RWC and EWT as determined from leaf dehydration experiments

2.1 Introduction

Plant water status is closely related to forest mortality and physiological processes, which are still poorly understood (Sala *et al*., 2010). Studies have showed that a decreased leaf water content slows the rate of photosynthetic carbon assimilation (Lawlor and Cornic, 2002) and strongly decreases the intrinsic photochemical efficiency and electron transport rate of PS II (Augusti *et al*., 2001), which would result in plant carbon starvation or hydraulic failure, leading to plant death (McDowell *et al*., 2008; McDowell *et al*., 2013; Sevanto *et al*., 2014). Therefore, leaf water status information is highly needed for monitoring plant physiological processes and assessing drought stress.

Traditional measurements on leaf water status are time-consuming, destructive, and point-based, which make it difficult to be up-scaled to reflect regional leaf water status (Penuelas *et al*., 1993). In recent decades, remote sensing has been shown to be an effective method to assess plant water status across different scales (Ceccato *et al*., 2001; Ceccato *et al*., 2002a, b; Gao, 1996; Hunt *et al*., 1987; Penuelas *et al*., 1993; Sims and Gamon, 2003; Zarco-Tejada *et al*., 2003). Two widespread remote sensing approaches, i.e. model inversion (Jacquemoud *et al*., 1996) and spectral indices (e.g. Ceccato *et al*., 2001), have been developed to retrieve leaf water status based on reflectance data. Compared to model inversion, the spectral indices approach, which is based on combinations of several narrow or broad spectral bands, is simple and correlates well with leaf water status. Thus, how to design a general spectral index to estimate vegetation water status by remote sensing data has consequently drawn more attention (e.g. Ceccato *et al*., 2002a, b; Sims and Gamon, 2003; le Maire *et al*., 2008).

A general approach to identify the best spectral indices is based on field measured datasets that are usually enclosed measurements of different species under different ecological conditions. Different water indices have been designed from previous studies such as the normalized difference water index (Gao, 1996) and water index (Penuelas *et al*., 1993), which generally use the typical absorption bands by water centered at around 970 nm, 1200 nm, 1450 nm, 1940 nm and 2500 nm; and strong correlations have been observed between these indices and leaf water content. However, these indices are usually calibrated based on a specific database, which means these indices may not be suitable for other databases (le Maire *et al*., 2008). In addition, the method is time and labor consuming, making it difficult to obtain a large dataset. Furthermore, numerous factors greatly affect the relationships, including water stress, plant species, growing conditions and phenological stages (Wang and Li., 2012b). Alternatively, simulated or a combination of simulated and measured datasets are proposed to generate universally applicable indices, e.g. Wang and Li (2012a, b) have reported two new hyperspectral indices (dSR(1510, 1560) and DDn(1530,525)) for temperate deciduous plant water status, using both simulated and field datasets across a wide range of species. Even so, simulated and field datasets seldom include extreme cases, leading to nearly all spectral indices being unable to retrieve the leaf water content under extreme water stress conditions. This renders these indices poorly applicable to monitoring forest mortality, because all of the datasets are mainly obtained from or simulated for healthy leaves under normal natural conditions. Although, on the other hand, simulated datasets may include all extremes theoretically, biological responses to such extremes are poorly distinguished, as for most cases only physically unrealistic combinations of different model inputs are prevalent, leading to inaccuracies in applying identified indices to real applications.

The reflectance of dying leaves in different stages of water stress is quite different from that of healthy leaves, and leaf reflectance significantly increases throughout the 400-2500 nm domain during the dehydration process (Carter, 1991, 1993; Foley *et al*., 2006; Richardson and Berlyn, 2002; Seelig *et al*., 2008b). Previous studies have shown that leaf dehydration experiments can provide a dataset with a wide range of leaf water conditions and biological realities, which may be more suitable for index identification than field measurements under water stress conditions, because experiments can not only trace the changes in leaf water status and physiological processes in a time and labor saving way, but can also obtain extreme leaf water conditions (Carter, 1991; Penuelas *et al*., 1993, 1997b; Seelig *et al*., 2008b). The water indices SR(970, 900) and SR(1300, 1450) have been presented based on progressive dehydration experiments (Penuelas *et al*., 1993; Seelig *et al*., 2008b). However, these studies only focused on a single type of index (simple ratios of two wavelengths near the water absorption bands) based on a dataset with only a few plant species.

Previous studies also demonstrated that the reflectance near 700 nm and its ratio with near infrared reflectance can provide the detection of plant water stress (Carter, 1994; Carter and Knapp, 2001; Carter and Miller, 1994). However, the wavebands near 700 nm are strongly influenced by pigments, meaning they cannot directly provide plant water information. To our knowledge, there has been no study examining the relationship between leaf water status and hyperspectral indices of various types. Commonly used types of indices, including reflectance at a given wavelength (R), wavelength difference (D), simple ratios (SR), normalized differences (ND) and double differences (DDn) then need to be explicitly examined. In addition, specific conversion on leaf original reflectance can usually be performed to improve the performance of indices. For instance, the derivative spectra technique (dR) can eliminate background noise and resolve overlapping spectral features (Demetriades-Shah *et al*., 1990).

The objectives of the current study were: 1) to provide leaf reflectance, leaf RWC and EWT variations of different broadleaved species in the temperate climate zone during dehydration processes to compose a comprehensive dataset within biological realities; 2) to validate the performance of existing spectral indices for tracking leaf water status; and 3) to identify the best hyperspectral indices for estimating leaf water status based on different types and different treatments of reflected spectra. This study was based on leaf dehydration experiments using five common species of temperate zone ecosystems.

2.2 Material and methods

2.2.1 Leaf sampling and dehydration measurements

Leaves of four deciduous species, i.e. *Zelkova serrata, Idesia polycarpa, Liquidambar styraciflua* and *Prunus x yedoensis*, were collected around the campus of Shizuoka University, and another dominant temperate deciduous species (*Fagus crenata*) was collected from Mount Naeba, Japan. All samples were collected by the detached branch technique which is recognized to be accurate and reliable for reflectance and photosynthesis parameter measurements under non-*in situ* conditions (Koike, 1986; Foley *et al*., 2006; Richardson and Berlyn, 2002). The branches with target leaf samples were cut pre-dawn, and re-cut under water to avoid a loss of branch conductance. The samples were stored hydrated under dim light, high humidity and cool temperatures before measurement. In total, 24 leaf samples were collected for five plant species, including 4 sunlit leaves and 4 shaded leaves for *F. crenata* and 4 sunlit leaves for each of the other four species. All the samples selected were mature fully expanded leaves.

The measurements were conducted in the laboratory in the middle of September, 2013, when mean day temperature was about 25°C and average relative humidity was around 75%. For each leaf sample, fresh leaf reflectance and weight were firstly measured, and then kept naturally under dehydrated conditions. Leaf reflectance and weights were measured synchronously at every 1h for the first 5h but less frequent in later during the entire leaf dehydration period (ca. 24 hours) until the leaf sample was air-dried to a stable weight. Finally, the air-dried samples were oven-dried at 70°C for 72 h and then weighed again. The total number of measurements was 224 for both leaf reflectance and leaf weight.

Leaf reflectance spectra were measured in the optical range (350-2500 nm) using a field spectroradiometer (ASD FR, USA) equipped with a leaf clip, in which a light source of a tungsten quartz halogen lamp was embedded. The spectral resolution was 3 nm at 700 nm and 30 nm at both 1400 nm and 2100 nm. The sampling interval was 1.4 nm from 350 nm to 1050 nm and 2 nm from 1000 nm to 2500 nm. White reference scan was made for the calibration before reflectance measurement, which was done in the leaf clip with matched openings for non-destructive contact measurements. Synchronously, leaf weight was measured using an electronic balance right after reflectance measurement to make sure both measurements were under similar water status as possible.

2.2.2 Leaf water status

Leaf relative water content (RWC) and equivalent water thickness (EWT) are commonly used as indicators for plant water status, both of which were selected for the current study. RWC refers to the ratio of the water content to the maximum water content at full turgor for one given leaf (Hunt *et al*., 1987). EWT is the amount of water content per unit leaf area, which is more associated with energy absorption (Jacquemoud *et al*., 1996). Here, we defined RWC as the ratio of the leaf water content at time T (h) to the water content of the fresh leaf, not the water content at full turgor. This ratio is positively correlated with the ratio using the leaf water content at full turgor.

$$RWC\ (\%) = (W_T - W_D)/\ (W_F - W_D);$$

$$EWT\ (g/cm^2) = (W_T - W_D)/LA.$$

where W_T, W_D, W_F and LA represent leaf weight at time T (h) after leaf cutting, dry weight, fresh weight and leaf area, respectively.

2.2.3 Published indices for estimating leaf water status

A number of hyperspectral indices have been developed for estimating plant water status based on normalized ratios or simple ratios of different wavelengths. In this study, six indices reported in previous works were selected to test their performance in monitoring leaf water status during the dehydration process. The selected indices are listed in Table 2-1.

Table 2-1 Published water indices for assessing leaf water status

Index	Formula	References
WI	R970/R900	Penuelas *et al*. (1993)
SR(1300,1450)	R1300/R1450	Seelig (2008b)
NDWI	(R860-R1240)/ (R860+R1240)	Gao (1996)
SRWI	R860/R1240	Zarco-Tejada *et al*.(2003)
NDII	(R819-R1600)/(R819+R1600)	Hardisky *et al*. (1983)
DDn(1530,525)	2R1530-R1005-R2055	Wang and Li (2012a)

2.2.4 Determination of the best indices

We used four different treatments of reflectance (original reflectance, reflectance difference, reflectance sensitivity and the first derivative of reflectance) and five types of indices (R, D, SR, ND and DDn), which are currently the most widely used, as reviewed by le Maire *et al*. (2008), to determine the best indices for RWC or EWT.

Reflectance difference = R_T-R_F

Reflectance sensitivity = (R_T-R_F)/R_F

First derivative=dR

where R_T, R_F and dR are reflectance at the time T (h) after leaf cutting, fresh leaf reflectance and first derivative of reflectance, respectively.

The same equations presented below were applied using the original reflectance,

reflectance difference, reflectance sensitivity and the first derivative reflectance. Specially, indices based on the first derivative treatment are termed as dR, dD, dSR, dND and dDDn.

$R=R_{\lambda 1}$

$D=R_{\lambda 1}-R_{\lambda 2}$

$SR=R_{\lambda 1}/R_{\lambda 2}$

$ND= (R_{\lambda 1}-R_{\lambda 2})/ (R_{\lambda 1}+R_{\lambda 2})$

$DDn=2R_{\lambda 1}-R_{\lambda 1-\Delta}-R_{\lambda 1+\Delta}$

where $R_{\lambda 1}$, $R_{\lambda 2}$ and Δ represent wavelengths at $\lambda 1$, $\lambda 2$ and interval wavelengths, respectively. R, D, SR, ND and DDn are reflectance at a given single wavelength, wavelength difference, simple ratio, normalized ratio and double difference, respectively.

2.2.5 Statistics

Identification of best hyperspectral indices for tracing leaf water status was based on a calibration dataset that was made of 18 leaf samples including three sun-leaves and three shade-leaves for F. *crenata* and three leaves each for the other four species (156 measurements in total), while the remainder (68 measurements for six leaf samples) were used for validating identified indices in this study. The tests were run on the calibration dataset to identify the best index. Once this was done and the best index selected was applied to the validation dataset to confirm its robustness.

The determination of indices was conducted by liner regression between a given index and RWC or EWT in the entire wavelength domain. Regression analysis was performed for all possible combinations of wavelengths for a given index type. The wavelength interval was 5 nm. Statistical criteria to evaluate the performance of published/identified indices were based on the root mean square error (RMSE) and the coefficient of determination (R^2). And the best index was identified as the combination with the lowest RMSE and the highest R^2.

2.3 Results

2.3.1 Temporal variation in RWC, EWT and leaf reflectance

Both RWC and EWT dropped rapidly from the maximum to a near minimum within 10 h after leaf cutting, particularly in the first 5 h. After 10 h, the values of RWC and EWT were maintained stably near zero for each species (Figure. 2-1), indicating the leaves were totally dehydrated. For RWC, the decreasing rates of all species were similar and could be fitted by an exponential curve, which had an intercept of 2.51%, approximated to the average water content of air-dried leaves. However, changes in EWT were relatively diverse due to the wide range of starting values of different species, with the highest value found for *L. styraciflua* and the lowest value for *F.crenata* (Figure. 2-1).

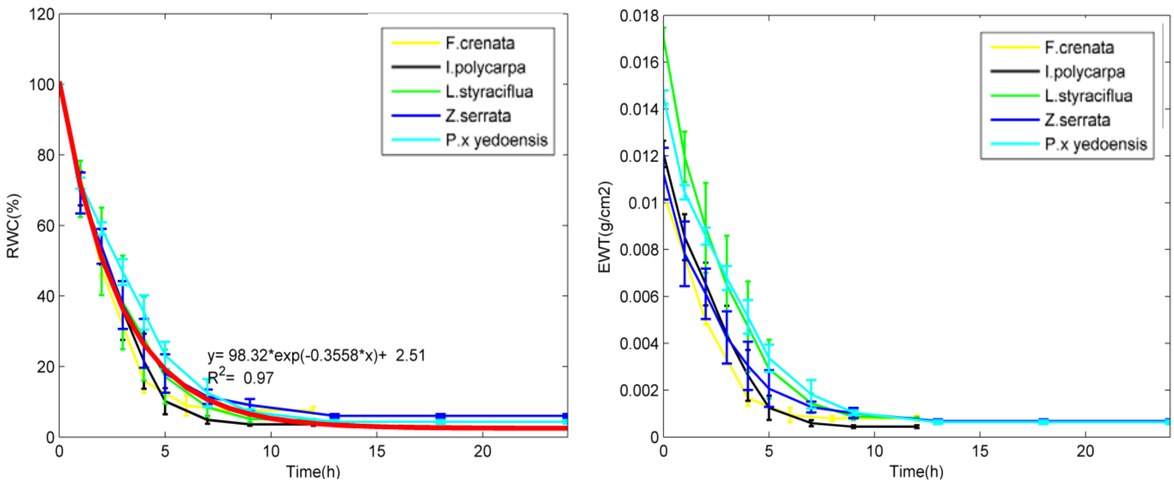

Figure 2-1 Changes in RWC and EWT over time following leaf cutting

Changes of measured reflectance, reflectance difference with the starting reflectance, reflectance sensitivity and the first derivative of reflectance for each species along the progress of leaf dehydration are shown in Figure 2-2. As RWC decreased, reflectance tended to increase throughout most of the 350-2500 nm range for all species, particularly within the 350-700 nm range and near the water absorption bands at 1450 nm, 1940 nm and 2500 nm, although there were some inconsistencies. This phenomenon was also shown by the increase in reflectance difference and reflectance sensitivity whose curves were much smoother. The most important difference among species in reflectance was the slope from 750 nm to 1000 nm; e.g., the reflectance ranging 750 nm to 1000 nm for *L. styraciflua* increased as the RWC decreased, yet the reflectance at the same range for *F. crenata* did not show such an increase, with higher reflectance appeared in RWC of 48% and lower reflectance in RWC of 16%. Variability in the reflectance of *I. polycarpa* was similar with that of *F. crenata*, and the reflectance variations of *Z. serrata* and *P. x yedoensis* were similar with *L. styraciflua*, generally increasing during leaf dehydration. This difference also can be seen in the reflectance difference and reflectance sensitivity among different plant species.

Compared with reflectance, reflectance difference and reflectance sensitivity, the first derivative of reflectance provided more detail information about the response to dehydration. Although there were some difference in reflectance within the 700-800 nm domain, “blue shift”, an indicator of senescence, could be seen from the first derivative of reflectance among all plant species. Correspondingly, the reflectance in the red edge increased with time. Contrary to “blue shift”, the left edges of the water absorption troughs centered at 970 nm, 1150 nm, 1450 nm and 1940 nm generally shifted to longer wavelengths, and the minima of the first derivative increased for the left edges in the troughs 970 nm, 1150 nm and 1450 nm, first decreasing and then increasing for the 1940 nm trough with a decrease in leaf water content. Meanwhile, several new reflectance peaks and troughs could be observed from the first derivative, which were in agreement with original reflectance variations ranging from 2000 nm to 2500 nm.

