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Estimation of Plant Flowering Phenology in Urban Ecosystems using Remote Sensing Techniques

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Estimation of Plant Flowering Phenology in Urban Ecosystems using Remote Sensing Techniques

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ABSTRACT

Phenology is the study of the timing of recurrent biological events, the causes of the timing with regard to biotic and abiotic forces, and the interrelation among phases of the same or different species. Plant reproductive phenology such as flowering and fruiting is closely related to nature-based tourism. For example, cherry blossom viewing during spring season is able to provide great amounts of social and economic benefits in Japan. On the other hand, plant reproductive phenology is one of the indicators to monitor climate change since the trend of spring phenology is able to reflect effects of climate change. It is well known that reproductive phenology of plants in urban areas has changed due to urban and global temperature increment in recent years. Therefore, monitoring reproductive phenology is crucial not only to identify biological and physiological status of cherry blossoms, but also to understand potential risk of nature-based tourism. However, monitoring reproductive phenology at highly heterogeneous urban area is a challenge at landscape level as the spectral signal of flower is generally weak. Utilizing remotely sensed technique could provide spatial and temporal extend datasets of plant reproductive phenology in heterogeneous environment. Therefore, this study aimed to develop remote sensing technology to monitor spring phenology in urban area.

Firstly, the ability to identify flowering cherry trees at landscape level was investigated to explore the existing remote sensing technique ability in identifying cherry blossoms in urban park. To test the ability of remote sensing technique, hard and soft classifications were employed on IKONOS image in identification of flowering cherry trees in urban park which has been investigated. Results of this study indicate that soft classifier employed on IKONOS image performed better than hard classifier in identifying flowering cherry trees in urban park. Results also suggest that both methods are able to classify cherry blossoms in an urban landscape, but soft classifier classified that cherry blossoms are more accurate than hard classifier. Therefore, I conclude that the accuracy of soft classifier could decrease due to the limited number of available bands (four for IKONOS) and the existence of endmembers, such as dry grass in this

study, with stronger signals than flowers. Therefore to overcome misclassification problem in order to improve soft classification accuracy, spectral characteristics and its properties exploration must be carried out.

Secondly, spectral properties of flowering cherry were explored as an input to develop spectral library at petal and branch levels, and effects of morphological characteristics were investigated. Effects of morphological characteristics were evaluated using established vegetation indices. The properties of flowering cherry at petal and branch levels varied at visible wavelength. The spectral properties variation at petal and branch levels may be due to morphological effects. In addition, results indicated that spectral radiometer evaluation of pink element was inconsistent from petal to branch level while green and yellow elements were consistent at petal to branch level. Despite that, results showed that spectral radiometer visual evaluation was consistent with human visual evaluation at petal level but inconsistent at branch level. As a conclusion, spectral properties of cherry cultivars collected in this study can be used to develop spectral library that can be used to identify cherry cultivars at landscape level. Besides that, consistency of spectral radiometer visual evaluation with human visual evaluation at petal level may suggest that spectral radiometer data can be used to identify cherry cultivars. Thus, it is recommended to develop cherry blossom index as each of cherry cultivars has different spectral pattern. Besides that, effects of phylogenetic and other morphological characteristics of cherry cultivars towards spectral properties should be further explore.

Based on the results obtained in this thesis, I strongly suggest that remote sensing techniques may have potential to monitor urban flowering plant spring phenological event even the urban landscape was highly heterogeneous. By using remote sensing approach, cherry blossoms spring phenological event can be monitored frequently and could improve the cherry blossoms management as cherry blossoms provide economic and social benefits.

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LIST OF ABBREVIATIONS

UHI	-	Urban heat island
IFOV	-	Instantaneous field of view
SMA	-	Spectral Mixture Analysis
NIR	-	Near Infrared
JMA	-	Japan Meteorological Agency
AVHRR	-	Advanced Very High Resolution Radiometer
MODIS	-	Moderate Resolution Imaging Spectroradiometer
EVI	-	Enhanced Vegetation Index
PRI	-	Photochemical Reflectance Index
RMSE	-	Root mean square error
LMM	-	Linear Mixed Model
NLMM	-	Non-linear Mixed Model
N-FINDR	-	Random N-finder
ML	-	Maximum likelihood
MTMF	-	Mixture tuned matched filtering

UTM	-	Universal transverse Mercator
WGS84	-	World geodetic systems 1984
GPS	-	Global positioning systems
GLCM	-	Gray level co-occurrence matrix
TD	-	Transform divergence
MT	-	Mixture tuning
MF	-	Matched filter
OA	-	Overall accuracy
AVIRIS	-	Airborne Visible / Infrared Imaging Spectrometer
TFSG	-	Tama Forest Science Garden
FFPRI	-	Forestry and Forest Products Research Institute
MCARI	-	Modified Chlorophyll Absorption Index
MARI	-	Modified Anthocyanin Reflectance Index
CRI	-	Carotenoid Reflectance Index
ANOVA	-	Analysis of Variance
VI	-	Vegetation Index

Chapter 1

General Introduction

1.1 Significance of studies on urbanization

Recently, urban growth is increasing rapidly where 45% of populations in the world are living in urban areas and estimates to increase to over than 60% in 2030 (United Nations, 2007). The urban area is expected to continue to grow in the future in emergence of very large urban agglomerations in developing country (Berry, 1990; United Nations, 2007).This is due to localization of population from rural to urban area. Urbanization extremely influence biodiversity and ecosystem function as well as climate and quality of life (Luck and Wu 2002 ; Li et al., 2011). One of the ecological consequences of urbanization is the urban heat island (UHI) effect, which leads to higher temperature in urban area than surrounding suburban or rural areas. UHI effect is one of the global climate change indicator that burden urban environments especially urban vegetation phenological event (Li et al. 2011).

1.2 Effects of urbanization on phenological events

Plant phenology has received much attention as it was strongly controlled by climate (Gordo and Sanz 2010). For example, Fitter et al. (1995) found that flowering timing in 90% of 243 studied plant species in England was significantly related to temperatures where the overwhelming majority of plants were able to tune their flowering dates accordingly to particular temperature condition of each year. In addition, Doi and Katano (2008) found that spring phenological events and autumn phenological events have been advanced and delayed, respectively, in recent decades, and both events tend to extend the length of growing season. Meanwhile, Aono and Kazui (2008) found that spring phenological events of cherry blossom for 732 years in Kyoto has changed according to imbalance temperature. Thus, phenological event monitoring is crucial to be monitored. However, lack of spatiotemporal data might be one of limitation to study phenological event (Numata et al., 2003, 2013; Badeck et al., 2004).

1.3 Remote sensing approach for monitoring plant phenological events

Remote sensing technology has been utilized in recent years at regional and geographical scale to assess inter-annual variation in phenology of deciduous vegetation (Delbart et al. 2006). Satellite remotely senses and measures the surface radiation based on visible and infrared wavelengths to monitor phenological cycle (Badeck et al. 2004). Satellite data and ground measurement can provide complementary information as the surface radiation measured by satellite can provide photosynthesis information which correlates with ground data especially the change of reflectance across red-edge wavelength which shows the characteristics features of photosynthesis active, chlorophyll-bearing plant organ (Myneni et al. 1997). Moreover, satellite data have capability to provide temporally frequent data where inter-annual variations and temporal trends in phenology can be observed. As satellite data can provide spatial data at large area extent, phenological pattern of entire globe especially place without ground observation can be carried out (Badeck et al. 2004; Botta et al. 2000).

However, mixed pixels occurrences in satellite image have challenged phenological studies as most satellites that provide temporally frequent data have coarse spatial resolution. High heterogeneity area like urban area with multiple land cover types may cause mixed pixels frequently occurred in coarse spatial resolution satellite image. Mixed pixels occurrences were inevitable when the target is smaller than instantaneous field of view (IFOV). Mixed pixels occurrences caused by multiple spectral responses in an IFOV where those spectral were mixed (Keshava and Mustard, 2002; Kanniah et. al., 2007; Boardman and Kruse, 2011; Quintano et. al., 2012). Due to spectrally mixed, observation on urban plant phenological events at landscape level will be a challenge. Despite that, remote sensing experts found that spectral mixing also a challenge to monitor phenological stages at canopy level. Spectral mixing occurrences at canopy levels due to plant canopy structure and spectral reflectance from soil. Therefore, to overcome mixed pixels at landscape level and spectral mixing at canopy level, researchers have developed spectral mixture analysis (SMA) approach which will be further discuss in Chapter 2.

1.4 Cherry blossom phenological events and its cultivation history

Flowering cherries are the most popular ornamental trees in Japan and flower synchronously in the spring in temperate zones of the Northern Hemisphere. Flowering cherries are of interest because they provide social and economic benefits from cherry blossom viewing, and they provide important information on the long-term impacts of climate change (Aono & Saito, 2010; Aono, 2014; Primack et al., 2009). Researchers have carried out numerous of studies on cherries flowering events and cultivation. This is because flowering cherries spring phenological event has shifted due to climate change (Aono, 1997; Yasuyuki Aono & Saito, 2010; Yasuyuki Aono, 2014). Thus, monitoring flowering cherries spring phenological event at landscape level is essential especially flowering cherries that been planted in urban areas. However, monitoring flowering cherries is challenging because urban environments are highly heterogeneous and the flowers produce a weak spectral signal. Besides that, there are more than hundreds flowering cherries in Japan.

Flowering cherries have been cultivated for more than 1,000 years (Flower Association of Japan 1982; Kuitert 1999). In Japan, more than 200 traditional cultivars are known (Kobayashi 1992), and they show diverse floral characteristics, including traits seldom found in the wild. Morphological studies on Japanese flowering cherry cultivars were initiated in the early twentieth century (Koidzumi 1913; Miyoshi 1916; Wilson 1916). Later works established a taxonomy for these cultivars (Flower Association of Japan 1982; Kawasaki 1993) that is now widely accepted (Ohba et al. 2007). Due to high number of flowering cherry cultivars, there are variations in their morphology and phylogeny trait. Thus, this variations made monitoring at landscape level more challenging due to its canopy structure and also various number of cultivars.

1.5 Research Objectives

The aim of this study is to develop remote sensing technology to monitor reproductive phenology in urban ecosystem. Numerous of studies on plant phenology that utilized remotely sensed data have been carried out (Reed et al. 1994; Zhang et al. 2003; Zhang et al. 2001). However, there are no attempt was carried out on plant reproductive organ except leaves. To achieve the aim of this study, a few objectives have been set up: (i) to estimate flowering cherry trees in a urban landscape using remote-sensing approach: Landscape level and (iii) to identify inter-specific variations in spectral properties of flowers by developing spectral library.

This study emphasize on the ability of remote sensing technique to estimate plant flowering phenology in urban ecosystems (Figure 1-1). In Chapter 2, spectral mixture analysis would be explained in details and it contribution to monitor plant flowering phenology. In Chapter 3, flowering cherry in urban park was identified at landscape level by utilizing IKONOS image. In this chapter, spectral mixture analysis and traditional image classifications abilities to identify flowering cherry. Spectral mixing is possible at canopy level where spectral variability from different plant reproductive organs. Spectral properties of cherry cultivars and inter-specific differences in spectral properties variations were identified in Chapter 5 to develop flowering cherry spectral library. As a conclusion, results obtained in this thesis indicate that remote sensing technology have potential to monitor flowering plant spring phenological event in high heterogeneous urban landscape as it can be identified by using soft classifier and the accuracy of the classification can be improved by utilizing spectral library obtained in Chapter 5. Therefore, remote sensing techniques can be used to improve flowering plant management in urban area effectively as flowering plant like cherry blossoms were of interest in nature-based tourism during spring season and it give high impact on social and economic benefits.

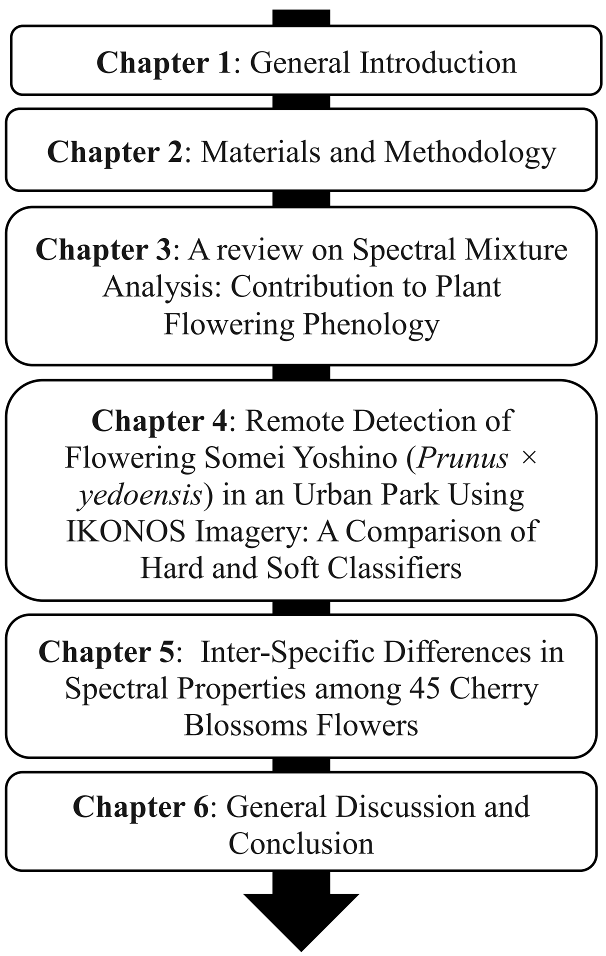


Figure 1-1: Structure of this thesis

Chapter 2

Materials and Methodology

2.1 Materials

2.1.1 Cherry blossoms

Forty five flowering cherry cultivars from twelve taxonomy groups were collected (as listed in Table 1) from Tama Forest Science Garden (TFSG; Hachioji, Tokyo, Japan) of the Forestry and Forest Products Research Institute (FFPRI). Flowering cherries (members of Prunus subgenus Cerasus, Rosaceae) are the most popular ornamental trees in Japan, and have been cultivated for more than 1,000 years (Flower Association of Japan 1982, Kuitert 1999). There are more than 200 traditional cultivars in Japan (Kobayashi 1992), which mainly differ in flower color, form, size and number of petals. Some have been exported widely and are grown world-wide. Most cultivars have been clonally propagated to avoid the dilution or loss of their unique characteristics and many are believed to have originated from native Japanese taxa (Kawasaki 1993, Koidzumi 1913, Kuitert 1999, Miyoshi 1916) (Table 2-1).