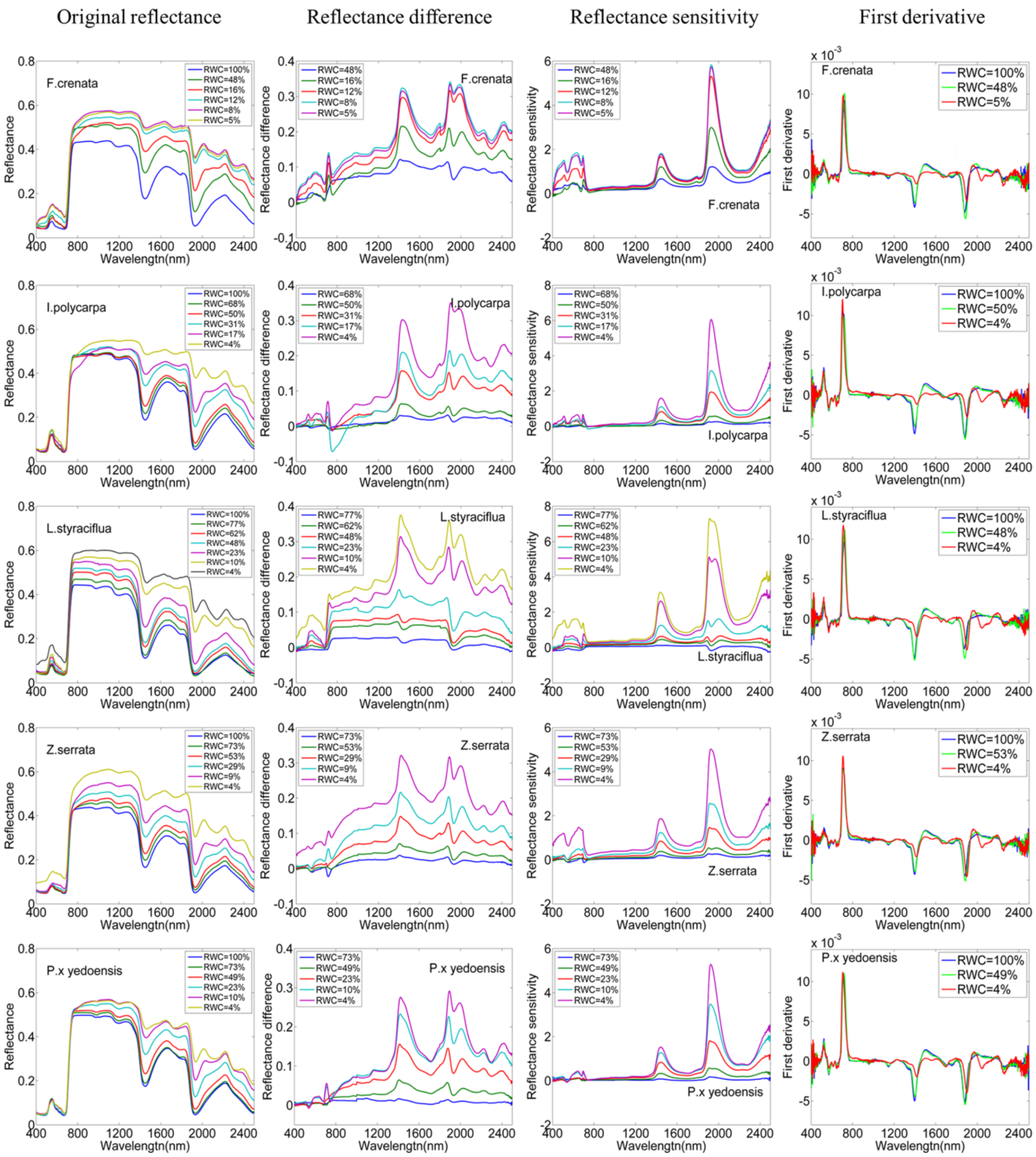

Figure 2-2 Changes of Reflectance spectra, reflectance differences, reflectance sensitivities and first-derivative reflectance spectra for different plant species attributed to progressive RWC

2.3.2 Performance of the reported indices

Table 2-2 presents the performance of all indices selected for tracing the variation in RWC and EWT. All correlations between either RWC or EWT and the six reported indices were significant. The performances of most indices were well for individual species (data not shown), with higher R^2 (all values of R^2 were greater than 0.78) and lower RMSE. However, when considering all the species, the performances were much poorer, especially for RWC, whose R^2 values were all below 0.73. For instance, the correlations between RWC and WI for *I. polycarpa*, *L. styraciflua*, *Z. serrata*, *P. x yedoensis* and *F. crenata* were significant with R^2 of 0.81, 0.93, 0.87, 0.88 and 0.86, respectively. However, the R^2 dropped to 0.70 with composite datasets from individual species. Judging from the R^2 and RMSE values, the best index for predicting RWC and EWT was R (1300, 1450) among the six indices for all measurements, with R^2 values of 0.73 and 0.94, and RMSE of 17.73% and 0.0010 g/cm^2, respectively. In general, all selected indices were better for EWT than for RWC, indicated by the higher R^2 values (Table 2-2).

Table 2-2 Published water indices tested for RWC and EWT based on measured datasets (all measurements = 224)

Indices	Indicators	R^2	RMSE(% or g/cm^2)
WI	RWC	0.70	18.43
	EWT	0.71	0.0022
SR(1300,1450)	RWC	0.73	17.73
	EWT	0.94	0.0010
NDWI	RWC	0.69	18.92
	EWT	0.66	0.0024
SRWI	RWC	0.70	18.59
	EWT	0.67	0.0024
NDII	RWC	0.68	19.28
	EWT	0.85	0.0016
DDn(1530,525)	RWC	0.67	19.57
	EWT	0.90	0.0013

(The number of measurements, n=224; P<0.001)

2.3.3 Newly identified indices for tracing leaf water status

For each type of index, the combination of different wavelengths with the highest R^2 and the lowest RMSE based on original reflectance, reflectance difference, reflectance sensitivity and the first reflectance derivative and their performance with validation dataset are listed in Tables 2-3, 2-4, 2-5, 2-6, and the R^2 matrix using validation dataset for RWC and EWT are shown in Figures 2-3 and 2-4. In general, specific wavelengths that correlated significantly with RWC or EWT could be determined for each type of index and each treatment, with most of R^2 values greater than 0.90 for individual species datasets and greater than 0.80 for all measurements.

For original reflectance, the most used wavelengths estimating RWC or EWT in all determined indices were near 1400 nm and 1900 nm (Table 2-3). The best indices were different for each species dataset and index (data not shown). Specifically, the identified best indices were D (525, 1380) for RWC (R^2=0.89, RMSE=10.58%) and SR (1670, 1880) for EWT (R^2=0.95, RMSE=0.0009 g/cm^2) with all measurements. They also maintained a good performance with the validation dataset (Table 3). In addition, since the sensitivity of single wavelengths (R type of index) to RWC (Figure 2-3) were similar to that for EWT (Figure 2-4), some of the determined indices for both RWC and EWT were similar for the same individual species (data not shown). The distribution of the R^2 matrix predicting RWC and EWT was also similar, with R^2 (RMSE) for the same index usually higher (lower) for EWT, except D and DDn types of reflectance difference and reflectance sensitivity (Figures 2-3 and 2-4).

Similarly, for the reflectance difference treatment, the most sensitive wavelengths for RWC or EWT were near 1400 nm and 1900 nm (Table 2-4, Figures 2-3 and 2-4). The R^2 matrix for RWC or EWT was similar with that of original reflectance for the R, D and DDn types of index, but quite different for both the SR and ND types of index (much lower R^2). The best indices for RWC and EWT with all measurements were D(530,1465) (R^2=0.88, RMSE=7.64%) and ND(1980, 2425) (R^2=0.82, RMSE=0.0013 g/cm^2). Although the identified index D(530,1465) performed well with validation dataset (R^2=0.92, RMSE=9.51%), the identified ND type of index (ND(1980, 2425)) failed when it was applied to the validation dataset (Table 2-4).

Table 2-3 Evaluation of five types of indices with original reflectance for leaf RWC and EWT

Indicators	Index type	Calibration dataset(n=156)				Validation dataset(n=68)	
		λ1	λ2 or Δ	R^2	RMSE	R^2	RMSE
RWC (%)	R	1385		0.87	11.77	0.90	11.66
	D	525	1380	0.89	10.58	0.88	12.68
	SR	1410	1830	0.88	11.25	0.88	12.81
	ND	1410	1830	0.89	10.78	0.87	13.03
	DDn	1405	1010	0.87	11.36	0.88	12.48
EWT(g/cm^2)	R	1395		0.88	0.0015	0.82	0.0016
	D	1300	1315	0.92	0.0012	0.90	0.0012
	SR	1670	1880	0.95	0.0009	0.96	0.0008
	ND	1370	1375	0.95	0.0009	0.96	0.0008
	DDn	1405	480	0.93	0.0011	0.95	0.0009

n: the number of measurements; unit of λ1, λ2 and Δ: nm; $P<0.001$ for regression.

For the reflectance sensitivity treatment (Table 2-5), the R^2 matrices of all five types of indices were much poorer than that of original reflectance (Figures 2-3 and 2-4). The identified best index for RWC was ND (1980, 2425) (R^2=0.83, RMSE=9.38%) and for EWT this was ND(1980, 2425) (R^2=0.81, RMSE=0.0014 g/cm^2). However, both performed poorly in validation.

For the first derivative of reflectance treatment (Table 2-6, Figures 2-3 and 2-4), except for a few wavelengths, the most sensitive wavelengths for RWC or EWT were within 1300-1600 nm and 1750-1900 nm. The identified best index for RWC was dND(1415,1530) (R^2=0.91, RMSE=9.46%), and for EWT was dSR(1530, 1895) (R^2=0.96, RMSE=0.0009 g/cm^2). Both indices performed ever better in validation, with an R^2 of 0.95 for dND(1415,1530) and an R^2 of 0.97 for dSR(1530, 1895) (Table 2-6), respectively.

Table 2-4 Evaluation of five types of indices with the treatment of reflectance difference for leaf RWC and EWT

Indicators	Index type	Calibration dataset(n=156)				Validation dataset(n=68)	
		λ1	λ2 or Δ	R^2	RMSE	R^2	RMSE
RWC (%)	R	1885		0.84	9.00	0.89	11.14
	D	530	1465	0.88	7.64	0.92	9.51
	SR	1960	2435	0.79	10.23	-	-
	ND	1960	2435	0.81	9.71	-	-
	DDn	1455	915	0.87	8.16	0.91	10.47
EWT(g/cm^2)	R	2035		0.76	0.0016	0.77	0.0017
	D	525	2075	0.81	0.0014	0.80	0.0016
	SR	2000	2220	0.81	0.0014	-	-
	ND	1980	2425	0.82	0.0013	-	-
	DDn	1560	40	0.80	0.0014	0.78	0.0017

n: the number of measurements; unit of λ1, λ2 and Δ: nm; $P<0.001$ for regression; "-":regression insignificant.

Overall, the performance of the five types of indices with original reflectance and the first derivative of reflectance were generally better than that with the reflectance difference and reflectance sensitivity, judging from the R^2 values and RMSE. Most of the best indices determined for different treatments were concentrated upon the SR or dSR and ND or dND types of indices and were different for different datasets.

Table 2-5 Evaluation of different types of indices with the treatment of reflectance sensitivity for leaf RWC and EWT

Indicators	Index type	Calibration dataset(n=156)				Validation dataset(n=68)	
		λ1	λ2 or Δ	R^2	RMSE	R^2	RMSE
RWC (%)	R	1390		0.53	15.50	0.85	13.13
	D	760	1335	0.77	10.79	0.87	12.47
	SR	1980	2425	0.80	10.11	-	-
	ND	1980	2425	0.83	9.38	-	-
	DDn	1535	770	0.74	11.46	0.83	14.23
EWT(g/cm^2)	R	1570		0.40	0.0024	0.69	0.0020
	D	555	700	0.70	0.0017	0.49	0.0026
	SR	1980	2425	0.77	0.0015	-	-
	ND	1980	2425	0.81	0.0014	-	-
	DDn	710	155	0.64	0.0019	0.48	0.0026

n: the number of measurements; unit of λ1, λ2 and Δ: nm; $P<0.001$ for regression.
“-”:regression insignificant.

Table 2- 6 Evaluation of five types of indices with the treatment of the first derivative of reflectance for leaf RWC and EWT

Indicators	Index type	Calibration dataset (n=156)				Validation dataset (n=68)	
		λ1	λ2 or Δ	R^2	RMSE	R^2	RMSE
RWC (%)	dR	1765		0.83	13.39	0.84	14.54
	dD	670	1765	0.85	12.40	0.92	10.20
	dSR	1840	2185	0.88	11.11	0.86	13.65
	dND	1415	1530	0.91	9.46	0.95	8.18
	dDDn	1865	25	0.85	12.39	0.84	14.55
EWT(g/cm^2)	dR	1305		0.92	0.0012	0.89	0.0013
	dD	1200	1310	0.91	0.0012	0.90	0.0012
	dSR	1530	1895	0.96	0.0009	0.97	0.0007
	dND	1530	1885	0.95	0.0009	0.96	0.0007
	dDDn	1560	425	0.94	0.0011	0.95	0.0009

n: the number of measurements; unit of λ1, λ2 and Δ: nm; $P<0.001$ for regression.