Table 2-1: Forty five cherry cultivars from twelve taxonomy groups

	Taxonomy groups	**Flower cherry cultivars**
1	*Prunus lannesiana*	(1)Matsume hayazaki, (2)Kyoto-no-mikurumagaeshi, (3)Angyou-no-shirayuki, (4)Angyou-no-ukon, (5)Kyoto-no-omuro ariake, (6)Angyou no Yokihi, (7)Angyou-no-shirotae, (8)Angyou-no-fukurokujyu, (9)Angyou-no-fugenzo, (10)Angyou-no-ichiyo, (11) Gioiko, (12)Angyou-no-shogetsu, (13) Sano-no-Taihaku, (14) Jindai-no-surugadai-nioi, (15) Uzu-zakura, (16) Kyoto-no-ohsawazakura, (17) Angyou-no-ojochin, (18) Beni-yutaka, (19) Sarasa, (20) Angyou-no-Edo,(21) Angyou-no-hatazakura, (22) Shizuka
2	*P. incisa var. incisa* (1 cultivar)	Kiyosumi-no-mamezakura
3	*P. campanulata* (Wild Cherry)	Mishima-no-kanhizakura
4	*Prunus*	Yoko
5	*P.* × *yedoensis* (4 cultivars)	(1) Somei yoshino, (2) Soto-ori-hime, (3) Sendai Yoshino (4) Akebono
6	*P. jamasakura (6 cultivars)*	(1) Sakunami yamazakura, (2) Wild yamazakura, (3) Tsukushi zakura, (4) Mishima-no-sendaiya, (5) Kyoto-no-hiyoshizakura, (6) Keta-shirokiku
7	*P. pendula* (3 cultivars)	(1) Taiunji-no-shidarezakura, (2) Chichibu benishidare, (3) Sano-no-yaebenishidare
8	*P. kanzakura* (2 cultivar)	(1)Kanzakura, (2) Kawazu-zakura
9	*P. incisa var. Incisa (Kinkiensis)*	Yamasaki-no-kinkimamezakura
10	*P.* × *takaenakae*	Mishima-no-tokaizakura
11	*P.* × *subhirtella*	Koshi-no-higan
12	*P. taiwaniana*	Yuki-no-mushazakura

2.1.2 Morphological data

Biological properties of cherry cultivar were examined by referring to morphology and phylogeny data of twenty three cherry cultivars obtained from published book by Parks and Open Space Association of Japan and FFPRI databased (http://db1.ffpri-tmk.affrc.go.jp/sakura/home.php) which contain information on diameter of flower, number of petal of each cultivar, characteristic of flower layer and color of each cultivar.

To identify the relationships of cherry cultivars spectral properties with other cherry cultivar biological properties (i.e. chemical content in the petal), few vegetation indices were identify in order to obtained information on chemical content in the flower petal by using spectral information.

2.1.3 Remotely sensed data

Multispectral IKONOS image [four bands: blue (445–516 nm), green (506–595 nm), red (632–698 nm), and near infra-red (NIR; 752–853 nm)] with 4-m resolution was used. The IKONOS data were recorded over the study area on 1 April 2006 and were purchased from Pasco, Japan. The image was chosen because flowering cherry was in full bloom at the time, according to information provided by the Japanese Meteorological Agency (JMA). The purchased data were radiometrically corrected and geo-referenced to the Universal Transverse Mercator (UTM) coordinate system, zone 54, WGS84 datum. This data were used to identify flowering cherry tree at landscape level which will be further explained in Chapter 4.

2.2 Methodology

2.2.1 Spectral data collection

Forty five flowering cherry cultivars samples were collected in TFSG from end of March until end of April, 2014. Spectral data were acquired by using hyperspectral radiometer (ASD Fieldspec Pro). Spectral data were collected at a spectral range 0.35–2.5 µm with spectral interval 3.3 nm. The spectral reflectance of each cultivar were measured in a laboratory under dark conditions using a spectroradiometer mounted at a nadir position 20 cm above the target with a 25° field of view. We recorded ten readings for each sample and calculated the average of spectral data for further analyses. The sensor was calibrated using a white Spectralon panel prior to data collection.

2.2.2 Moving average

In the field of digital signal processing, the definition of a spectrum $s_0(\lambda)$ in Eq. (2-2) observed by a spectrometer is given by the sum of the true signal of the spectrum $s_t(\lambda)$ and the noise $n(\lambda)$ where λ indicates wavelength.

$$s_0(\lambda) = \mathrm{s_t}(\lambda) + \mathrm{n}(\lambda)$$

(2-1)

Thus, the definition of spectral smoothing is the estimation of $s_t(\lambda)$ in Eq. 2-2 from the observed spectrum $s_o(\lambda)$. An estimate $\hat{s}_t(\lambda)$ can be calculated by the convolution of the observed spectrum $s_o(\lambda)$ with a weighting function (i.e. smoothing filter) $g(\lambda)$ chosen by the practitioner:

$$s_t(\lambda) = s_0(\lambda) * g(\lambda)$$

(2-2)

The operator * denotes convolution integral (Oppenheim and Schafer, 1975; Lyon, 2004). There are many types of smoothing filters $g(\lambda)$ adopted by remote sensing practitioners for hyperspectral applications including linear and non-linear methods (Savitzky and Golay 1964;

Kawata and Minami, 1984; Tsai and Philpot, 1998; Foody et al., 2004; Schmidt and Skidmore, 2004). The most popularly used smoothing filters is moving average (Vaiphasa 2006).

A mean filter simply takes the mean spectral value of all points within the specified window as the new value of the middle point of the window in Eq. 2-3.

$$\hat{s}\,(\lambda) = \frac{\sum s(\lambda_i)}{n}$$

(2-3)

where n (number of sampling points) is the filter size and j is the index of the middle point of the filter. If the user specifies an even number of points as the filter size, the mean is assigned as the new value of the nearest point right of the center (longer wavelength).

Chapter 3

A Review on Spectral Mixture Analysis: The Contribution to Plant Flowering Phenology Study in Urban Landscape

3.1 Issues in monitoring plant phenology using remote sensing approach

Phenology, by definition, means the timing of recurring biological phases (e.g. unfolding of leaves) (Linderholm 2006; Menzel et al. 2006). Phenology of many organism types in terrestrial ecosystems has been clearly identified to be disturbed by climatic changes (Walther et al. 2002; Parmesan and Yohe 2003; Root et al. 2003). In recent years, remote sensing satellite data have been used at regional and global geographic scales as an objective means to assess the inter-annual variations in the phenology of deciduous vegetation.

The majority of remote sensing efforts across the region have fit vegetation growth curves as remote sensing dataset able to provide spatially and temporally extend data, such as AVHRR and MODIS (Liang et al. 2011; Beurs and Henebry 2010; Fisher et al. 2006). For example, White et al.(1997) compared AVHRR derived Normalized Difference Vegetation Index (NDVI) to lilac leaf out with a mean absolute error of 26 days. A MODIS derived Enhanced Vegetation Index (EVI) was used by Zhang et al. (2003) to predict full canopy cover at Hubbard Brook with a mean absolute error of 10 days. Liang et al. (2011) improved accuracy to a mean absolute error of 2 days using MODIS derived EVI and weighting field observations by dominant forest community type. However, these studies are utilizing coarse spatial resolution data which is several scale-based limitations at regional perspective especially urban landscape. This due to large degree of heterogeneity in urban landscape (mixed pixels) the use of such coarse resolution assessments limits the evaluation of spatial variability in phenology (Fisher et al., 2006; Ibanez et al., 2010; Kramer and Hänninen, 2009).