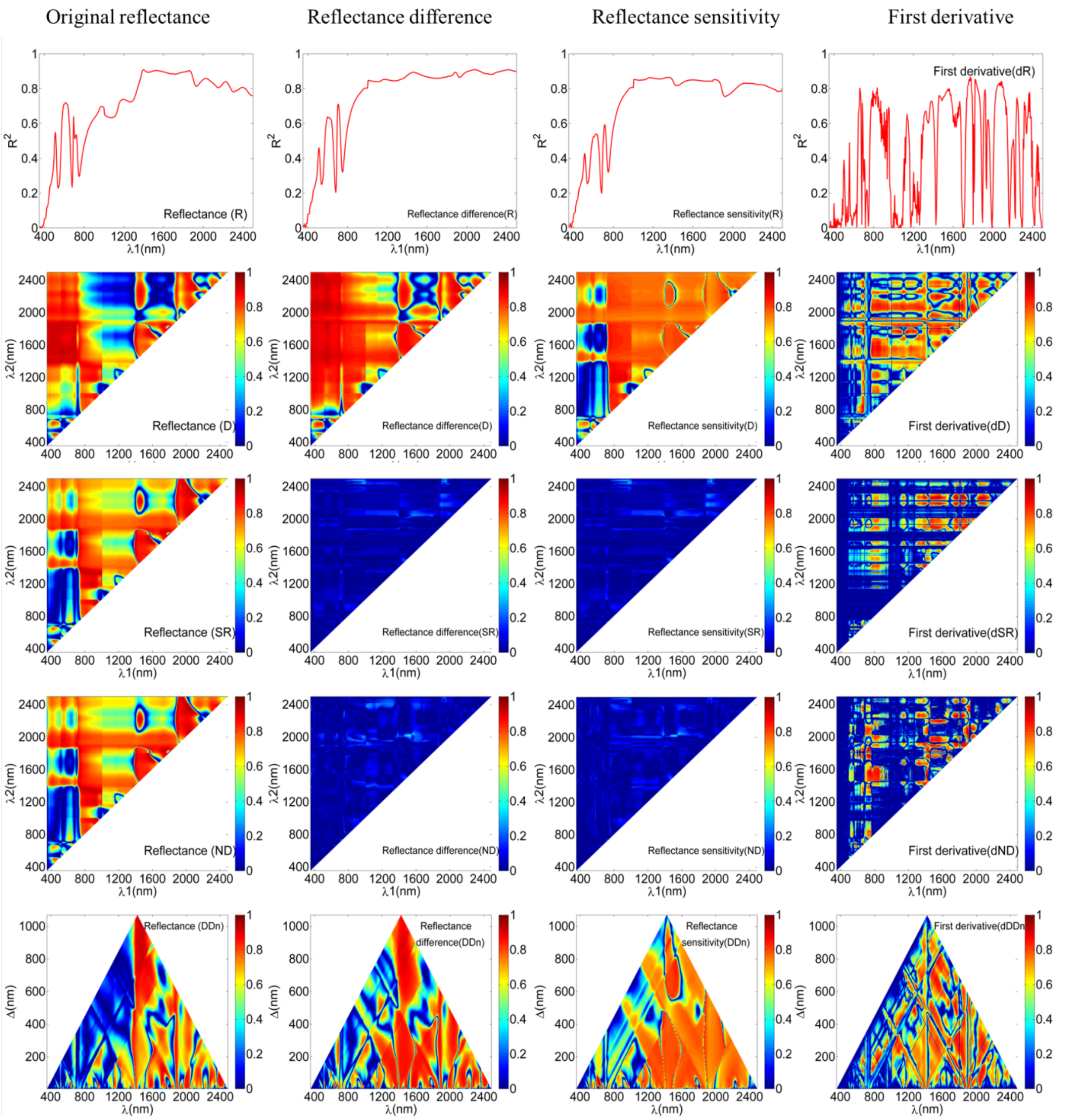

Figure 2-3 R^2 of leaf RWC prediction with different type indices

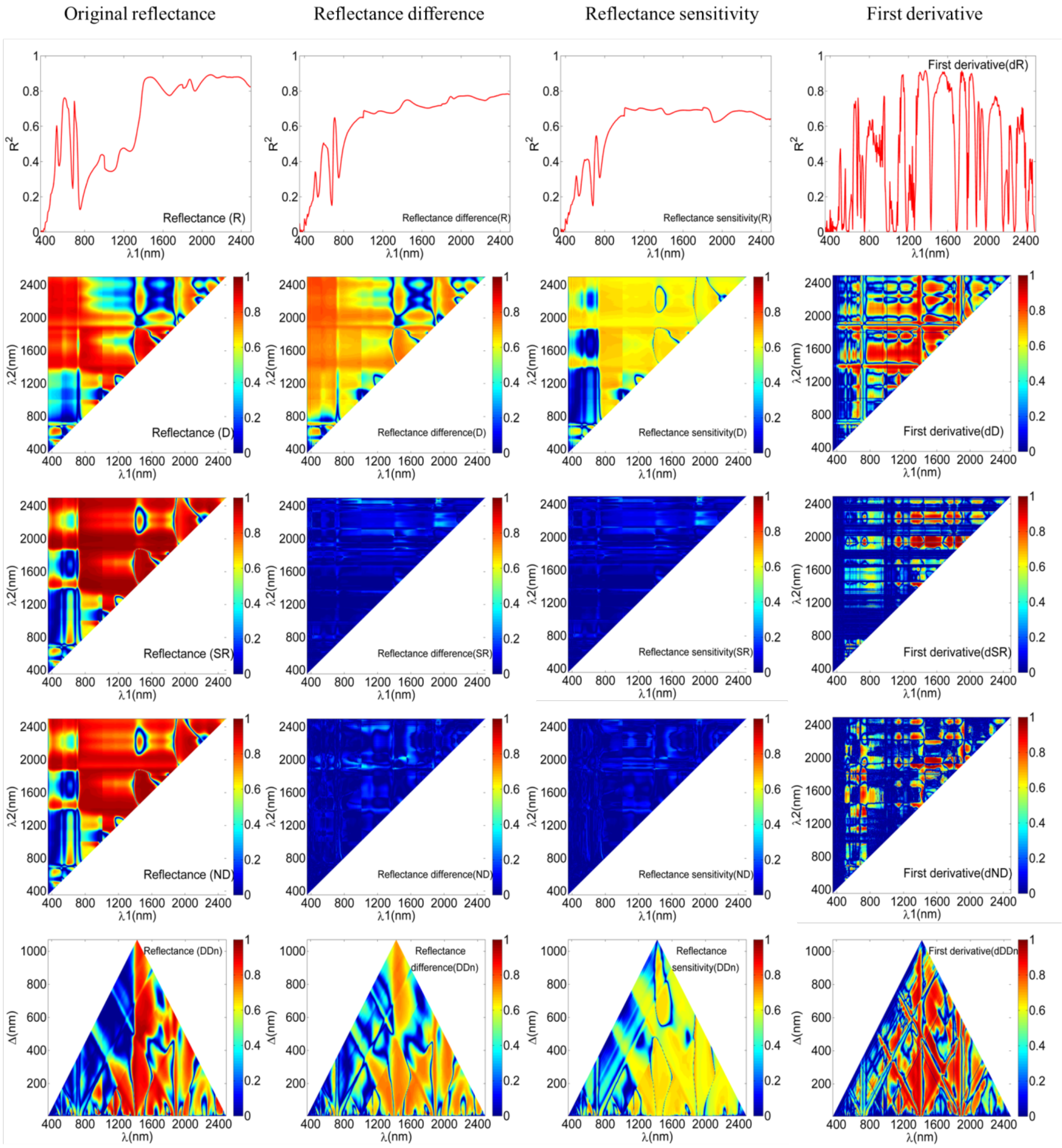

Figure 2-4 R^2 of leaf EWT prediction with different type indices

2.4 Discussion

2.4.1 Leaf dehydration dataset for water index identification

Numerous studies on leaf dehydration have demonstrated similar leaf reflectance responses to those described here: increased reflectance across most of the 350-2500 nm domain with a decrease in leaf water content, particularly within the 350-700 nm and 1300-2500 nm ranges (Carter, 1991; Penuelas *et al*., 1993; Foley *et al*., 2006; Seelig *et al*., 2008b). This phenomenon was called the "primary effect" by Carter (1991), suggesting that a decrease in leaf water content is the most important reason for changes in leaf reflectance, offering the possibility of the assessment of leaf water content. In addition, our results indicate that leaf dehydration experiments can provide a wider range of RWC (3%-100%) and EWT (0.0003-0.0180 g/cm^2) (Figures 2-1 and 2-2) than other field-measured datasets in Japan, with EWT ranging from 0.0026-0.0158 g/cm^2 (Wang and Li, 2012b). Foley *et al*. (2006) also obtained a similar EWT range (within 0-0.0200 g/cm^2) for five different tropical species during leaf dehydration. Meanwhile, the RWC or EWT ranges of the leaf dehydration dataset focus on much lower values (extreme drought) compared with other field sites. For instance, Sims and Gamon (2003) estimated EWT using the spectral reflectance of 23 species across a wide range of functional types, with leaf EWT ranging from 0.0103 g/cm^2 to 0.0728 g/cm^2. Colombo *et al*. (2008) also estimated field leaf EWT from 0.0091 g/cm^2 to 0.0154 g/cm^2 using hyperspectral indices. Similarly, de Jong *et al*. (2014) observed leaf EWT ranging from 0.0082 g/cm^2 to 0.0209 g/cm^2 for three plant species in the Mediterranean region where water availability is a strong indicator of plant stress. However, the extreme drought ranges of the leaf dehydration dataset are not included in these ranges. Although Ceccato *et al*. (2001) extracted a dataset with EWT ranging from 0.0002 to 0.0524 g/cm^2 for 37 species, only a few data points were below 0.0050 g/cm^2. On the other hand, a similar range of leaf EWT was simulated by PROSPECT (Jacquemoud and Baret, 1990; Jacquemoud *et al*., 1996). However, model inversion was only suitable for a specific dataset, and indices calibrated using a particular database could be unsuitable for other databases, since the retrieval of leaf water status is also affected by plant species, growing conditions and growth stage, etc. (le Maire *et al.*, 2008). Hence, a leaf dehydration dataset may have more advantages over other field datasets and simulated datasets under water stress conditions.

However, light absorption by leaves within the 350-750 nm range is also affected by pigments (Sims and Gamon, 2002). Chlorophyll breakdown (Carter and Knapp, 2001; Sun *et al*., 2008) and stomata closure (Souza *et al*., 2004; Brodribb and Holbrook, 2003) will occur during leaf dehydration or under water stress, which may influence photosynthesis or other biochemical reactions, thereby affecting leaf reflectance (Richardson and Berlyn, 2002; Reddy *et al*., 2004; Sarlikioti *et al*., 2010). Carter (1991) tested this hypothesis in rehydrating experiments; this is now viewed as a "secondary effect" and can also be evidenced by a blue shift, which was associated with the chlorophyll concentration (Rock *et al*., 1988) in all five plant species in this study. Moreover, a similar response can be found in visible reflectance with different plant stresses (e.g. ozone) (Carter, 1993; Carter and Knapp, 2001). This means that leaf dehydration is a particularly complicated physiological process, and it is difficult to distinguish the exact reason why leaf reflectance within 350-750 nm varies as the leaf water content decreases. This evidence suggests that index identification using wavelengths in the 350-750 nm range are unsuitable for estimating leaf water status, although some indices have been developed and used to retrieve vegetation water status, for example NDVI (Serrano *et al*., 2000). In fact, some studies have verified there are no significant correlations between NDVI and leaf water content for some plant species (Wang and Li, 2012b; Seelig *et al*., 2008b; Sims and Gamon, 2003).

Similarly, the wavelengths within the 750-1300 nm range are closely related to leaf structure (Jacquemoud and Baret, 1990; Jacquemoud *et al*., 1996). The responses of leaf structure to dehydration are quite different for different species, e.g. cells are quickly and clearly broken for *Floss silk*, while only shrinking occurs for *Common guava* and *Purple guava* after a few hours of leaf dehydration (Foley *et al*., 2006).

Additionally, variations in leaf thickness (Foley *et al*., 2006; Seelig *et al*., 2008a; Seelig *et al*., 2009) and homogeneity of leaf area (Seelig *et al*., 2008a) may also affect the response of leaf reflectance to dehydration. Our results also show that the most considerable variability among species in reflectance is the slope from 750 nm to 1000 nm, which may be caused by differences in the leaf structure of individual plant species. Thus, the wavelengths from 750 to 1300 nm probably are not suitable for leaf water status estimation using leaf dehydration dataset.

The most sensitive wavelength to leaf water status is the range from 1300 nm to 2500 nm, which has been demonstrated in quite a number of studies (Danson *et al*., 1992; Hunt *et al*., 1987; Carter, 1991; Knipling, 1970; Tucker, 1980), although some bands are absorption features (e.g. near 1730 nm and 2100 nm) attributed to leaf dry matter (Cheng *et al*., 2011). Actually, the leaf dry weight almost remained constant during short periods of leaf dehydration and the reflectance in this region gradually increased as the leaf water content decreased. The leaf water content can be seen as the main factor influencing leaf reflectance within the 1300-2500 nm range. However, several new absorption troughs ranging from 2000 nm to 2500 nm were observed during leaf dehydration, which may bring some uncertainties when retrieving leaf water status. Thus, the most suitable range is 1300-2000 nm for estimating leaf water status with a leaf dehydration dataset.

2.4.2 Best indices for tracing leaf water status

All reported indices selected in this study are based on water absorption bands, such as 970 nm for WI (Penuelas *et al*., 1993), 1240 nm for NDWI (Gao, 1996) and SRWI (Zarco-Tejada *et al*., 2003), 1600 nm for NDII (Hardisky *et al*., 1983; *Ceccato et al*., 2001), 1530 nm for DDn(1530,525) (Sims and Gamon, 2003; Wang and Li, 2012a) and 1450 nm for SR(1300, 1450) (Seelig *et al*., 2008b). These indices have been used in different species and under different climate conditions to assess leaf water status and usually have a significant relationship with leaf or canopy water status (Penuelas *et al*., 1993, 1997b; Sims and Gamon, 2003; Seelig *et al*., 2008b; Cheng *et al*., 2008; Colombo *et al*., 2008; Wang and Li, 2012a; de Jong *et al*., 2014), but only a few studies have been conducted under extreme or progressive drought conditions (Penuelas *et al*., 1993, 1997b; Seelig *et al*., 2008b). Our results show that all selected indices show good relationships with RWC or EWT, especially for individual plants. It seems that these indices are suitable for estimating leaf RWC or EWT for certain plant species. However, as shown above, the wavelengths of 819 nm, 860 nm, 900 nm, 970 nm, 1005 nm and 1240 nm are closely linked to leaf structure during leaf dehydration, which may cause errors in the estimation of RWC or EWT when using WI, NDWI, SRWI, NDII and DDn(1530,525). This was shown by Penuelas *et al*. (1997b), who used WI to estimate the plant water content for several Mediterranean species submitted to progressive desiccation. They found that WI was significantly correlated with the plant water content for all species, but this relationship was failed for the wider range of plant water content obtained with extreme desiccation. Similarly, Seelig *et al*. (2008b) found that WI and NDWI exhibit a lower sensitivity to leaf water content for *Spathiphyllum lynise* than SR(1300, 1450) due to the relatively small absorption troughs and the response of reflectance to dehydration within the range of 750-1300 nm. Thus, except for SR(1300, 1450), the other indices are probably not suitable for monitoring the leaf dehydration process, but may be used for specific plant species and conditions.

In the current study, in order to obtain the best water indices, five types of indices and four treatments of reflectance data were used. The results indicate that the indices determined by the treatments of reflectance difference and reflectance sensitivity were weaker for RWC and EWT and thus could not effectively estimate the leaf water status compared with the other two treatments, although the DDn type of index had a better R^2 value. Since the results calculated by the DDn formula within 1300-2000 nm show that the DDn type of index can only reflect information around 1400 nm, and may not track leaf water status during leaf dehydration. Similarly, the R^2 of the R and D types of indices were usually weaker than the SR and ND types of indices within

1300-2000 nm for original reflectance and the first derivative of reflectance. Actually, the most frequently applied techniques for leaf water indices are the normalized differenced index (ND) and simple ratios (SR), which usually exploit typical water absorbing wavelengths, for instance WI, NDWI and SRWI. One important reason for this is that more than one reference wavelength is usually needed when the indices are designed to compensate for signal variation or to avoid background effects. Our results also indicate that the SR and ND types of indices with the first derivative of reflectance are more sensitive to leaf water status, with the best indices being dND(1415,1530) (R^2=0.95, $p<0.001$) for RWC and dSR(1530, 1895) (R^2=0.97, $p<0.001$) for EWT with validation dataset. Compared with original reflectance, the first derivative of reflectance has some advantages, including removing the noise signal and improving the index's performance, which is often used to obtain reflectance information, such as the well-known red edge for photosynthesis (Filella and Penuelas, 1994; Horler *et al*., 1983). Danson *et al*. (1992) found that the first derivative of reflectance at the slopes of water absorption bands was highly correlated with leaf water content, which was similar to our results. The performance of the selected indices, i.e. dND(1415,1530) and dSR(1530, 1895), was better than that reported for SR(1300, 1450) and indices with original reflectance determined in this study, probably due to the slope variations at the water absorption bands, 1400 nm and 1900 nm. On the other hand, the first derivatives of 1400 nm and 1900 nm tended to shift to long wavelengths and may be used as indicators of senescence and can also track leaf water status. Moreover, d1530 was tested by Wang and Li (2012b) and found to be sensitive to EWT. Hence, both of the new recommend indices are more accurate for assessing leaf water status during leaf dehydration. It was noted that the distribution of the R^2 matrix for RWC and EWT was similar for the treatment of the first derivatives, with R^2 relatively better for EWT, suggesting that EWT is more sensitive to leaf dehydration.

2.4.3 Stability of the recommend indices and ecological application

The performance of the recommended derivative-based hyperspectral indices is better than other types of indices and reported indices in this study. Theoretically, an efficient index should be tested on different random percent datasets for calibration and maintain high stability under different wavelength resolutions, since the most commonly used remote sensing data are multispectral and are usually noisy. The test of different percent datasets for calibration ranging 40% to 100% for both recommended indices showed that the determined wavelengths of the best indices were similar and robust (R^2>0.90), with dND λ1 near 1415 nm and dND λ2 near 1530 nm for RWC, and dSR λ1 near 1530 nm and dSR λ2 near 1895 nm for EWT (Figure 2-5). We have also validated the stability with different bandwidths for leaf water parameters (Figure 2-6). dSR(1530, 1895) for EWT had similar and high R^2 values up to a bandwidth of 100 nm, while dND(1415,1530) for RWC had nearly similar R^2 values up to a bandwidth of 20 nm. This result suggests that both recommended indices are suitable for different wavelength resolutions, particularly dSR(1530, 1895) for EWT. In addition, there was a good match between the simulations and measurements (Figure 2-7). Hence, the stabilities of these new recommend indices can satisfy future applications and can also be potentially extendable to larger scales. Although there are currently no multispectral remote sensing data can be used to calculate these suggested indices for RWC and EWT, rapid progress in hyperspectral remote sensing in recent will provide the solution and hence their wide applications can be expected.

Furthermore, leaf dehydration is followed by decreased leaf photosynthesis and hydraulic failure (Augusti *et al*., 2001; Lawlor and Cornic, 2002), which is an extreme drought condition, to some degree, similar to the plant mortality caused by drought (McDowell *et al*., 2008; McDowell *et al*., 2013). Actually, under severe drought stress, leaf stomatal conductance quickly decreases (Souza *et al*., 2004), thereby slowing the leaf photosynthesis rate; if there is no water supply, the plant will die. Recently, drought-induced forest mortality has occurred worldwide and is expected to be exacerbated due to rising temperatures (Allen *et al.*, 2010). In this sense, both new indices can probably be used to monitor these plant mortalities across different scales in the future, especially in Mediterranean regions where water availability is an important limiting factor for plant growth. However, only five deciduous species in Japan were used in our study and the experiments were conducted under lab-controlled conditions. To obtain a general index suitable for different scales and species, more plant species and field-measured datasets should be included in future work.

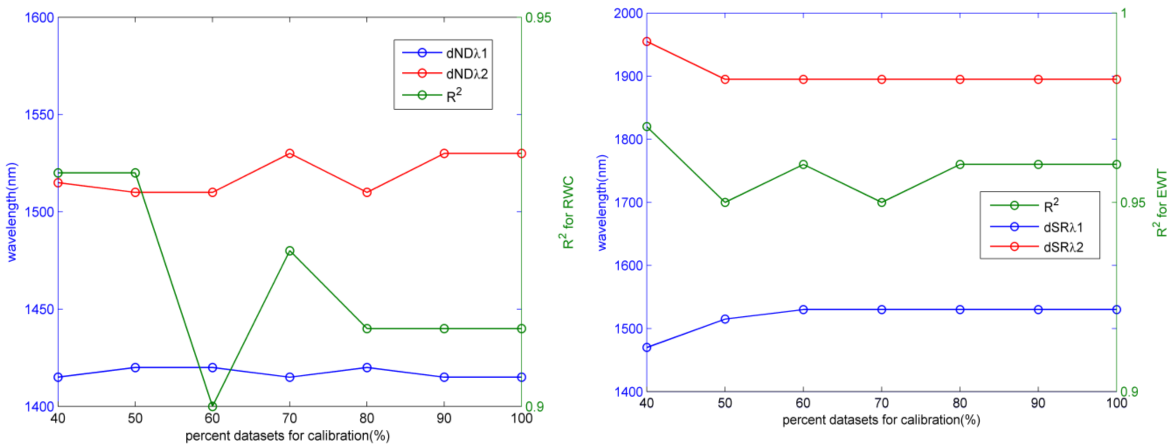

Figure 2-5 Tests of the recommended indices for RWC and EWT with different percent datasets for calibration.

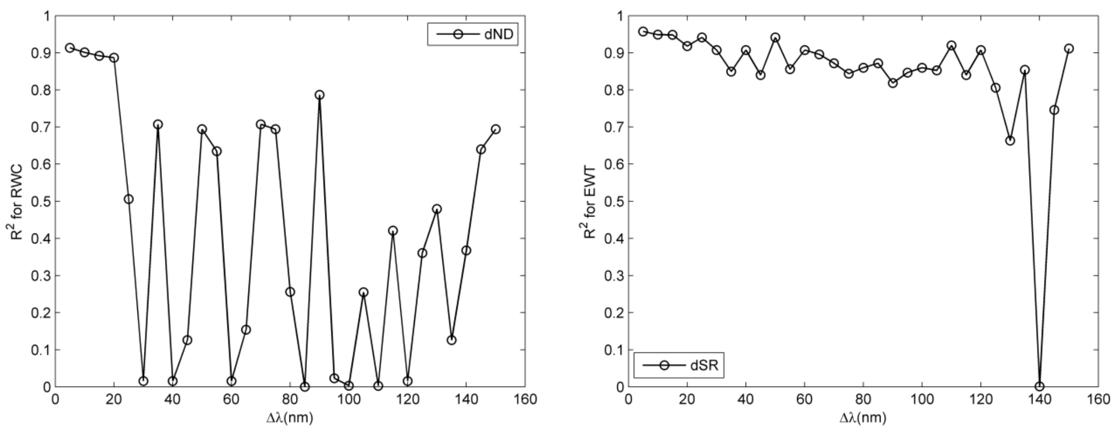

Figure 2-6 Stability of the recommended indices for RWC and EWT with different bandwidths.

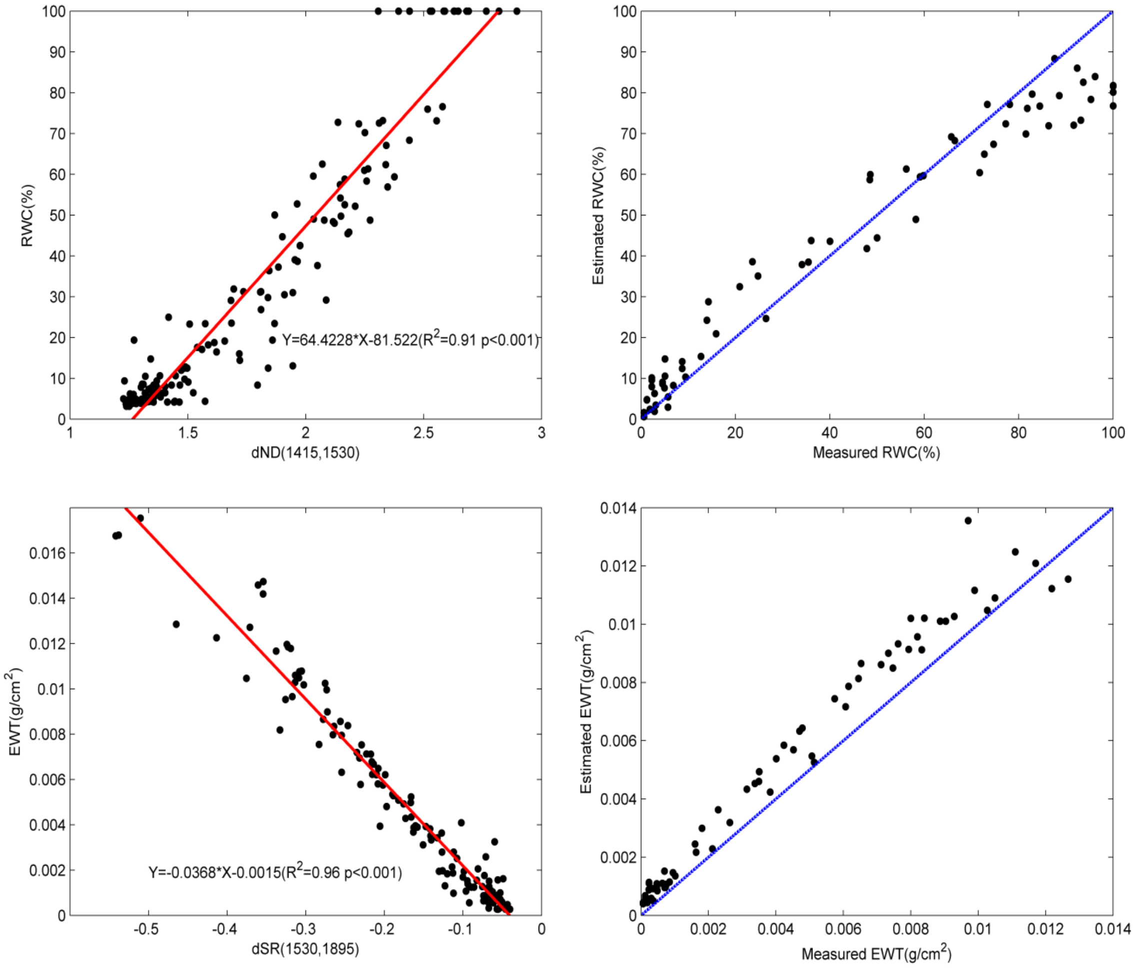

Figure 2-7 Regressions between the recommend indices and the parameters of RWC and EWT (above) and plots of estimated parameter values vs. measured parameter values (below).

2.5 Conclusions

We examined the relationship between leaf reflectance and leaf water status (RWC and EWT) based on leaf dehydration datasets. We found that dND(1415,1530) and dSR(1530, 1895) were most sensitive to the leaf water status during leaf dehydration. The dSR(1530, 1895) is particularly recommended for its stability on both aspects of central wavelengths and band resolution and its potential for large scale monitoring. However, much work still needs to be done to scale these water estimation relationships to larger scales and to understand the leaf dehydration process.

Chapter 3 Estimation of fluorescence-based PSII quantum yield with hyperspectral indices

3.1 Introduction

Global hydrological cycle is significantly affected by human-induced climate change and will be amplified over the coming century, leading to an increase in the frequency of drought extremes (Jentsch et al. 2007) which further cause widespread forest mortality globally (Adams et al. 2009; Allen 2009; Allen et al. 2010). Forest photosynthetic status are greatly affected by drought and always turn forest from carbon sinks to carbon sources, resulting in a positive feedback to global warming (Anderegg et al. 2013; Breshears and Allen 2002). Hence, estimation of photosynthetic status is required to obtain more information of forest mortality and accurately predict transient carbon responses to rapid climate change by the dynamic global vegetation models (Cramer et al. 2001; Sitch et al. 2008; Sitch et al. 2003).

A non-invasive technique to monitor plant photosynthetic status is the approach of chlorophyll fluorescence (CF) (Kautsky et al. 1960). The underlying principle of CF analysis is based on modulation of three fates of light energy absorbed by chlorophyll: photochemistry, excess energy dissipated as heat and CF emission. Any changes associated with the efficiency of one will have a reverse effect on the other two (Baker 2008; Kooten and Snel 1990; Maxwell and Johnson 2000). For example, the light absorbed by leaf is more than the requirement for photosynthesis when photosynthesis is limited under light stress. Heat dissipation and reemit of CF are specific mechanisms to prevent photosynthetic apparatus from impairment by excess energy(Demmig-Adams and Adams Iii 1992). Consequently, information of photochemistry and heat dissipation could be observed from the measurement of CF. Among all the parameters, quantum yield of PSII and non-photochemical quenching (NPQ) are most commonly used, one is for photochemistry efficiency of PSII, an indicator for photosynthetic status and the other one is linearly related to heat dissipation (Baker 2008; Krause and Weis 1991; Maxwell and Johnson 2000; Schreiber et al. 1995). Up to now, much effort has been made to detect photosynthetic information using CF technique. However, most of these studies are only focused on relatively small scales using time-consuming pulse amplitude modulating fluorimeters. The application to large spatial scales is still limited although fluorescence imaging has been developed to resolve entire leaf or plant spatial heterogeneity of photosynthetic performance (Buschmann et al. 2001).

Remote sensed vegetation index is one alternative method to estimate plant photosynthesis activity and offer the possibility for upscale to large areas. However, most exited indices are often used for estimating net primary productivity or spatial distribution of vegetation, for example, Normalized Difference Vegetation Index (NDVI, [R800−R680]/[R800+R680]) is directly related to fractional vegetation cover and aboveground net primary production of terrestrial vegetation (Carlson and Ripley 1997; Gamon and Qiu 1999; Gamon et al. 1995; Running and Nemani 1988; Steltzer and Welker 2006). But NDVI cannot trace the variation of dynamic carbon, particularly for evergreen species (Gamon et al. 1995). Photochemical Reflectance Index (PRI, [R531−R570]/[R531+R570]) (Gamon et al. 1990; Gamon et al. 1992; Gamon et al. 1997) is a special index for photosynthetic function, because 531 nm is related to the de-epoxidation state of the xanthophyll cycle which is an energy decay process of excited chlorophyll for protection of photosynthesis (Demmig-Adams and Adams 1996; Niyogi 1999). Previous studies demonstrated that PRI could track the diurnal and sensonal changes in photosynthetic efficiency at leaf and canopy scales and well correlated with quantum yield of PSII under light or nutrient stress (Gamon et al. 1997; Garbulsky et al. 2011; Weng et al. 2010; Weng et al. 2005). It also was a good indicator for water stress (Suárez et al. 2009; Suárez et al. 2010; Suárez et al. 2008; Thenot et al. 2002) or tracer for steady-state chlorophyll fluorescence(Dobrowski et al. 2005; Flexas et al. 2000; Flexas et al. 2002), but the reports about relationship between PRI and quantum yield of PSII or photosynthetic efficiency under drought stress were varied (Gamon et al. 1992; Harris 2008; Peguero-Pina et al. 2008; Sims et al. 2006; Van Gaalen et al. 2007). PRI was not always the best index for tracking photosynthetic status, for example, Harris (2008) found out that the relationship between quantum yield of PSII and PRI were much weaker than the other indices (e.g. NDVI) during progressive drought period. Thus, it is necessary to determine the best spectral indices for quantum yield of PSII under drought stress. Studied had been showed that leaf leflectance (Carter 1993) and phisiological paremeters (Brodribb and Holbrook 2003; Richardson and Berlyn 2002) were simultaneously changed in response to water stress. In this study, I hypothesised that leaf reflectance from 400 nm to 800 nm and their different combanation as review by le Maire *et al*. (2008) could offer the posibility to determine the best indices for quantum yield of PSII as they were only sensitive to photosyhthesis and insensitive to leaf water content.

The objectives of this study were: 1) to investagate the response of chlorophyll fluorescence to progressive drought for different broadleaved species; 2) to validate the performance of PRI and NDVI for tracking quantum yield of PSII; 3) to identify the best hyperspectral indices for tracing quantum yield of PSII based on origin reflectance and first derivative of reflectance ranging 400-800 nm and different types of indices.

3.2 Material and methods

3.2.1 Leaf sampling

Four deciduous species around the campus of Shizuoka University and another dominant temperate deciduous species from Mount Naeba, Japan were collected. The details of sample species and sampling method have given in Chapter 2.2. In total, 18 leaf samples were used for five plant species, including 3 sunlit leaves and 3 shaded leaves for *F. crenata* and 3 sunlit leaves for each of the other four species.

3.2.2 Leaf dehydration experiment

The details of experiment design and measurement of leaf reflectance and weights have given in Chapter 2.2. Chlorophyll fluorescence was measured with Mini-Pam (Walz, Effeltrich, Germany), a portable pulse amplitude modulated photosynthesis yield analyzer. The actual quantum yield of PSII was calculated as follows:

$$\Delta F/F'm = (F'm - F)/F'm$$

where F is the steady-state value of fluorescence and Fm' is the maximum light-adapted fluorescence when a saturating light pulse duration is imposed. The time interval of each measurement is same with leaf reflectance during entire leaf dehydration period.

3.2.3 Determination of the best indices

Two treatments of original reflectance and first derivative reflectance (dR) and five types of indices (R, D, SR, ND and DDn) as reviewed by le Maire *et al*. (2008) were used to identify the best indices for quantum yield of PSII. The equations of five types of indices had given in chapter 2.2.

3.2.4 Statistics

The determination of indices was conducted by linear regression between a given index and quantum yield of PSII ranging 400-800 nm. Regression analysis was performed for all possible combinations of wavelengths for a given index type. The wavelength interval was 1 nm. Statistical criteria to evaluate the performance of published/identified indices were based on the root mean square error (RMSE) and the coefficient of determination (R^2). And the best index was identified as the combination with the lowest RMSE and the highest R^2.

3.3 Results

3.3.1 Variation of chlorophyll fluorescence and leaf reflectance following the intensity of drought stress

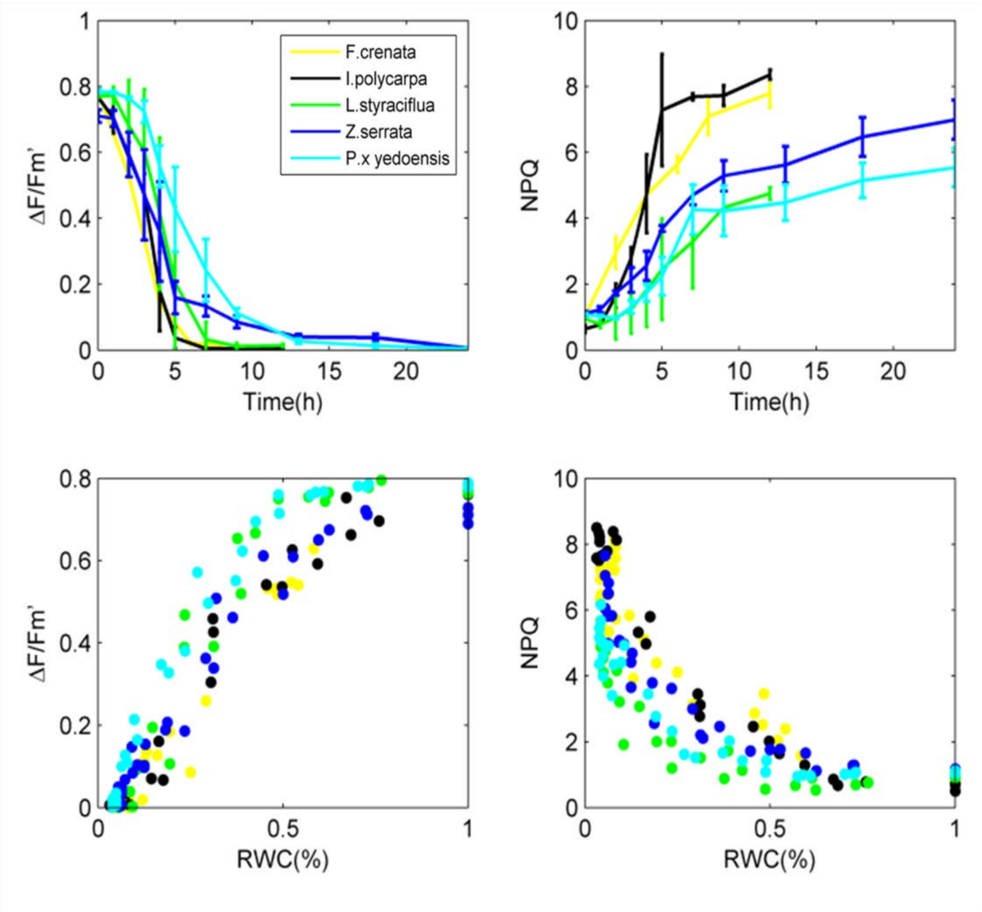

Figure 3-1 Variations of chlorophyll fluorescence though time since leaf cutting and RWC *vs* ΔF/F'm and NPQ.

Values of ΔF/F'm for different plant species were rapidly decreasing in the first 5 h since leaf cutting. At the time of around 12 h, ΔF/F'm of each species was near zero, meaning that all leaf samples were almost totally died (Figure 3-1). Although the values of ΔF/F'm for individual plant species were different with each other, the variation trends were similar over the course of the drought treatment. On the contrary, NPQ showed an increase trend for all plant species, after 12 hours, the values of NPQ were up to the largest and then kept stable later. However, the magnitude of the change in NPQ varied between species (Figure 3-1). There was a significant positive correlation between RWC and quantum yield of PSII ($p<0.01$) and a significant negative correlation between RWC and NPQ ($p<0.01$) (Figure 3-1).

Increases in reflectance spectra of all five species at all wavelengths from 400 to 800 nm were observed, although the increasing magnitudes were quite different between species, with the least for *P. x yedoensis* and the largest for *L. styraciflua* (Figure 3-2). The most pronounced bands in all species were near green-yellow wavelengths (500-600 nm) and 750-800 nm. Another common characteristic in the change of reflectance in response to dehydration was the transition from red edge to near infrared plateau (700-750 nm) which became less sharp with the decrease of RWC (Figure 3-2). The variations of first derivative reflectance were similar between species, in particular, the increase in red edge and blue shift during the progressive drought. The derivative reflectance spectra around 500-530 nm and 650-700 nm also showed large changes over the drought intensity, both ranges were near the carotenoids and chlorophyll absorption region, respectively (Figure 3-2).