Most studies have implemented Normalized Difference Vegetation Index (NDVI) derived from the NOAA/AVHRR (Advanced Very High Resolution Radiometer) sensors for some time now to evaluate phenological characteristics over larger areas and time periods (Badeck et al. 2004; Doktor et al. 2009; Bégué et al. 2011). Other studies have also implemented new sensors with a higher spectral and spatial resolution for deriving vegetation phenology such as MODIS (MODerate Resolution Imaging Spectroradiometer) and SPOT-VEGETATION (Jönsson et al. 2010; S. Li et al. 2010). Several authors have used the NDVI temporal profile to derive and model phenological key stages such as budburst and senescence (e.g. Botta et al. 2000), whereas Myneni et al. (1997) used the NDVI to monitor plant growth. However, deriving and modelling phenology based on the NDVI is not always straightforward and subject to some difficulties. Deriving the phenology in heterogeneous landscapes such as urban area with several species of vegetation and other land cover types can therefore be problematic (Doktor et al. 2009; Hu, Inannen, and Miller 2000; Schwartz and Reed 1999; Lausch et al. 2015).

The identification of plant phenology based only on certain spectral wavelengths limits the opportunity to investigate the significance of other important biochemical–biophysical vegetation parameters to characterise the phenological changes to vegetation. Remote sensing could also detect such changes by using wavelengths outside the range included in NDVI (Nakaji et al. 2006; Jönsson et al. 2010; Grace et al. 2007). Hyperspectral remote-sensing data have a high spectral range of 400–2500 nm with a spectral resolution of 2.5–10 per spectral band. They are thus ideally suited to answer questions about deriving indicators of seasonal vegetation changes. Hyperspectral imagery has been applied more frequently over recent years. With the launch of the satellite hyperspectral sensors EnMAP (Environmental Mapping and Analysis Program) foreseen for 2017, the routine implementation of hyperspectral satellites will be possible for a more precise spectral diagnostic and quantitative monitoring of the status and phenology of vegetation over larger areas (Lausch et al. 2015).

Previous investigations based on the implementation of airborne hyperspectral sensors show that in addition to the previously used phenology indicators, there are others that will be able to model the senescence of vegetation over time more accurately (Ye et al. 2009; Filella et al. 2004; Nakaji, Oguma, and Fujinuma 2006). In this way, Ye et al. (2009) and Dzikiti et al. (2011) were able to show in their investigations on citrus vegetation based on hyperspectral imagery that the photochemical reflectance index (PRI) is very suitable for characterising vegetation phenology. Nakaji et al. (2006) were also able to quantify seasonal changes in coniferous forests by using the PRI. Kneubühler (2002) also confirms that the phenological stages can be differentiated from one another by looking at the water content of the vegetation. Kneubühler (2002) even considers the water content of vegetation to be one of the most promising vegetation parameters used to estimate and derive phenological stages. Filella et al. (2004) looked at how the remote sensing vegetation indices NDVI and PRI responded to seasonal and annual changes in an early successional stage of the canopy for Mediterranean coastal shrubland. They were able to show that the NDVI and PRI are good indicators strongly reflecting the species.

So far, those studies were focusing on plant leaves only and there are no plant phenology monitoring was carried out based on plant reproductive organs spectral signal as they believed flower spectral signal are weak and it is impossible to monitor plant phenology especially in high heterogeneous urban landscape (Chen et al. 2009). However, by utilizing high spatial resolution and hyperspectral remote sensing data and availability of spectral mixture analysis in remote sensing technique, plant spring phenology of urban plant can be identify more accurately based on plant reproductive organ spectral signal. In the following subsections, the fundamental concepts related to the extraction of biophysical parameters of vegetation, particularly in identifying vegetation species from spatial and spectral aspects were discussed.

3.1 Plant spectral characteristics

Most of the studies at the initial stage are focused on spectra measured from leaves only. (e.g. Miller & O'Neill 1997; Daughtry 2001). Some later studies have selected components of plant stands such as branches of tree, stacks of branches, barks and soil (e.g. Williams 1991). Detailed plant characteristics, such as the structure of plant canopies and their physiological condition may valuable in monitoring plant physiological status (Avissar 1996). However, there are less studies focused on plant reproductive organs to monitor plant physiological status. This is may be because of spectral signal characteristics of plant reproductive organs are weak and not suitable to be used in high heterogeneous urban landscape. Nevertheless, exploration on spectral properties of plant reproductive organs are important as it may contribute to spectral reflectance at crown canopy level. In addition, flowering status of plant could reflect ecological process in assessing plant phenological response to global warming (Chen et al. 2009). Herold et al. (2004) suggest that the visible region of the electromagnetic spectrum provides the most prominent spectral information required for separating urban land cover materials. Moreover, most of researchers found that visible and near infrared are the most pertinent spectral region to identify vegetation (Gates et al. 1965). Thus, plant reproductive organs may also have their sensitive spectral regions as leaves. Therefore, in order to carry out spectral analysis in monitoring plant phenology, the knowledge on factor's that controlling plant reflectance is important.

There are few dominant factors controlling leaf reflectance in the region from 0.35 to 2.6 μm, namely various leaf pigments in the palisade mesophyll, including the chlorophyll a and b, and β-carotene. Pioneering research demonstrated the importance of understanding how pigments, internal scattering and leaf water contents affects the reflectance and transmittance properties of leaves (Gausman et al. 1969; Gates et al. 1965; Allen and Richardson 1968; Knipling 1970). The spectral reflectance characteristic of healthy, green vegetation for the wavelength interval 0.4-2.6 μm is shown in Figure 3-1. It shows that the primary chlorophyll absorption bands occur at 0.43-0.45μm and 0.65-0.66μm in the visible region while the primary water absorption bands occur at 0.97, 1.19, 1.45, 1.94, and 2.7μm.