3.3.2 Variation of reflectance indices and performance for estimating quantum yield of PSII

Reflectance incices of both PRI and NDVI had small variation ranges during the dehydration period, with the values from -0.07 to 0.05 and 0.65 to 0.85, respectively, particularly within species (figure 3-3). Although PRI and NDVI in all species showed slightly decrese over dehydration time, the patterns and values between species were greatly varied. For example, PRI and NDVI of *F.crenata* rapidly droped from around 0.05 to -0.04 in the first 5 h, while PRI of *L. styraciflua* slowly decreased from about 0.05 to 0.03. PRI and NDVI could not well track the variation of $\Delta F/F'm$ due to these varied features, and no significant correlations were observed between $\Delta F/F'm$ and PRI (R^2=0.27), and between $\Delta F/F'm$ and NDVI (R^2=0.25) when all species were considered (figure 3-3).

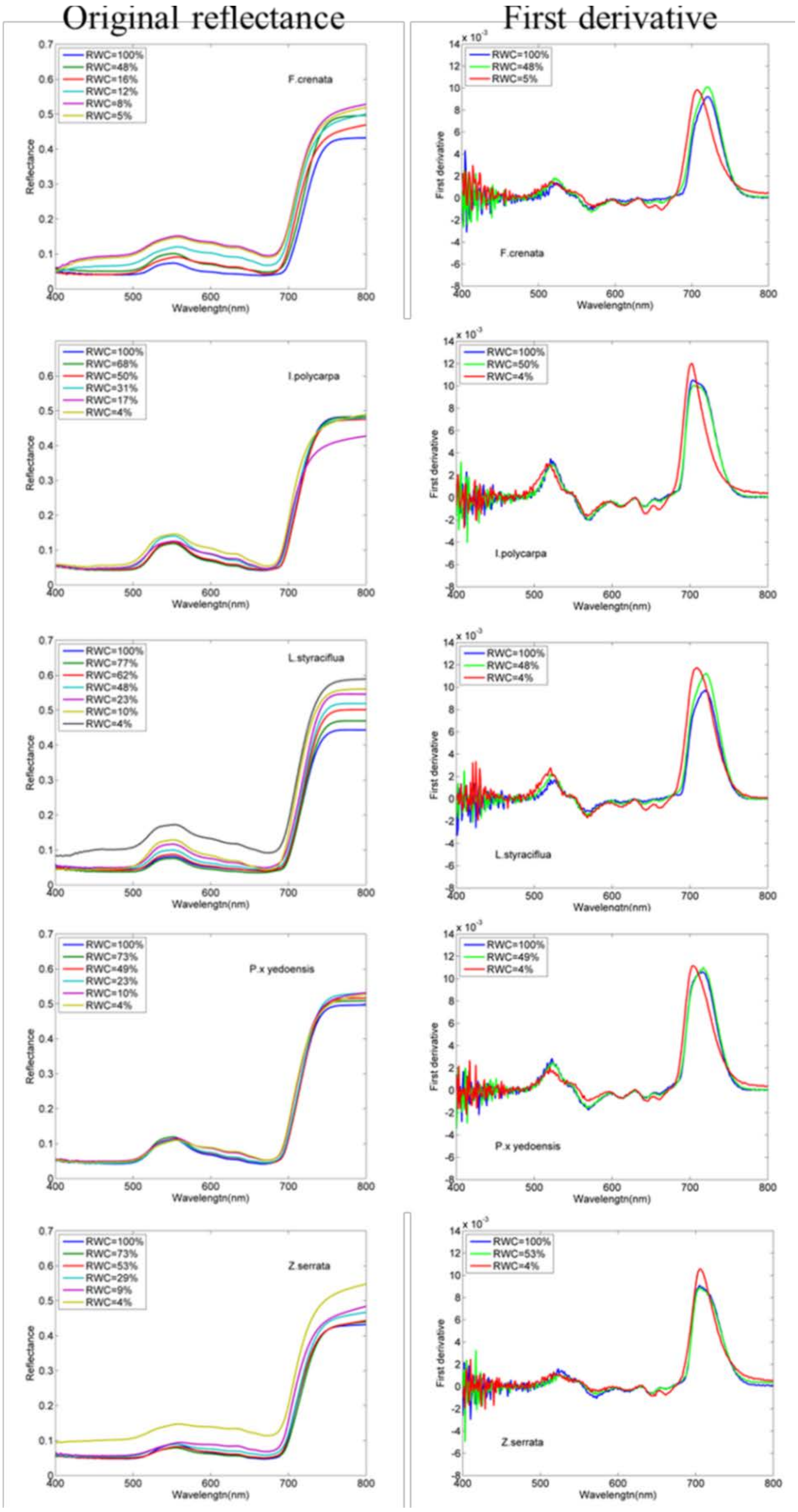

Figure 3-2 Changes of reflectance spectra (400-800 nm) and first-derivative reflectance spectra for different plant species attributed to progressive RWC

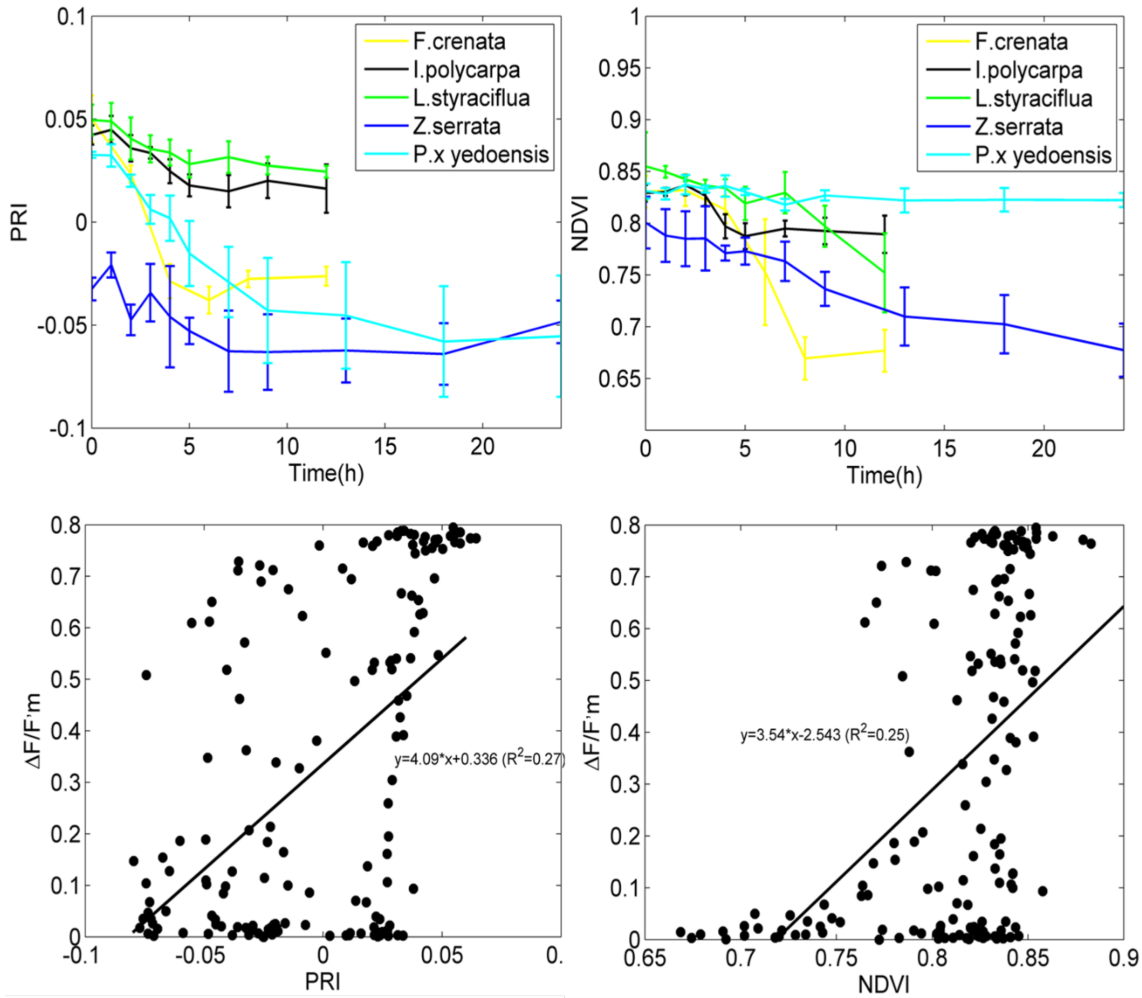

Figure 3-3 Changes of RRI and NDVI for different plant species following leaf cutting and PRI *vs* ΔF/F'm, NDVI *vs* ΔF/F'm

3.3.3 Newly identified indices for estimating quantum yield of PSII

The identified best indices for estimating ΔF/F'm based on both original reflectance and first derivative spectra were presented in Table 3-1. The indices selected based on first derivative spectra were better than that based on original reflectance. The newly identified dND (533, 686) was the best one for estimating ΔF/F'm across different type of indices, with an R^2 of 0.88 and an RMSE of 0.11 (Table 3-1 and figure 3-4). The performance of dND (533, 686) was also better than PRI (R^2=0.27) and NDVI (R^2=0.25).

Table 3-1 Evaluation of five types of indices with the treatment of the first derivative of reflectance for leaf ΔF/F'm

dataset	Index type	origin reflectance				first derivative reflectance			
		λ1	λ2 or Δ	R2	RMSE	dλ1	dλ2 or Δ	R2	RMSE
All (n=156)	R	707		0.73	0.16	d663		0.79	0.14
	D	659	672	0.79	0.14	d533	d687	0.85	0.12
	SR	420	647	0.75	0.16	d533	d693	0.82	0.13
	ND	417	642	0.74	0.16	d533	d686	0.88	0.11
	DDn	684	4	0.82	0.13	d664	23	0.83	0.13

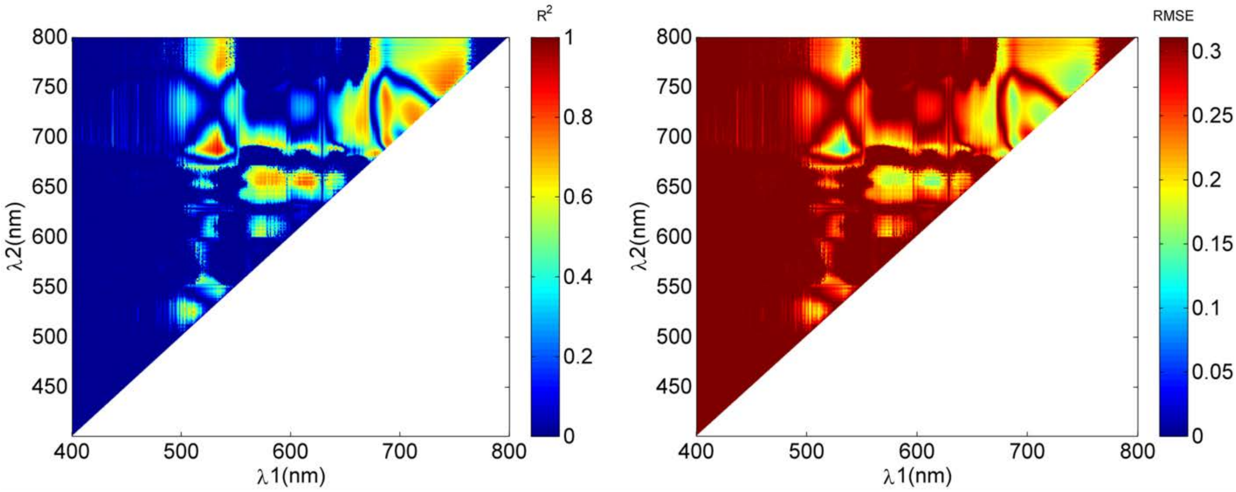

Figure 3-4 R^2 and RMSE of leaf ΔF/F'm estimation with different ND type of index based on first derivative of reflectance

3.4 Discussion

A sharp decline in ΔF/F'm of the studied broadleaf species caused by the rapid dehydration (Figure 3-1) indicated that the photosynthetic apparatus had been impaired, which would result in the reduction of photosynthetic pigments and further impede the electron donation in PS II until the leaves were totally died (Demmig-Adams and Adams Iii 1992; Niyogi 1999). Similar results also were observed from other plant species over the different drought courses (Harris 2008; Peguero-Pina et al. 2008; Richardson and Berlyn 2002). In addition, the differences of NPQ between species were probably due to the amount variation of carotenoids for each species such as xanthophyll cycle involved Zeaxanthin, violaxanthin and antheraxanthin which regulated heat dissipation of light energy absorbed by chlorophyll (Demmig-Adams and Adams Iii 1992; Demmig-Adams and Adams 1996). Therefore, the changes of ΔF/F'm are tightly related to the variation of pigments which can be reflected by the changes of leaf reflectance although it exhibits a positive correlation with leaf RWC (Figure 3-1), suggesting that the hypothesis of this study is reasonable.

Similar results of an increase in reflectance from 400 to 800 nm with the reduction of leaf water content had also been observed in other plant species(Carter 1991; Seelig et al. 2008a). Although drought probably was the direct reason for the observed changes in leaf reflectance, the leaf reflectance from 400 nm to 800 nm were not affected by leaf water content(Feret et al. 2008; Jacquemoud and Baret 1990). This common increased reflectance has been partly attributed to the degradation of pigments and leaf structure which can change the light scattering at the interfaces of cell wall-water-air (Carter 1991, 1993). Leaf structure parameter N is an input for PROSPECT, simulated results show that leaf reflectance from 400 nm-800 nm is gradually and proportionally increasing with an increase of N (Feret et al. 2008; Jacquemoud and Baret 1990), indicating that the effects of leaf structure can be removed by special technology such as normalized indices. Thus, the information about photosynthesis status can be fairly extracted from the leaf reflectance. For example, the “blue-shift” or decreases of the red edge position are the evidences of chlorophyll degradation (Figure 3-2) (Carter 1993; Richardson and Berlyn 2002).

However, the commonly used vegetation indices NDVI and PRI had no significant correlations with ΔF/F'm (Figure 3-3). NDVI is an indicator for greenness or a characteristic of green vegetation (Gamon et al. 1995; Running and Nemani 1988), with narrow changes during entire dehydration period (Figure 3-3) probably due to relative changeless of leaf green color, causing it is unsuitable for tracing ΔF/F'm. PRI incorporates the band at 531 nm, which are directly related to the xanthophyll cycle pigments (Gamon et al., 1992). However, chlorophyll degradation is occurred in the experiments, disturbing the relationship between ΔF/F'm and PRI. Hence, it is necessary to determine new spectral indices for tracing the variation of ΔF/F'm under drought stress.

In this work, in order to identify the best indices for estimating ΔF/F'm, two treatments of origin reflectance and first derivative reflectance, and five types of indices of R, D, SR, ND and DDn were used. The best index was dND (533, 686), with an R^2 of 0.88 and an RMSE of 0.11 (Table 3-1), which was better than NDVI (R^2=0.25) and PRI (R^2=0.27). It is noted that the wavelength of 533 nm which is near xanthophyll-cycle-related 531 nm and 686 nm is near one of the emission peak of chlorophyll fluorescence, 690 nm (Meroni et al. 2009). dND (533, 686) may incorporates the information of both chlorophyll fluorescence and xanthophyll cycle, and therefore it is suitable for ΔF/F'm estimation under water stress. It also can be as a water stress indicator because of the significant relationship with RWC.

3.5 Conclusions

This work retrieved ΔF/F'm with leaf reflectance and first derivative reflectance range from 400 nm to 800 nm obtained from dehydration experiment. The identified best indices for estimating ΔF/F'm was d (533, 686) across different type of indices, with an R^2 of 0.88 and an RMSE of 0.11, which was better than NDVI and PRI. The selected d (533, 686) probably could provide a remote mean to track the variation of photosynthetic status for plants due to that the wavelength of 533 nm was near 531 nm and 686 nm was near the chlorophyll fluorescence emission peak, 690 nm.

Chapter 4 Retrieval of fuel moisture contents in different fuel types

4.1 Introduction

Fuel moisture content (FMC) has an overwhelming importance in understanding different eco-physiological processes and wildfire behavior prediction among all the forest fuel properties as it significantly affects wildfire ignition and propagation andCO_2 emission from the combustion of organic materials (Chuvieco et al., 2004a; Rothermel, 1972; Werf et al., 2004; Viegas et al., 1992; Yebra et al., 2008; Yebra et al., 2013). FMC can be categorized into two different components based on fuel type: the water content in dead fuels, which are most easily to ignite (e.g. dry leaves, littler and fallen branches), and that in live fuels (e.g. live leaves).

Direct measurements of FMC are severely limited by the available reliable data obtained from field sampling, particularly for large areas where such sampling is generally not feasible. Thus, FMC in dead fuel has often been computed by models associated with meteorological variables over the past several decades, because it is mainly controlled by changes in atmospheric conditions (Aguado et al., 2007; Camia et al., 2003; Nieto et al., 2010; Viegas et al., 2001; Viney, 1991). However, meteorological indices are not satisfactory for estimating FMC in live fuel due to the complex water-use strategies of live plants, which are regulated by plant physiological processes, for example water loss by leaf evapotranspiration and water uptake by roots. Even certain relationships between live FMC and meteorological codes were also noted for some specific species (Carlson and Burgan, 2003; Dimitrakopoulos and Bemmerzouk, 2003). In addition, hardly any meteorological data may be obtained from sparsely populated regions where no meteorological stations are available. Hence, there is a great need for an alternative approach that can provide temporal and spatial information on FMC.