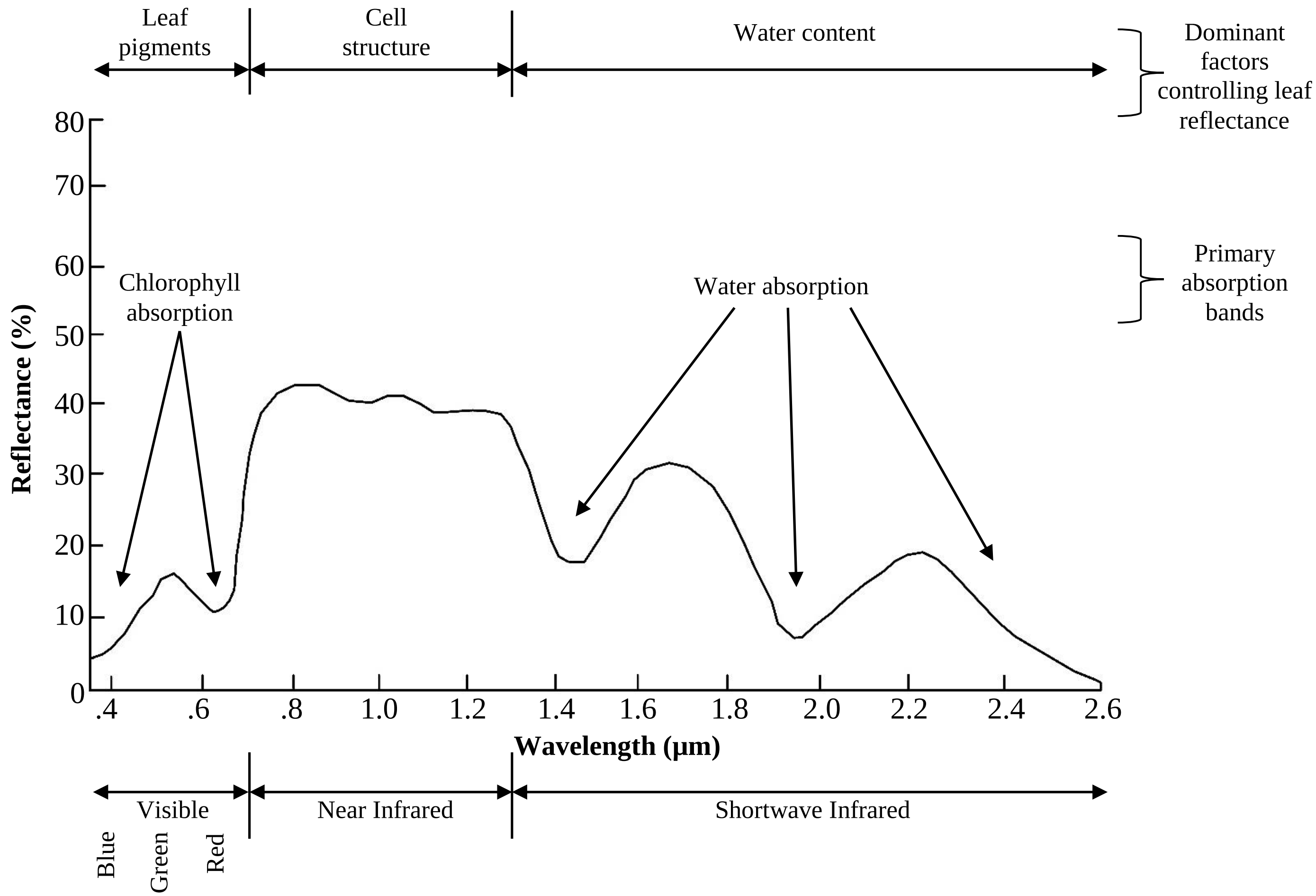


Figure 3-1: Spectral properties of a healthy, green vegetation for the wavelength interval 0.4 to 2.6 µm (after Hoffer, 1978)

3.2 Plant spatial characteristics

As been discussed in previous section, there are few factors that influenced plant spectral reflectance. Other than the factors that dominate plant spectral reflectance, there are also other attributes at leaf, branch and canopy level that affect the spectral properties of plants. At leaf scale, the spectral reflectance recorded was controlled by (1) leaf biochemical properties (e.g water, photosynthetic pigments, structural carbohydrates) which create wavelength specific absorption features and (2) leaf morphology (e.g. cell-wall thickness, air spaces, cuticle wax) that affect photon scattering (Asner 1998; Dar a. Roberts et al. 2004). Spectral variability at visible region are low due to strong absorption by chlorophyll (Cochrane 2000). The spectral response at near infrared gives high transmittance and reflectance result from photon scattering within leaf air-cell wall interfaces, such as in spongy mesophyll (Grant, 1987; Woolley, 1971). In shortwave infrared 1 (SWIR1) and shortwave infrared 2 (SWIR2), water absorption tends to obscure other absorption features produced by biochemical constituents (e.g., lignin and cellulose) (Asner, 1998).

At the branch scale, the spatial arrangement of canopy elements (for example, leaves, shoots, reproductive organs, bark) and their light-absorbing and scattering properties dominate. The electromagnetic radiation scatters among these components will tend to increase the expression of leaf biochemical absorption features, especially within crowns with large, densely-distributed and/or horizontally-oriented leaves (Asner, 1998). Relative to leaf scales, these factors are known to increase branch-scale spectral variability and enhance separability of certain vegetation and broadleaf trees (Roberts et al., 2004). This has been proven by Fung et al. (1998)

by using a laboratory derived, branch-scale hyperspectral data (400–900 nm, 90 bands) and a linear discriminant classifier to discriminate 12 subtropical tree species.

The electromagnetic radiation scattering received by the sensors at canopy scale was depended on architectural arrangement of vegetation and other non-vegetation components that exist within the canopy (Asner, 1998). Aardt and Wynne (2007) have shown that the spectrum within visible, near infrared and shortwave infrared regions are useful for discriminating species of temperate forest conifer and hardwood species when using in situ crown-scale hyperspectral data (sunlit sides of crowns). By using the spectral derivatives analysis, the best overall classification accuracies of 84% were achieved for conifer species and 93% for hardwood species. Cochrane (2000) provides the investigation of tropical forest crown-scale hyperspectral data for automated species recognition (350–1050 nm data). The study used laboratory spectra from 11 tree species to simulate branch and crown scales. From the study, it was proven that the species discrimination was possible at crown scales, while the accuracy decrease at branch and leaf scales. Crown-scale spectra were best separated in the visible-near infrared transition (i.e., the ‘‘red edge’’) and near infrared regions.

Most studies carried out at leaf, branch and canopy level focused on plant leaves in forest and no study was discovered on flowering plant in urban landscape like cherry blossoms. Cherry blossom was grouped into two type of cherry blossom which is (1) the flower blooms before the leaf flushing and (2) the flower blooms as the leaf flushed. Many studies have reported the factors that controlling plant flowers (e.g. Chittka & Shmida 1994; Arnold et al. 2010) where flower also have similar characteristics that control its spectral reflectance. For example, pigments existed in the flower (e.g. anthocyanin and carotenoid) was the factor that controlling spectral reflectance. However, no further study was carried out at flower, branch and canopy level of flowering plant.

3.3 Temporal changes in plant characteristics

Temporal changes in plant characteristics play an important role in identification of plant types or plant biophysical parameters extraction from remotely sensed data. Intimate knowledge of plants temporal phenological cycle is necessary for selecting the most appropriate date for data collection especially for flowering plant phenology.

Plant spectral reflectance properties can be influenced by background soil or understory materials present that cause spectral properties different due to different in plant percent canopy closure, soil moisture, and biomass. Discrimination of two different plant types is possible when the proportion background materials present within instantaneous field of view. The amount of understory background materials present is largely a function of the stage of the plant in its phenological cycle. Thus, identification of phenological cycle characteristics of flowering plant at initial stage is essential in identifying tree species using remotely sensed data. This information is then used to determine the optimum time of the year to collect the remotely sensed data when discriminating one vegetation type from another.

There is another important temporal factor which cannot be overlooked, that is, the plant productive growth period. All vegetation needs water to grow. The productive growth period is always associated with the most intense periods of precipitation and associated cloud cover. As a result, the identification of the optimum date of remotely sensed data must be planned using the phenological calendar with the consideration of spectral limitation, as passive mode remote sensing always has cloud coverage problem. If considerable clouds free being an important criteria, then higher temporal resolution sensor may be needed. It is useful to review the phenological cycles of both natural plant systems and managed agricultural systems in order to gain an insight as how important the cycles are when attempting to use remote sensing to extract the vegetation biophysical parameters (Jensen, 2000).

However, monitoring plant phenological cycle using remotely sensed data was challenging especially for monitoring spring phenology in urban area. Spatially and spectral extend dataset are needed in order to monitor spring phenology in urban area due to multiple land cover type in urban ecosystems may cause mixed pixel. Nevertheless, not all high spatial resolution satellite image has temporally frequent data. Therefore, spectral mixture analysis (SMA) approach might be usable in monitoring spring phenology in urban ecosystems. According to Keshava and Mustard (2002), spectral unmixing is a process of decomposing mixed pixels into a collection of constituents spectra or endmembers and a set of corresponding fractions called abundances which indicates the proportions of each endmembers in a scene. Endmembers are spectra that is a proxies for materials on the ground and normally it’s corresponds to familiar microscopic object in the scene (Keshava and Mustard 2002; Adams and Gillespie 2006).

3.4 Hard and soft classifications

Image classification approaches have been used to identify tree species and their composition (Foody and Cutler 2006) to detect land use changes (Kerr & Ostrovsky 2003; Munyati 2000), and to identify plant conditions (Zhang et al. 2014) based on the spectral signal of canopy greenness. Two approaches have been used in previous studies: (1) hard classification and (2) soft classification. Hard classification selects the class label with the greatest likelihood of being correct and unambiguously assigns each pixel to a single class (Schowengerdt, 2006; Foody, 2010). The decision boundaries of the feature space are well defined for hard classification. In soft classification, pixels are assigned based on the relative abundance of each class in the spatially and spectrally integrated multi-spectrum of each pixel (Schowengerdt, 2006).Therefore, the decision boundaries of the feature space are considered fuzzy (Schowengerdt, 2006) in soft classification because each pixel can have multiple or partial class memberships (Foody, 2002 and Wang 1990). Due to its ability to assign multiple classes to a single pixel, soft classification has been widely used to monitor mineral, soil, and vegetation status, especially in highly heterogeneous areas, because it can divide multiple spectral responses within a pixel and provide proportional information for each class.

Spectral mixture analysis (SMA) a part of soft classification approach can be implemented without constrains (e.g., Harsanyi & Chang 1994), but physically meaningful abundance estimates are often obtained by constraining the coefficients to sum to unity and to be positive (Adams et al. 1993). The accuracy of SMA is often quantified based on the fit between the modeled and observed mixed spectral signals. Model fit can be assessed by an error metric such as the residual term ε (Rogge et al. 2006) or the Root Mean Square error (RMSE; Roberts et al. 1998). In cases where accurate ground reference data are available, the suitability of the selected endmembers and the quality of the subpixel abundance estimates can be assessed more reliably by checking the discrepancy between the estimated and real endmember fractions (Plaza et al. 2004). The fraction abundance error (Rogge et al., 2006; Somers et al. 2009) and the coefficient of determination (Elmore et al. 2000; McGwire 2000; Zhang et al. 2004) are widely used discrepancy measures.

3.5 Linear Mixed Model

According to Somers et al. (2011), generally mixed pixels can be modelled either by using linear mixed model (LMM) or nonlinear mixed model (NLMM). Mixed pixels can be considered as linear if the features or mixtures of the pixels components appeared in spatially segregate pattern as shown in Figure 3-2 (Keshava and Mustard, 2002). Figure 3-2 shows that the spectral reflectance appeared in systematic linear combinations without interference from others reflectance. This systematic linear combination of mixtures known as macroscopic mixtures (Heinz and Chang, 2001; Singer and McCord, 1979). However, systematic reflectance is depending on the heterogeneity of the land surface and it should be spatially segregate pattern. High heterogeneity of ground surface may affects the systematic linear combinations of spectral reflectance due to reflectance scatterings from other materials existed in that area.

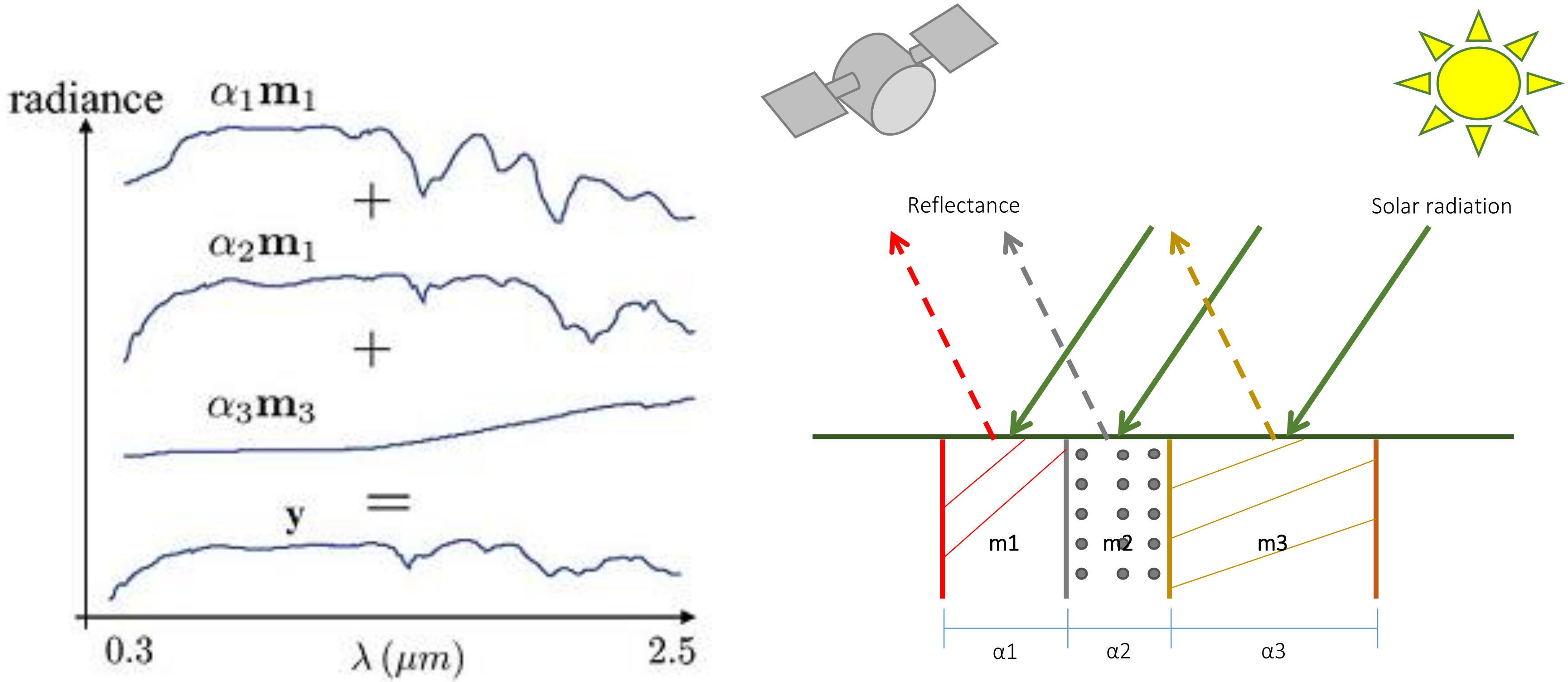


Figure 3-2: Linear mixed model theory

(Modified from Bioucas-Dias et al., 2012)

To achieve satisfactory of abundance results, two abundances constrain should be taken into considerations which are (1) non-negativity and (2) sum-to-one (Raksunthorn and Du, 2010; Raksunthorn and Du, 2009; Chen et al., 2013). Raksunthorn and Du (2009) stated that LMM may provide satisfactory results as it ignoring multiple scattering effects but, too many endmembers involved in LMM may result abundances estimations error as the model sensitive to the noise, atmospheric contamination and trivial spectral variations. LMM has been utilized in many types of applications study such as mineral soil (Mustard & Pieters, 1987, 1989; Nash & Conel, 1974; Shipman & Adams, 1987) and vegetation (e.g. Arai, 2008; Borel & Gerstl, 1994; Chen & Vierling, 2006; Huete, 1986; Ray & Murray, 1996; Roberts et al., 1993; Somers et al., 2009; Zarco-Tejada et al., 2001). Although LMM has obvious advantage, in some situations, it may be not appropriate due to multiple light scattering effects especially when observing complex vegetated surfaces (Chen et al., 2013; Ray and Murray, 1996). Therefore, LMM might be not giving encourage results to study phenological pattern of flowering due to the complexity of tree structure and soil background effects especially trees in tropics which have high density of forested area. High complexity of tree structures needs more than two endmembers to decompose mixed pixel problem and may cause multiple light scattering from other endmembers. Therefore, nonlinear mixed model is better to be used to study phenological pattern of flowering plant.