Remote sensing approaches which provide spectral information on plant water and dry mater content on multiple scales may overcome some of the above mentioned challenges (Hunt Jr et al., 1987; Tucker, 1980; Wang et al., 2011a; Wang et al., 2011b; Zarco-Tejada et al., 2003). Currently, equivalent water thickness (EWT) is a commonly estimated water status parameter, since it is directly related to leaf reflectance (Ceccato et al., 2001; Ceccato et al., 2002a; Ceccato et al., 2002b; Jacquemoud and Baret, 1990; Jacquemoud et al., 1996; Jacquemoud et al., 2009). While FMC can be linked to EWT via leaf mass area (LMA), in contrast to the popularly retrieved EWT, estimating FMC is proving to be more difficult due to the masking effect of leaf water content on dry matter, which makes it hard to effectively distinguish the spectral information of leaf dry matter from leaf water content (Riaño et al., 2005; Romero et al., 2012; Wang et al., 2013; Yebra et al., 2013).

Even so, a number of studies have attempted to retrieve FMC using reflected spectra. These studies mainly focus on three aspects, as follows:1) empirical methods based on spectral indices which are physically related with leaf water content or dry matter content (several indices are listed in Table 1) (Dennison et al., 2005; Roberts et al., 2006; Wang and Li, 2012; Wang et al., 2013); 2) combining meteorological data and spectral data to estimate FMC (Chuvieco et al., 2004b; Chuvieco et al., 2004c; García et al., 2008; Nieto et al., 2010); 3) generalizing from simulated datasets because EWT and LMA are two important input parameters for commonly used leaf and canopy radiative transfer models (e.g. PROSPECT and PROSAIL) (Bowyer and Danson, 2004; Danson and Bowyer, 2004; Riaño et al., 2005; Wang and Li, 2012; Yebra and Chuvieco, 2009). Although inverse retrieval from radiative transfer models is much a mechanism-based approach, challenges still exist and might be even greater than for empirical methods since the approach not only requires plant physiological and structural inputs that are frequently unavailable in nature but also faces a serious ill-posed problem (Bowyer and Danson, 2004; Li and Wang, 2011; Yebra and Chuvieco, 2009; Yebra et al., 2013). On the contrary, the spectral index approach is a rapid and simple way to estimate FMC. Its estimation accuracy may further be improved if indices are made up of bands whose absorption features are sensitive to EWT and LMA and insensitive to background effects (Dennison et al., 2005; Roberts et al., 2006; Wang et al., 2013; Wang and Li, 2012).

However, most of the previous studies were always oriented toward live FMC with only water indices or dry matter indices from satellite data, like NOAA-AVHRR and MODIS. For instance, Dennison et al (2005) estimated live FMC using NDVI and NDWI from MODIS reflectance data, while Roberts et al (2006) used WI and NDWI from AVIRIS and MODIS data. Furthermore, Chuvieco et al. (2004c) combined NDVI and surface temperature to estimate live FMC with NOAA-AVHRR data. Although empirical relationships were found between live FMC and these selected indices, the spectral information of dry matter remains unclear.

Riaño et al (2005) suggested that measurements of dry leaf samples were necessary to accurately estimate FMC because dry matter can only be accurately estimated when leaf material is dry. Leaf dehydration processes can clearly track the changes of leaf state transition from the fresh live situation to the dry dead situation, with leaf reflectance increasing significantly in the domain from 400 to 2500 nm (Carter, 1991; Foley et al., 2006; Seelig et al., 2008), which may simultaneously provide more spectral details about leaf water and dry matter. Wang et al. (2013) demonstrated that NDII/NDMI was significantly correlated with FMC based on the hypothesis that FMC could be estimated by the indices combining the water index and the dry matter index calculated from hyperspectral data using both fresh and drying green leaves. However, the wavelengths in both the numerator and the denominator of NDII/NDMI are not only affected by water or dry matter content as hypothesized by the authors. Moreover, most existing indices for estimating FMC are usually based on origin reflectance, but no study has ever concentrated on the first derivative spectra, which can provide information on key spectral locations it can eliminate the other background noise, such as the red edge and water absorption peaks (Filella and

Penuelas, 1994; Horler et al., 1983). Furthermore, there is only a little knowledge about the estimation of FMC for dead fuel types using spectral indices, such as litter, although litter is usually masked by the overstory vegetation, the widespread drought-induced tree mortality have leaded to much higher exposure rate of litter on the regional scale. Therefore, new types of spectral indices for estimation of different fuels' FMCs are expected.

The objectives of this study were: 1) to compare the variations of leaf reflectance and first derivative spectra in two different fuel types during dehydration processes: green live leaves and litter fallen from different broadleaved species in the temperate climate zone; 2) to validate existing spectral indices to estimate the FMC of both green live and fallen litter fuels; 3) to determine the best hyperspectral indices for FMC based on different types of indices with an attempt to separate FMC estimation in the two fuel materials and 4) to investigate the difference of published and selected indices between measured-dataset and simulated-dataset developed from leaf scale radiative transfer model (PROSPECT) and attempt to examine whether the reflectance of fallen litter leaf can be simulated by PROSPECT.

4.2 Materials and methods

4.2.1 Leaf dehydration and litter refreshing experiments

Two fuel materials, green live leaves and fallen litter, were used for the leaf dehydration experiment and litter refreshing experiment, respectively. Green leaves of five deciduous species were collected, namely *Zelkovaserrata*, *Idesiapolycarpa*, *Liquidambar styraciflua*, and *Prunus× yedoens is*from the campus of Shizuoka University and *Fagus crenata* from Mount Naeba, Japan. All branches with target green leaf samples were first cut pre-dawn and then re-cut under water, which can make the measurements of leaf reflectance accurate and reliable under non-in-situ conditions (Foley et al., 2006; Richardson and Berlyn, 2002). After that, all samples were covered by plastic bags and quickly transported to the laboratory. The samples were stored under high humidity, dim light, and cool temperatures before reflectance measurements were taken. Four to five green mature leaves for each species, making a total of 24 samples, were used for the next experiments. Five fallen litter leaf samples of each of the same species, with no broken holes on the surface, making a total of 25 samples, were collected on the top ground as well. The colors of all litter samples were brown and there were no visible indications for the presence of leaf chlorophyll in the leaves.

Leaf mass was measured with an electronic balance and leaf areas were scanned using a scanner. Spectral reflectance (350–2500 nm) was measured with a field spectroradiometer (ASD FR, USA) equipped with a leaf clip, in which a light source of a tungsten quartz halogen lamp was embedded. The spectral resolution was 3 nm in the VNIR (350-1000 nm) and 30 nm in SWIR (1000-2500 nm). A white reference scan was made for the calibration before taking the reflectance measurement in the leaf clip with matched openings for non-destructive contact measurements.

Reflected spectra of green leaf samples were measured after samples were taken back to the laboratory. Then, the leaves were cut with scissors and leaf mass was measured immediately. After that, the leaves were placed on an experimental bench for dehydration, and leaf reflectance and mass were measured synchronously at progressive time intervals of 30 min, 1 h, 2h, and 4h during the entire dehydration period until the leaf sample was air-dried to a stable weight. Finally, the air-dried samples were oven-dried at 70°C for 72 h and then weighed again. A total of 224 measurements were made for 24 green leaves.

All fallen litter leaf samples were first soaked in water for 48 hours at 20°C to refresh them and to ensure there was sufficient water in the samples for dehydration. Then, water on the sample surface was wiped off and all samples were placed on an experimental bench for dehydration. Reflectance measurements and leaf mass were measured synchronously at progressive time intervals of 10 min, 30 min, 1 h, and 2h until all samples were air-dried. Finally, air-dried samples were oven-dried at 70°C for 72 h and then reweighed. The total number of measurements was 299 for all 25 litter samples.

4.2.2 Simulated dataset

PROSPECT 4 (Féret et al., 2008) was used to simulate leaf reflectance from 400 to 2500 nm with 1 nm step as a function of leaf structure index (N), leaf total chlorophyll content (CHL, µg/cm^2), water content (EWT, g/cm^2), and dry mass content (LMA, g/cm^2). In order to generate various reflectance and FMC, a uniform distribution within a wide range of each input parameter was chosen. Because CHL had no effect on water and dry matter indices, a constant value of 50µg/cm^2 was held. A dataset of 5000 simulations was built (Table 4-1).

Table 4-1 Input parameters and values for simulated dataset (n=5000) with PROSPECT model

Parameters	Minimum	Step	Maximum
N	1	0.2	3
CHL (µg/cm^2)	50	0	50
EWT(g/cm^2)	0.0025	0.0025	0.05
LMA(g/cm^2)	0.002	0.002	0.05

4.2.3 Calculation of FMC and reported spectral indices for FMC estimation

FMC is normally expressed by the ratio of the leaf water content to the leaf dry weight:

$$\text{EWT (g/cm}^2\text{)} = (W_f - W_d)/A \qquad (1)$$

$$\text{LMA} = W_d/A \qquad (2)$$

$$\text{FMC (\%)} = ((W_f - W_d)/W_d) \times 100 = \text{EWT/LMA} \qquad (3)$$

where W_f was the leaf mass during the dehydration processes for green leaf and fallen litter samples. W_d and A were the leaf dry weight, and leaf area, respectively.

A wide range of spectral indices for estimating plant water and dry matter have been devised based on different combinations of wavelengths. In this study, five water indices[WI, SR(1300, 1450), SRWI, NDWI, and NDII], four dry matter indices [NDMI, ND(2309, 1495), LCA, and CAI], and one ratio of water index to dry matter index reported in previous studies were selected to test their performance in monitoring FMC during the dehydration process. The details of all selected indices are shown in Table 4-2.

Table 4-2 Published indices for water content and dry matter

Index	Formula	References
WI	R970/R900	Peñuelas et al. (1993)
SR(1300,1450)	R1300/R1450	Seelig (2008a)
SRWI	R860/R1240	Zarco-Tejada *et al*.(2003)
NDWI	(R860-R1240)/ (R860+R1240)	Gao (1996)
NDII	(R860-R1650)/(R860+R1650)	Hardisky et al. (1983)
NDMI	(R1649−R1722)/(R1649+R1722)	Wang et al. (2011b)
ND(2305,1495)	(R2305−R1495)/(R2305+R1495)	Romero et al. (2012)
NDII/NDMI	((R860-R1650)(R1649+R1722))/((R860+R1650) (R1649−R1722))	Wang et al. (2013)
LCA	2R2205−(R2165+R2330)	Daughtry et al. (2005)
CAI	0.5(R2031 −R2211) – R2101	Nagler et al. (2000)

4.2.4 Determination of the best indices

Four commonly used types of indices (R, D, SR, and ND) (le Maire et al., 2008) based on both the original reflectance and the first derivative of reflectance were used to determine the best indices for FMC. The equations of the four types of indices for original reflectance are as follows:

$R=R_{\lambda1}$

$D=R_{\lambda1}-R_{\lambda2}$

$SR=R_{\lambda1}/R_{\lambda2}$

$ND= (R_{\lambda1}-R_{\lambda2})/(R_{\lambda1}+R_{\lambda2})$

where R, D, SR, and ND are the reflectance at a given single wavelength, wavelength difference, simple ratio, and normalized ratio, respectively. $R_{\lambda1}$ and $R_{\lambda2}$ are the wavelengths at λ1 and λ2, respectively. Indices based on the first derivative of reflectance are termed dR, dD, dSR, and dND, respectively. And the calculations of the indices based on the derivative spectra are analogous in their computation to the non-derivative spectral indices.

There different datasets, the green dataset, the litter dataset and simulated dataset, were used to determine the best hyperspectral indices for FMC estimation. The determination of indices was carried out based on linear regression between FMC and a given index which covered all possible combinations of wavelengths from 400 to 2500nm with a wavelength interval of 5 nm. The root mean square error (RMSE) and the coefficient of determination (R^2) were used as statistical criteria to evaluate the performance of published/identified indices. Let y_i, y_i', and $\bar{y}$ be the measured values, predicted values, and the average of the observed values, respectively, and n the number of observations; then:

$$R^2 = 1 - \sum_{i=1}^{n}(y_i' - y_i)^2 \Big/ \sum_{i=1}^{n}(y_i' - \bar{y})^2$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2}$$

4.3 Results

4.3.1 Changes in leaf reflectance of different fuel type during leaf dehydration

Figures 4-1 and 4-2 show the changes of reflectance and first derivative of reflectance for green leaf and litter samples of each plant species attributed to progressive dehydration, respectively. The reflectance of green leaf samples generally increased in the range from 400 to 2500 nm as FMC decreased for different species, particularly around the two water absorption bands of 1450 and 1940 nm. Meanwhile, new peaks near 2000 and 2400 nm gradually appeared and differences in reflectance among species were very clearly observed from 400 to 1200nm. The reflectance of litters showed increasing trends similar to those of green leaves, and new peaks appeared near 2000 and 2400 nm as well. The most apparent difference in reflectance between green leaves and litter samples is within the wavelength domain from 400 to 1200 nm. For instance, there were no chlorophyll absorption bands in the litter samples, and therefore the slopes around 750 nm were much steeper for green leaves than for litters, which can also be clearly noted in the corresponding wavelengths of the first derivative spectra.

A common characteristic of the first derivative spectra for both materials was that there is a shift towards long wavelengths on the left side edges near to water absorption troughs centered at 1450 and 1940 nm, corresponding to the decrease of FMC. Moreover, a “blue shift” in the red edge was found for green leaves. Further, the peaks of the first derivative spectra near 2050–2100 and 2250–2300 nm were observed, in agreement with the variations of original reflectance near to both 2000 and 2400nm.

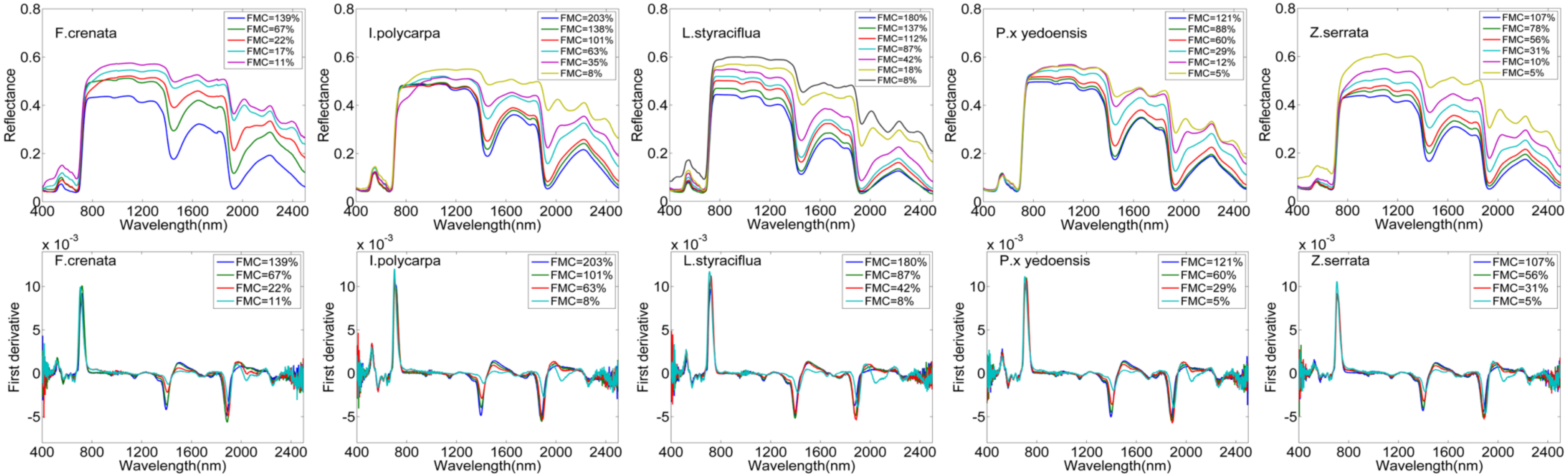

Figure 4-1 Variations of reflectance and first-derivative reflectance for green leaves of different plant species attributed to progressive dehydration

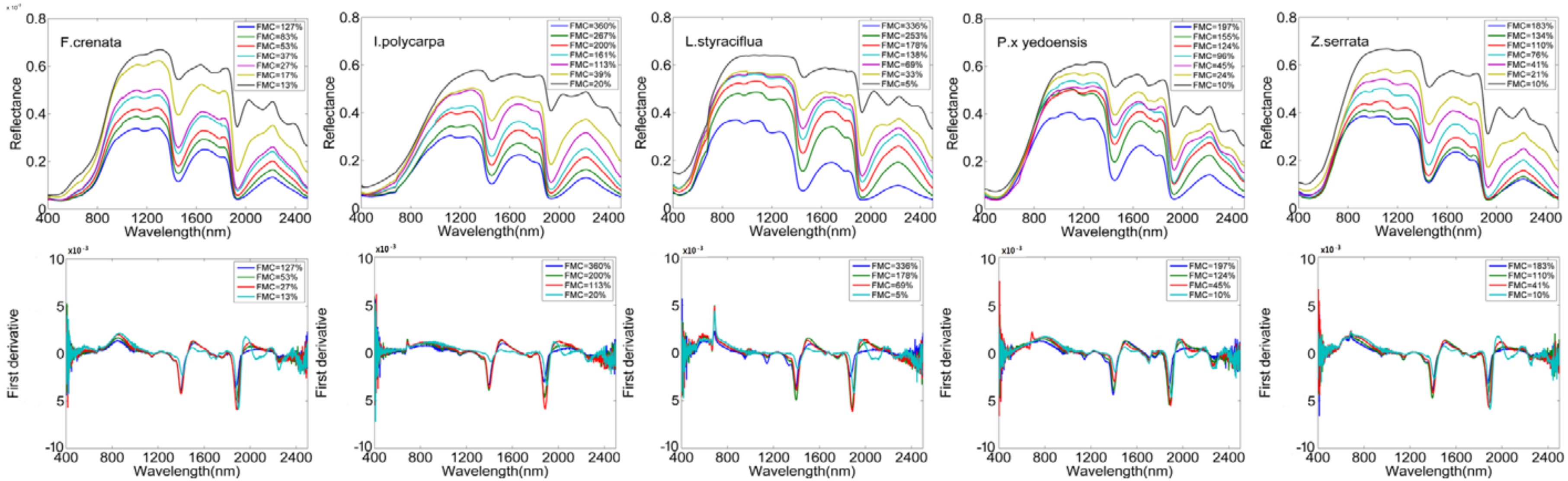

Figure 4-2 Variations of reflectance and first-derivative reflectance for litters of different plant species attributed to progressive dehydration

4.3.2 Performance of reported indices for estimating FMC based on measured datasets

Five water indices were all significantly correlated with FMC and EWT in the green leaf dataset, but these correlations were very weak for the litter dataset, except for SR (1300, 1450), which had the highest R^2 for FMC and EWT in different datasets. There were no significant relationships between all five water indices and LMA (Table 4-3). In contrast to water indices, dry matter indices had smaller correlations with FMC for all datasets, and only CAI showed significant correlations with EWT, while the ND (2305, 1495) was well correlated with LMA when using different datasets. NDII/NDMI was significantly correlated with FMC and EWT in the green leaf dataset, but failed for litters, and its correlation with LMA was also insignificant (Table 4-3). As a result, SR (1300, 1450) was the most sensitive index to FMC and EWT but was insensitive to LMA, while ND (2305, 1495), on the contrary, was most sensitive to LMA but insensitive to EWT and FMC.

4.3.3 Identified best indices for FMC estimation of different fuel types

The identified best indices based on both original reflectance and first derivative spectra for estimating FMC are presented in Tables 4-4 and 4-5. Among all selected indices of original reflectance, the ND (1630, 1680) was the best one for estimating FMC across different datasets, with an R^2 of 0.79 and an RMSE of 37.69% when all datasets were pooled. The SR (1820, 1830) had similarly higher values of R^2 but the two wavelengths used were too close together given the spectra resolution. Furthermore, the performance of ND (1630, 1680) with EWT was significant as well, with an R^2 of 0.78 and an RMSE of 0.0023 g/cm^2. However, none of the identified indices had significant correlations with LMA.

Table 4-3 Published spectral indices for FMC, EWT, and LMA based on different datasets

Related to	Indices	Green leaf dataset(n=224)		Litter leaf dataset(n=299)		Pooled dataset(n=523)	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
FMC (%)	WI	0.69	30.42	–	–	–	–
	SR(1300,1450)	0.74	27.77	0.67	53.42	0.70	44.95
	SRWI	0.67	31.17	–	–	–	–
	NDWI	0.66	31.74	–	–	–	–
	NDII	0.60	34.18	–	–	–	–
	NDMI	–	–	–	–	–	–
	ND(2305,1495)	–	–	0.31	77.15	0.33	67.80
	NDII/NDMI	0.73	28.22	–	–	–	–
	LCA	0.25	47.05	0.39	72.69	0.38	65.02
	CAI	0.53	37.00	0.61	58.25	0.57	54.14
EWT (g/cm^2)	WI	0.71	0.0022	–	–	–	–
	SR(1300,1450)	0.94	0.0010	0.86	0.0018	0.89	0.0016
	SRWI	0.67	0.0024	–	–	–	–
	NDWI	0.66	0.0024	–	–	–	–
	NDII	0.82	0.0018	–	–	–	–
	NDMI	–	–	–	–	–	–
	ND(2305,1495)	–	–	–	–	–	–
	NDII/NDMI	0.67	0.0024	–	–	–	–
	LCA	–	–	0.44	0.0037	0.38	0.0038
	CAI	0.74	0.0021	0.80	0.0022	0.76	0.0023
LMA (g/cm^2)	WI	–	–	–	–	–	–
	SR(1300,1450)	–	–	–	–	–	–
	SRWI	–	–	–	–	–	–
	NDWI	–	–	–	–	–	–
	NDII	–	–	–	–	–	–
	NDMI	0.60	0.0014	–	–	0.27	0.0018
	ND(2305,1495)	0.71	0.0012	0.61	0.0011	0.61	0.0013
	NDII/NDMI	–	–	–	–	–	–
	LCA	–	–	–	–	–	–
	CAI	–	–	–	–	–	–

$P<0.001$; "–": $R^2<0.25$.

Table 4-4 Evaluation of four types of indices with original reflectance for FMC, EWT, and LMA

Datasets	Index type			Green leaf dataset(n=224)		Litter leaf dataset(n=299)		Pooled dataset(n=523)	
		λ1	λ2	R^2	RMSE	R^2	RMSE	R^2	RMSE
FMC (%)	R	1390		0.80	24.02	0.68	52.86	0.70	44.91
	D	420	1385	0.81	23.75	0.70	50.71	0.74	42.40
	SR	1820	1830	0.88	18.83	0.76	45.85	0.79	38.02
	ND	1630	1680	0.83	22.28	0.78	43.81	0.79	37.69
EWT (g/cm^2)	R	1390		0.84	0.0016	0.79	0.0023	0.81	0.0021
	D	420	1385	0.84	0.0017	0.81	0.0022	0.82	0.0020
	SR	1820	1830	0.88	0.0014	0.86	0.0019	0.87	0.0017
	ND	1630	1680	0.84	0.0016	0.73	0.0026	0.78	0.0023
LMA (g/cm^2)	R	1390		–	–	–	–	–	–
	D	420	1385	–	–	–	–	–	–
	SR	1820	1830	–	–	–	–	–	–
	ND	1630	1680	–	–	–	–	–	–

$P<0.001$; "–": insignificant regression.

Table 4-5 Evaluation of four types of indices with first derivative of reflectance for FMC, EWT, and LMA

Datasets	Index type			Green leaf dataset(n=224)		Litter leaf dataset(n=299)		Pooled dataset(n=523)	
		λ1	λ2	R^2	RMSE	R^2	RMSE	R^2	RMSE
FMC (%)	dR	1915		0.72	28.45	0.62	56.83	0.64	49.56
	dD	1550	1985	0.70	29.64	0.68	52.19	0.71	44.68
	dSR	1655	1910	0.68	30.62	0.82	39.34	0.81	36.17
	dND	1900	2095	0.87	19.33	0.83	38.19	0.85	31.53
EWT (g/cm^2)	dR	1915		0.72	0.0022	0.75	0.0025	0.75	0.0024
	dD	1550	1985	0.85	0.0016	0.80	0.0022	0.82	0.0020
	dSR	1655	1910	0.68	0.0023	0.61	0.0031	0.64	0.0029
	dND	1900	2095	0.83	0.0017	0.73	0.0026	0.76	0.0023
LMA (g/cm^2)	dR	1915		–	–	–	–	–	–
	dD	1550	1985	–	–	–	–	–	–
	dSR	1655	1910	–	–	–	–	–	–
	dND	1900	2095	–	–	–	–	–	–

$P<0.001$; "–": insignificant regression.

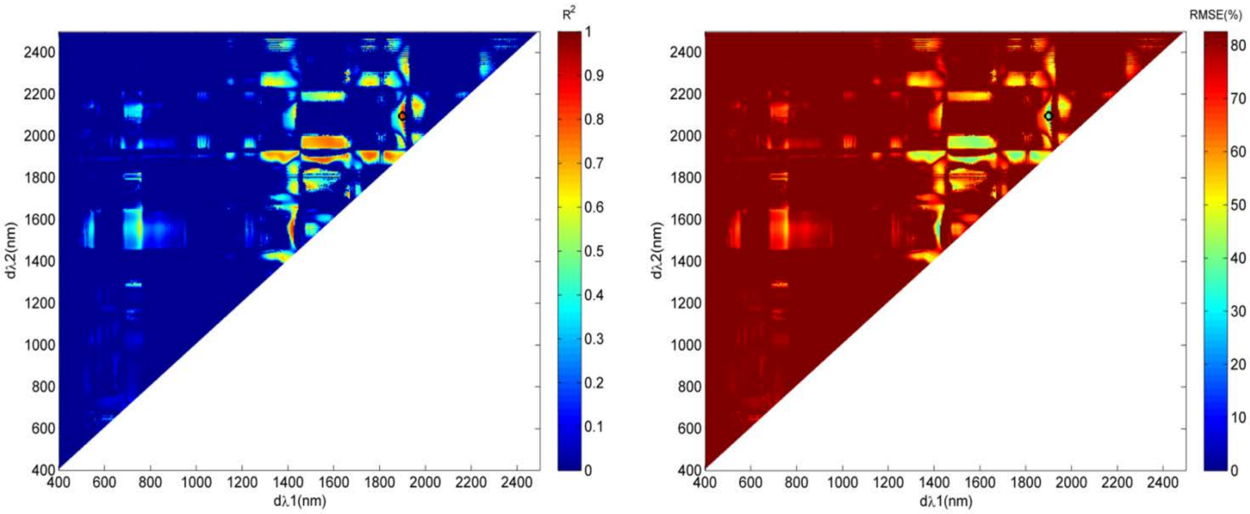

Figure 4-3 R^2 and RMSE of FMC estimation with dND type indices. The positions with black circles in the figures are the selected dND (1900, 2095)

On the other hand, the best identified indices using first derivative spectra were the dND (1900, 2095) (Table 4-5 and Figure 4-3), for both green leaves and litters, with an R^2 of 0.87 and an RMSE of 19.33% for the green leaf dataset and an R^2 of 0.83 and an RMSE of 38.19% for litters. The overall R^2 reached 0.85 when all datasets were pooled and the RMSE was 31.53%. The dND (1900, 2095) was also closely correlated with EWT but had no significant correlation with LMA. Compared with the original reflectance based indices, the first derivative spectra based dND (1900, 2095) is apparently superior to SR (1300, 1450) and ND (1630, 1680), with higher R^2 and lower RMSE when estimating FMC for different datasets.

4.3.4 Performance of published and selected indices for FMC estimation with simulated dataset

The performances of published indices for FMC (Table 4-6) estimation using simulated dataset were quite different with that using green leaf or litter measured-dataset (Table 4-3). For example, all water indices (WI, SR(1300, 1450), SRWI, NDWI and NDII) showed weaker relationship with FMC in simulated dataset than that in green leaf dataset (Table 4-3), and they were still significantly correlated with EWT but no relationship with LMA (Table 4-6).

Table 4-6 Performance of published and selected indices for FMC, EWT and LMA estimation based on simulated dataset

	FMC (%)		EWT(g/cm²)		LMA(g/cm²)	
Indices	R^2	RMSE	R^2	RMSE	R^2	RMSE
WI	0.22	283.89	0.90	0.0046	0.04	0.0141
SR(1300,1450)	0.15	296.84	0.88	0.0051	0.00	0.0144
SRWI	0.17	292.99	0.88	0.0050	0.01	0.0143
NDWI	0.17	293.43	0.89	0.0049	0.01	0.0143
NDII	0.04	316.52	0.79	0.0066	0.07	0.0139
NDMI	0.33	263.96	0.01	0.0143	0.88	0.0050
ND(2305,1495)	0.38	254.64	0.08	0.0138	0.76	0.0070
NDII/NDMI	0.86	119.83	0.24	0.0126	0.46	0.0106
LCA	0.01	321.41	0.33	0.0118	0.26	0.0124
CAI	0.01	320.89	0.26	0.0124	0.33	0.0118
R(1390)	0.03	318.13	0.59	0.0092	0.06	0.0140
D(420, 1385)	0.01	319.88	0.53	0.0098	0.08	0.0138
SR(1820,1830)	0.37	255.91	0.62	0.0089	0.34	0.0117
ND(1630, 1680)	0.44	240.68	0.35	0.0116	0.62	0.0089
dR(1915)	0.07	311.57	0.62	0.0089	0.0028	0.0144
dD(1550, 1985)	0.27	276.13	0.70	0.0079	0.0687	0.0139
dSR(1655,1910)	0.00	322.30	0.00	0.0144	0.0000	0.0144
dND(1900, 2095)	0.00	322.26	0.00	0.0144	0.0000	0.0144

However, except SR (1300, 1450), the performance of the other water indices were similar between simulated and litter dataset for FMC estimation. The best indices for FMC estimation using simulated dataset was NDII/NDMI (R^2=0.86, RMSE=119.83%), but it failed in litter dataset (Table 4-3). The selected dND(1900, 2095) based on green and littler datasets was insignificantly correlated with FMC in simulated datasets. All in all, there were no indices that synchronously significantly correlated with FMC in all three datasets.

4.4 Discussion

4.4.1 FMC estimation with spectral indices

Retrieval of FMC based on spectral indices has been attempted in many former studies (Yebra et al., 2008; Yebra et al., 2013 and references therein). However, those indices are usually designed only based on the absorption features of leaf water or leaf dry matter but ignoring that FMC is regulated by both parameters, although several indices were found to be correlated with FMC (Table 4-3). Our results clearly indicated that only SR (1300, 1450) (Seelig et al., 2008a) and CAI (Nagler et al., 2000) were satisfactory for estimating FMC and EWT simultaneously for both green and litter fuel types among all published indices, and both had insignificant relations with LMA (Table 4-3). A high R^2 with EWT (Table 4-3) but low R^2 with LMA of the FMC index suggested that the leaf dry matter information in FMC was mostly suppressed by leaf water content. In addition, statistically much stronger relationships with leaf EWT than with FMC were also found by Danson and Bowyer (2004) using different spectral vegetation indices.

The most likely reason for the failure of the other published indices examined in this study may be primarily due to the big difference in the reflected spectra within the domain of 400 to 1200 nm for both fuel types (Figures 4-1 and 4-2). Most reported indices selected in this study used wavelengths in this domain, such as the wavelengths of 970 nm in WI (Penuelas et al., 1993) and 860 nm in NDWI (Gao, 1996), SRWI (Zarco-Tejada et al., 2003), and NDII (Hardisky et al., 1983; Ceccato et al., 2001). Furthermore, these water indices were designed solely on a physical basis with leaf water content, such as 1240 nm in NDWI and SRWI and 1650 nm in NDII. Similarly, the wavelengths in NDMI (Wang et al., 2011b), ND (2305, 1495) (Romero et al., 2012), and LCA (Daughtry et al., 2005) were only determined by dry matter content. To solve this problem, Wang et al (2013) proposed an index ratio of NDII/NDMI for correlation with FMC, in which NDII was only correlated with leaf water content and uncorrelated with leaf dry matter content while NDMI was only correlated with leaf dry matter content and uncorrelated with leaf water content. However, the performance of NDII/NDMI for the litter dataset was failed (Table 4-3), mainly due to the applied wavelength of 860 nm in NDII. Therefore, new types of indices need to be designed for FMC estimation for different fuels.

Leaf reflectance progressively increased and dry matter bands gradually appeared in association with the process of leaf dehydration, hence providing an opportunity to couple the spectral information of both leaf water and dry matter (Figures 4-1 and 4-2). These increasing trends were also observed in other plant species in response to dehydration (Carter, 1991; Foley et al., 2006; Peñuelas et al., 1993; Seelig et al., 2008). Our results revealed that the most evident positions that appeared as a result of dry matter wavebands in this study were near to 2100 and 2300 nm, which were similar to the dry matter bands such as cellulose, lignin, and proteins found by former studies (Cheng et al., 2011; Cheng et al., 2012; Romero et al., 2012). Most importantly, the reflectance changes from 1200 to 2500 nm of both green leaves and litter materials were similar during the entire dehydration (Figures 4-1 and 4-2), suggesting that FMC in both materials could be estimated by the same index in this wavelength range.

In order to identify the most sensitive combinations of different wavelengths to FMC, four common types of indices based on either original reflectance or first derivative spectra were used in the current study. The dND (1900, 2095) was determined as the best index to estimate FMC for both green leaves and litters (Table 4-5), and was better than all published indices examined or the best performing indices based on original reflectance in this study (Table 4-4). Moreover, unlike that of SR (1300,1450),the correlation coefficient between dND (1900, 2095) and FMC was higher (R^2=0.85) than that for EWT (R^2=0.76), probably due to the high relationship between the d2095 and dry matter content, which changed from positive to negative due to the appearance of dry matter bands near 2100 nm (Figure 4-4).The variation of d1900 was largely caused by the decreasing depth of the water absorption band near 1940 nm (Figures 4-1, 4-2, and 4-4). Therefore, dND (1900, 2095) has accurately coupled information reflecting both leaf water and dry matter. As a comparison, other reported indices such as SR (1300, 1450) were only correlated with EWT while ND (2305, 1495) was only correlated to LMA (Table 4-3). The synthetic index proposed by Wang et al. (2013), the ratio of SR (1300, 1450) to ND (2305, 1495), was also tested for FMC estimation in this study. The smaller R^2(=0.81) together with a larger RMSE (=35.38%) compared to those of dND(1900, 2095) for the pooled dataset (Figure 4-5) indicated that such a straightforward combination might not be the best, although both ratios were the best for individual parameters.