3.6 Endmember selection

Endmember selection plays an important role to obtain optimum results of Spectral Mixture Analysis (SMA)(Somers et al., 2011; Elmore, 2000) especially in plant phenological studies. As stated in previous section, too many endmembers may cause misleading unmixing output. Raksuntorn and Du (2010) said that endmembers selections also depending on the number of bands of the data used. The number of endmembers cannot exceed the number of bands. As the hyperspectral data was used for the study, the number of endmember can be more than two but if multispectral data were used, the number of endmember cannot exceed than two endmember (Raksunthorn and Du, 2009).

Thus, many types of endmembers selection method have been proposed to fulfil SMA requirement for example N-FINDR (Winter, 1999), pixel purity index (PPI, Boardman et al., 1995), and virtual endmembers (Tompkins et al., 1997). Endmember also can be defined by building spectral library based on the spectral reflectance collected using spectro-radiometer (e.g. Hassan and Hashim, 2011; Asner and Lobell, 2000; Roberts et al., 1998).

3.7 Endmember variability in plant

SMA provides fractions estimates accuracy that always affected by residual spectral errors caused by inaccurate atmospheric corrections, insufficient signal-to-noise ratio and model structure input (Borel and Gerstl, 1994). Bateson et al. (2000) add that SMA might be compromised by variation of canopy structure and biochemistry when a single endmember spectrum represents top-of-canopy reflectance. Meanwhile Asner (1998) emphasized that plants reflectance would be influenced by primarily functions of tissue (leaf, woody stem, and standing litter), optical properties of the plants itself, canopy biophysical attributes (e.g. leaf and stem area, leaf and stem orientation and foliage clumping), soil reflectance, illumination condition and viewing geometry. Thus, for flowering phenology study that applying SMA, biochemical of the flower should be extract first for endmember selection and to avoid endmember variability during SMA process.

Endmember variability reduction has been used to achieve abundance optimization. Endmember variability can be classified into two types (1) variability within an endmember class (intra-class variability) (Somers et al., 2011) and (2) the similarity among endmember (inter-class variability) (Zhang et al., 2006). For plant applications, the main problem usually classified as inter-class variability due to similarity of spectral reflectance among endmembers. For example, crops and weeds spectral reflectance almost similar in Somers et al. (2009) study. Thus, the accuracy of classification would be low. Gong and Zhang (1999) stated that spectral reflectance similarity among endmembers may lead to unstable inverse matrix and hampers the estimation accuracy. Numerous of studies regarding endmember variability reduction approaches have been carried out as reviewed by Somers et al. (2011).

3.8 Summary

Plant phenology study has been carried out by many scientists using remote sensing technology. However, most of the studies are fully utilized spectral information of plant leaves. On the other hand, most of them are utilizing normalized different vegetation index (NDVI) to monitor plant phenology. There are few studies are focusing on spring phenological event using NDVI and some of studies have utilized hyperspectral data to monitor plant phenology. However, there are no study use spectral information of reproductive organ which may also contribute to spectral reflectance at branch to crown level as most scientist believed that plant reproductive organs have weak spectral signal. In addition monitoring spring phenological event in urban ecosystems using coarse spatial resolution was challenging as it contain multiple land cover types that cause mixed pixels. Thus, utilizing spectral mixture analysis (SMA) might be one of solution to monitor spring phenological event by using spectral information of plant reproductive organs. In order to achieve abundance satisfactory in SMA, an endmember selection is important to be taken into considerations especially for plants phenological studies. This is because plants have complex structure where every single part of plants may reflect the radiance from sun towards sensor including chemical content in the plants. Therefore, for spring phenology study, endmember variability reductions plays a crucial role in SMA as flower may contains similar water content and chemical with other parts of the tree. Most of the studies reviewed mostly focused on canopy layer of the plants including nonphotosythetic part and soil. However, flower has been neglected as it gives weak reflectance especially in visible spectrum but flower may reflect high reflectance in infrared spectrum as it contains water.

Chapter 4

Remote Detection of Flowering Somei Yoshino (*Prunus* × *yedoensis*) in an Urban Park using IKONOS Imagery: Comparison of Hard and Soft Classifiers

4.1 Introduction

Plant phenology is gaining attention as an important indicator of global and local climate change. Ground observations on a large spatial scale are expensive and time consuming, so remotely sensed data have been used to detect changes in plant phenology, such as leaf-out, senescence and dormancy (Reed et al. 1994; Zhang et al. 2003; Zhang et al. 2001), and flowering (Zhang et al. 2003; Delbart et al. 2006; Ahl et al. 2006; Testa 2014). Most studies have focused on changes in basic vegetation indices, such as the Normalised Difference Vegetation Index (NDVI) (Zhang et al. 2003; Delbart et al. 2006; Ahl et al. 2006). However, vegetation indices do not utilise the full information content of remotely sensed imagery in the way that image classification methods can (Foody and Cutler 2006), especially for phenological events. Vegetation indices typically focus on certain spectral bands that represent the spectral reflectance of canopy greenness, and therefore, provide little information on flowering status, flower abundance, and flowering dates (Chen et al. 2009). Moreover, the spectral bands used by vegetation indices may sometimes represent ground features such as soil that can cause errors in classifying land cover type (Huete 1988).

Image classification approaches have been used to identify tree species and their composition (Foody and Cutler 2006), to detect land use changes (Kerr and Ostrovsky 2003; Munyati 2000), and to identify plant condition (Zhang et al. 2014) based on the spectral signal of canopy greenness. Two approaches have been used in previous studies: (1) hard classification and (2) soft classification. Hard classification selects the class label with greatest likelihood of being correct and unambiguously assigns each pixel to a single class (Schowengerdt 2007; Foody 2002). The decision boundaries of the feature space are well defined for hard classification. In soft classification, pixels are assigned based on the relative abundance of each class in the spatially and spectrally integrated multi-spectrum of each pixel (Schowengerdt 2007). Therefore, the decision boundaries of the feature space are considered fuzzy (Schowengerdt 2007) in soft classification because each pixel can have multiple or partial class membership (Wang 1990; Foody 2002). Due to its ability to assign multiple classes to a single pixel, soft classification has been widely used to monitor mineral, soil, and vegetation status, especially in highly heterogeneous areas, because it can divide multiple spectral responses within a pixel and provide proportional information for each class.

Cherry blossoms of *Prunus* species flower synchronously in the spring in temperate zones of the Northern Hemisphere. Cherry blossoms are of interest because they provide social and economic benefits from cherry blossom viewing, and they provide important information on the long-term impacts of climate change (Aono & Saito, 2010; Aono, 2014). However, identification of cherry blossoms is challenging because urban environments are highly heterogeneous and the flowers produce a weak spectral signal. Therefore, an initial hypothesis can be made where soft classifier approach may be more useful to identify cherry blossoms in urban areas due to its ability to separate multiple spectral responses from different land cover types.

In this study, the ability of hard and soft classifiers to identify cherry blossoms in an urban landscape from high spatial resolution images was explored. The most common cherry cultivar in Japan, Somei Yoshino (hereafter SY) (*Prunus* × *yedoensis*) was chosen, for identification of cherry blossoms. Maximum Likelihood (ML) was used as a hard classification method and Mixture Tuned Matched Filtering (MTMF) as a soft classification method. The accuracy of these two classifiers using was compared high-spatial-resolution IKONOS imagery of an urban park in Tokyo, Japan.