However, the band of 1900 nm falls in atmospheric water vapor absorption windows, which limits the use of dND (1900, 2095) with airborne hyperspectral data. Even so, dND (1900, 2095) might principally incorporates the information of both leaf water and dry mass which the other reported indices usually have ignored. Considered the use for landscape scale, after removing the three noisy spectrum regions because of high absorption of atmospheric water vapor (1350-1450nm, 1800-1950 nm and 2200-2500 nm), the best indices for FMC estimation with pooled dataset are ND (1630, 1680) (R^2=0.79, RMSE = 37.69%) and dSR (1655, 1965) (R^2=0.80, RMSE = 36.93%). Both indices probably could be extrapolated to the landscape scale, but the information of spectral wavelengths in both indices is unclear compared with dND (1900, 2095).

Nevertheless, dND (1900, 2095) was failed in simulated dataset, suggesting that the simulations by PROSPECT were greatly different with litter measured-dataset (Table 4-6), the model need to be improved before the use for FMC estimation in different fuel types. The Simulations of PROSPECT were probably suitable for parameter estimation of green leaf, because the water indices were significantly correlated with EWT based on green leaf dataset and simulated dataset, respectively, and the performances of NDII/NDMI between green leaf dataset and simulated dataset were similar (Table 4-3 and Table 4-6). Even so, compared with other indices among different datasets, index of dND(1900, 2095) was the best one for different fuel types.

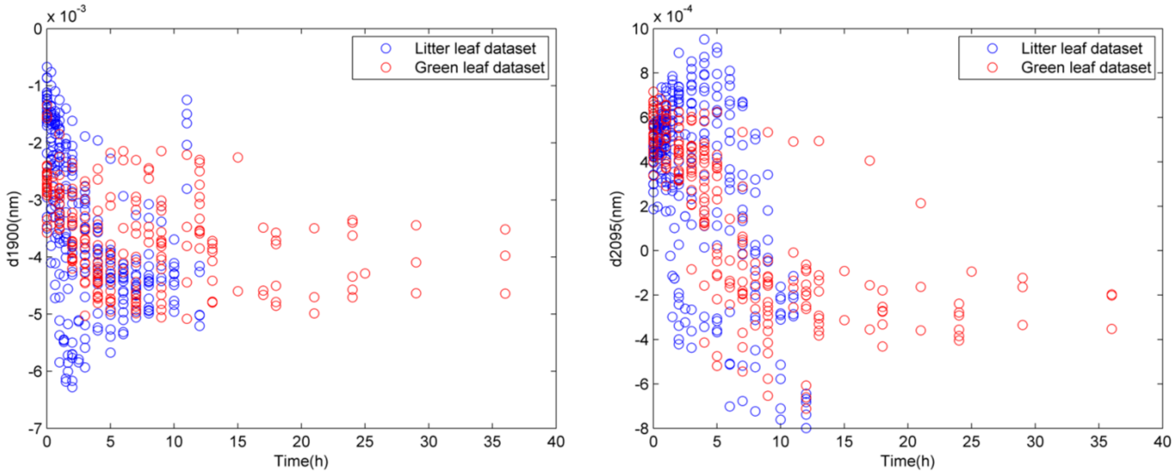

Figure 4-4 Variations of first derivative spectraat 1900nm (d1900) and 2095 nm (d2095) with dehydration time

4.4.2 Separately estimating FMC for different fuel types

As the biochemical compositions differ greatly between green leaves and litters, it might be necessary to separate them from each other in reality and hence the approach of Wang et al. (2013) might be a good choice. The apparent difference in reflected spectra from 400 to 1200 nm could help to solve this issue. We therefore designed a synthetic index by combining the dND (1900, 2095) with NDVI (800,680), which is a vegetation index commonly used to estimate the degree of greenness (Carlson and Ripley, 1997). The result indicated that the synthetic index could decouple green leaves from litters in FVC estimation, with an R^2 of 0.85 and an RMSE of 21.25% for the green leaf dataset and an R^2 of 0.45 and an RMSE of 69.26% for litters (fitted by exponential curves, see Figure 4-6). The poorer performance of the litter dataset was caused by the different NDVI values of individual species, suggesting that the indices needed to be validated with more plant species and the state of litter decomposition also should be considered as the spectral properties of the leaves will continue to change as a function of litter age, and ultimately converge on a uniform spectrum representative of organic soil. For example, NDVI is usually strongly affected by the soil background when applied to green vegetation cover. Hence, although satisfactory results were obtained for the synthetic index in this study, it needs thorough validations in future studies.

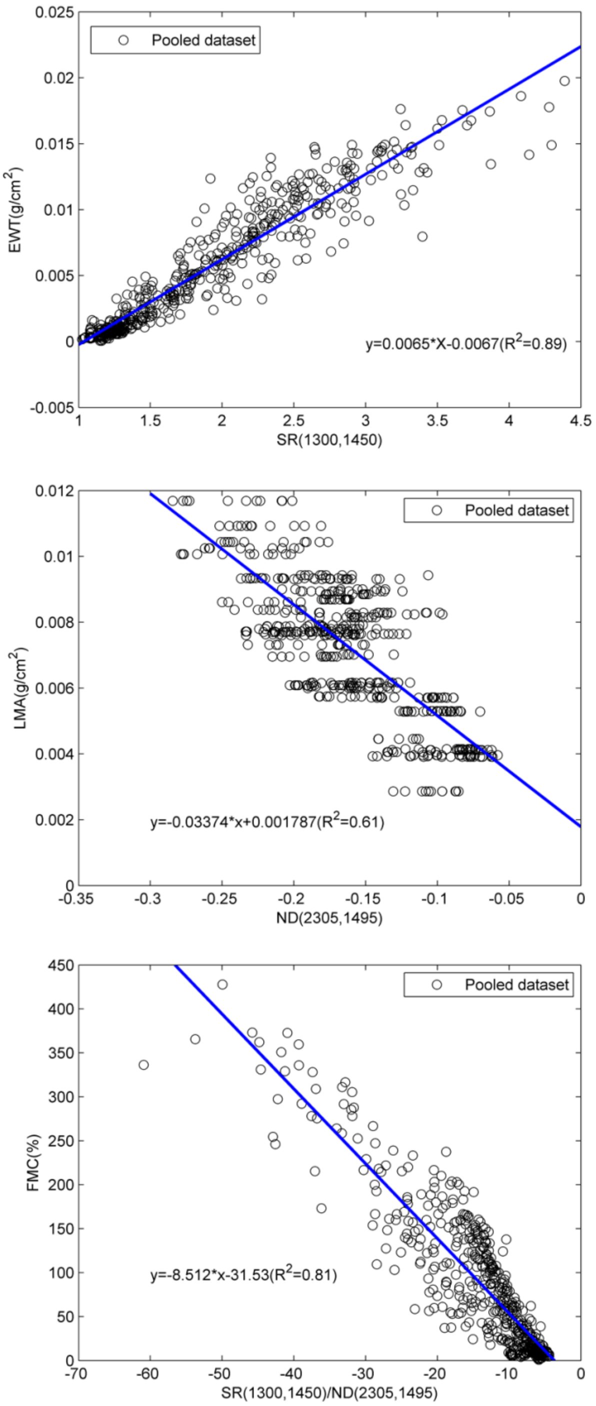

Figure 4-5 Regressions of SR (1300, 1450) and EWT, ND (2305, 1495) and LMA, and SR (1300, 1450)/ND (2305, 1495) and FMC

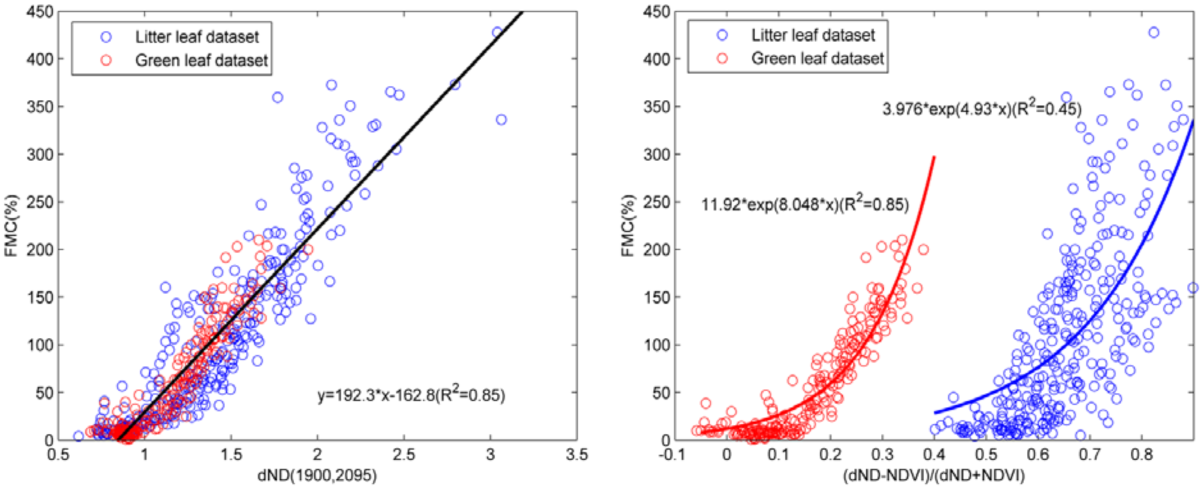

Figure 4-6 Regressions of dND (1900, 2095) and FMC and (dND-NDVI)/(dND+NDVI) and FMC

4.5 Conclusions

In this study, four commonly used types of indices (R, D, SR and ND) and two treatments of reflectance (original reflectance and first derivative of reflectance) were used to estimate FMC for both green and litter fuels based on leaf dehydration experiments. dND(1900, 2095) was identified as the best index to estimate FMC although it was failed in simulated dataset by PROSPECT. The reason was that the two derivative wavelengths used by the index, d1900 nm and d2095 nm, were closely related to leaf water content and leaf dry matter content, respectively. Furthermore, by applying NDVI, which can indicate the differences between green leaves and litters, a synthetic index which normalized dND(1900, 2095) with NDVI had effectively separated green leaves from litters during FMC estimation. But NDVI was strongly affected by many in situ factors, and dND(1900, 2095) combined with other indices such as relative greenness index might help to improve estimation further and needs extensive research in future.

Chapter 5 Synthesis and further developments

Widespread drought-induced forest mortality and forest fire have substantially affected the global hydrological cycle and carbon cycle, how to remotely and quantitatively monitor and assess the two disturbances have not been effectively addressed until now. Remote sensing approach has been recognized as a reliable and practical mean to estimate the distribution and risk of forest drought and fire by the retrieval of related biochemical and biophysical vegetation variables. Leaf water status, RWC and EWT, greatly varied when responding to drought, which can be used as the indicators for leaf water stress. Another leaf water state, FMC, can be used as the indicator for estimating the risk of forest fire. Photosynthetic status such as quantum yield of PSII is also substantially affected by drought, the detection of which can provide the function information related to drought. There are two common remote sensing approaches for estimating these indicators, model inversion and spectral indices. Hence, a simulated plant-mortality experiment, fresh leaf dehydration is designed to obtain the variations of reflectance spectra and physiological characteristics (chlorophyll fluorescence) and identify the best hyperspectral indices for RWC, EWT (chapter 2) and quantum yield of PSII (chapter 3) in this study. The other experiment, litter refreshing experiment is also conducted to identify the best index for estimating FMC in different fuel types with a combination of PROSPECT model (chapter 4).

5.1 Remote retrieval of ecological indicators for forest drought detection

In chapter 2, I selected five typical deciduous broadleaf species in Japan as the dehydration experiment materials which could obtain a relatively comprehensive dataset with the ranges of RWC and EWC that were difficult to obtain in field measurements. Moreover, five common types of hyperspectral indices [single reflectance (R), wavelength difference (D), simple ratio (SR), normalized ratio (ND) and double difference (DDn)] and four treatments of reflectance (original reflectance, reflectance difference, reflectance sensitivity and first derivative reflectance) were applied to determine the best RWC and EWT indices.

Both RWC and EWT dropped rapidly from the maximum to a near minimum within 10 h after leaf cutting, particularly in the first 5 h. After 10 h, the values of RWC and EWT were maintained stably near zero for each species. The RWC or EWT ranges of the leaf dehydration dataset focus on much lower values (extreme drought) compared with other field sites. Values of original reflectance, reflectance difference and reflectance sensitivity increased significantly within all wavelengths with a decrease in leaf water, particularly the ranges of 350-700 nm and 1300-2500 nm. This feature suggested that a decrease in leaf water content was the most important reason for changes in leaf reflectance, offering the possibility in the assessment of leaf water content. However, ranges of 350-750 nm, 750-1300 nm and 2000-2500 nm were also evidently affected by pigments, leaf structure and dry matter. Hence, the most suitable range was 1300-2000 nm for estimating leaf water status with a leaf dehydration dataset.

The identified best indices for RWC and EWT, when all the species were considered together, were the first derivative reflectance based ND type index of dND (1415, 1530) and SR type index of dSR (1530, 1895), with R^2 values of 0.95($p < 0.001$) and 0.97 ($p < 0.001$), respectively, better than previously published indices [WI, SR (1300, 1450), NDWI, SRWI, NDII and DDn (1530, 525)]. The recommend indices provide a means to monitor drought-induced plant mortality in temperate climate regions.

In chapter 3, $\Delta F/F'm$ was retrieved using the same leaf reflectance dataset and method in chapter 2. However, the range of reflectance only focused on 400-800 nm because leaf water content and dry mater content had minimal impact on these bands. Results showed that values of $\Delta F/F'm$ for different plant species were rapidly decreasing in the first 5 h since leaf cutting. At the time of around 12 h, ΔF/F'm of each species were near zero, meaning that all leaf samples were almost totally died. The changes of ΔF/F'm could not be traced by the published indices of NDVI and PRI. There were no significant correlations between ΔF/F'm and between ΔF/F'm and NDVI when all species were considered. The identified best indices for estimating ΔF/F'm was dND (533, 686) across different type of indices, with an R^2 of 0.88 and an RMSE of 0.11. The band of 533 nm was near the carotenoid absorption region and 686 nm was affected by chlorophyll fluorescence emission. Thus, the selected dND (533, 686) could provide a remote mean to track the variation of photosynthetic status for plants under drought.

5.2 Remote retrieval of ecological indicator for wildfire detection

In chapter 4, two fuel materials, green live leaves and fallen litter, were used for the leaf dehydration experiment and litter refreshing experiment, respectively. The plant species were same with that in chapter 2 and 3. Moreover, a simulated dataset was built using PROSPECT model, including 5000 simulations with a wide range of input parameters. Five water indices [WI, SR (1300, 1450), SRWI, NDWI, and NDII], four dry matter indices [NDMI, ND (2309, 1495), LCA, and CAI], and NDII/NDMI reported in previous studies were selected to test their performance in monitoring FMC. Totally, there datasets of green leaf dataset, litter dataset and simulated dataset were used to determine the best FMC indices.

The reflectance from 400 to 1200 nm were quite different between green live leaves and fallen litters, while the changes from 1200 to 2500 nm were similar with the decreasing FMC. Meanwhile, dry matter bands were gradually appeared. Five water indices were all significantly correlated with FMC in the green leaf dataset, but except for SR (1300, 1450), these correlations were very weak for the litter and simulated datasets. In contrast to water indices, dry matter indices had smaller correlations with FMC for all datasets. NDII/NDMI was significantly correlated with FMC in both the green leaf dataset and simulated dataset, but also failed in litter dataset.

The identified best index for FMC in both fuel types was dND(1900, 2095), with an R^2 of 0.85 and an RMSE of 32%, although it was failed in simulated dataset by PROSPECT. The reason was that the two derivative wavelengths used by the index, d1900 nm and d2095 nm, were closely related to leaf water content and leaf dry matter content, respectively. Furthermore, by applying NDVI, which could indicate the differences between green leaves and litters, a synthetic index which normalized dND(1900, 2095) with NDVI had effectively separated green leaves from litters during FMC estimation.

5.3 Future works

The detection of forest drought and fire is often based on the changes in leaf water status and photosynthetic status since leaf is the most vulnerable component and it directly links to optical observations by satellite. However, the distributions of the two disturbances had spread worldwide in different ecosystems. Hence, several potential future research works are needed and listed as follows:

(1) Leaf scale reflectance is greatly affected by leaf structure and plant species, one of the future works is to extend the methods used and developed in this study to more different plant species, including shrubs, grass and coniferous plants. After then, the applications of forecast and mapping to large scales (canopy, regional and global) of the selected indices need to be put into practice which is depended on the development of hyperspectral space-borne sensors.

(2) More information of mechanism of function degradation of plant mortality caused by drought is required because it will obstacle the research on the relationship between leaf spectra and physiological processes. It also makes how to distinguish drought and fire from the other types of disturbance is difficult. Moreover, the

spectral responses of different materials or physiological processes should be extended to exploit the attribution and discern different types of disturbance.

(3) The differences between simulations of PROSPECT and measured-litter reflectance are evident, new models are required to determine the universal indices for various vegetation biochemical and biophysical parameters of different martials at different scales.

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