4.2 Materials and Methodology

4.2.1 Study site

The study was conducted in Yanagisawanoike Park, Hachioji City, Tokyo, Japan (35°37’06.28” N, 139°22’36.17” E, altitude 128 m). The dominant tree cultivar in the park is a deciduous cherry, Somei Yoshino (*Prunus* × *yedoensis*). It is mixed with other cherry cultivars, such as Kanzakura (*Prunus sato-zakura 'Sekiyama'*), Mamezakura (*Prunus incisa*), and Shidarezakura (*Prunus sapchiana*), as well as other deciduous trees, such as Japanese red pine (*Pinus densiflora*) and hornbeam (*Carpinus laxifolia*), and evergreen trees, including camphor (*Cinnamomum camphora*), Chinese evergreen oak (*Quercus mysinaefolia*), and Japanese black pine (*Pinus thunbergii*). The mean canopy size of the flowering SY trees was 5 m and the mean height was 3 m.

4.2.2 Materials

4.2.2.1 Remotely sensed data

A multispectral IKONOS image [four bands: blue (445–516 nm), green (506–595 nm), red (632–698 nm), and near infra-red (NIR; 752–853 nm)] with 4-m resolution was used. The IKONOS data were recorded over the study area on 1st April 2006 and were purchased from Pasco, Japan. The image was chosen because SY was in full bloom at the time, according to information provided by the Japanese Meteorological Agency (JMA). The purchased data were radiometrically corrected and geo-referenced to the Universal Transverse Mercator (UTM) coordinate system, zone 54, WGS84 datum. Reflectance data conversion was conducted on the image to estimate areas of blooming SY. To avoid multiple spectral responses, asphalt roads and lakes were masked using a threshold approach. Each features of the study site in IKONOS image were firstly digitized and overlaid in Google Earth and were measured approximately.

4.2.2.2 Spectral data collection

To validate the spectral reflectance of flowering SY in the IKONOS image, we collected spectral reflectance data of flowering SY in Yanagisawanoike Park using a spectroradiometer (ASD Fieldspec Pro) in April 2014. The data were collected at a spectral range of 0.35–2.5 µm with a spectral interval of 3.3 nm. The spectral reflectance of ten flowers from five blooming SY individuals were measured in a laboratory under dark conditions using a spectroradiometer mounted at a nadir position 20 cm above the target with a 25° field of view. Ten readings for each sample was recorded and calculated the average of spectral data. The sensor was calibrated using a white Spectralon panel prior to data collection.

4.2.2.3 Ground data collection

In addition to the spectroradiometer measurements, XY-coordinates of flowering SY trees, soil, dry grass, and evergreen trees was collected using a handheld GPS unit (Garmin GPSmap 60CSx) on 1st April 2014. According to the park manager and Google Earth, the SY trees on this date were the same as in the 2006 imagery. We used these coordinates as reference data to assess classification accuracy.

4.2.3 Methodology

4.2.3.1 Methods used to identify flowering SY

Two types of image classification were used to identify flowering SY from IKONOS imagery: hard classification and soft, or fuzzy, classification. Maximum Likelihood (ML) was used for hard classification, as it has been widely used for many purposes, such as discrimination of tree species (Dian et al. 2013; Miao et al. 2011). Mixture Tuned Matched Filtering (MTMF) was used for soft classification because it has been used to identify targets in highly heterogeneous areas, such as urban areas, by decomposing the pixel into its constituent classes and estimating the proportion of each class.

4.2.3.1.1 Maximum Likelihood Classification

To obtain optimal classification using ML, the spatial and spectral information for a set of training pixels was first examined. We collected spatial information on texture using the Gray Level Co-occurrence Matrix (GLCM) method on the IKONOS image with a 3×3 window. The mean, variance, entropy, homogeneity, contrast, dissimilarity, second moment, and correlation of pixels for each training area was calculated (Fig. 4-1). Because there was spatial variability and contrast among classes, textural analysis was used in addition to the spectral information to improve the classification results.

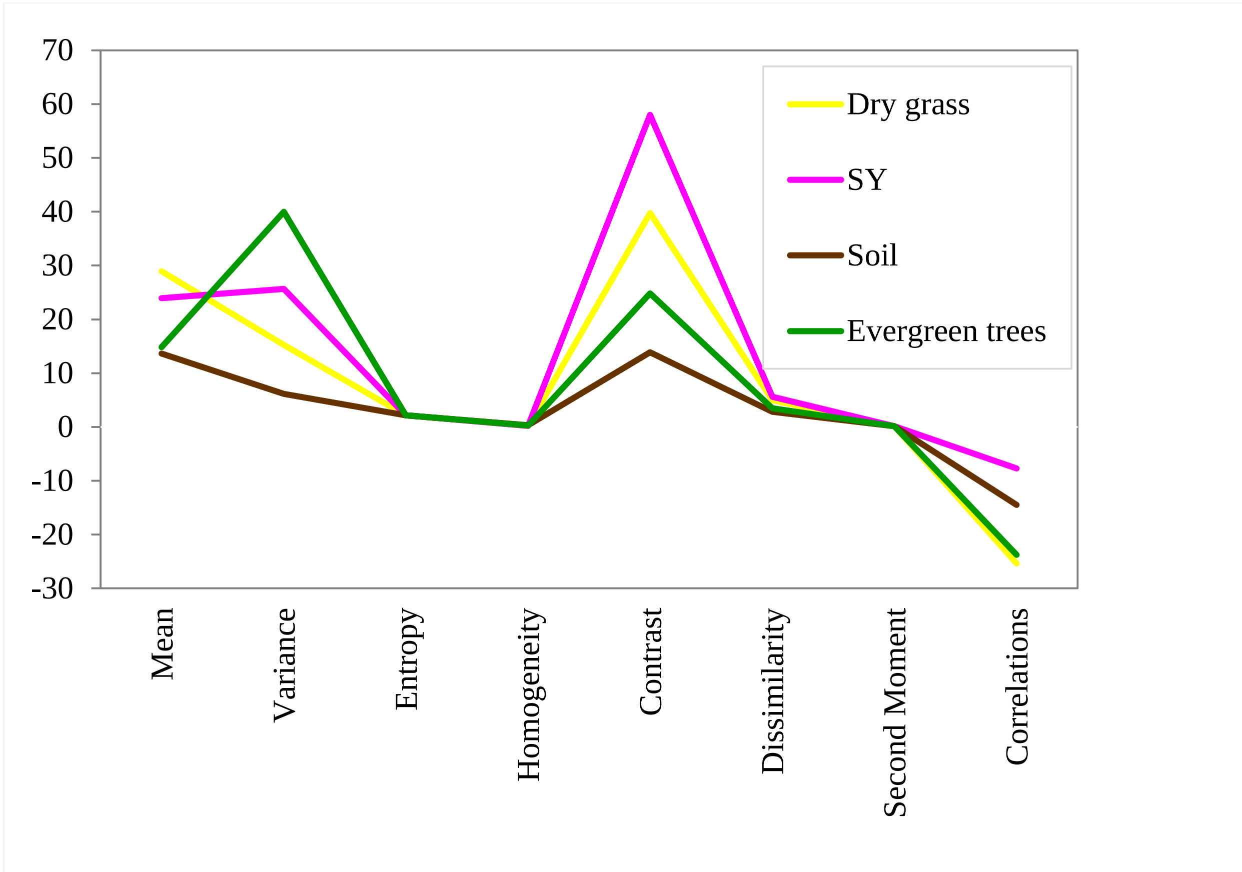


Figure 4-1: Mean values of textural features calculated from training pixels. Textural analysis conducted on the IKONOS image included mean, variance, entropy, homogeneity, contrast, dissimilarity, second moment, and correlations for each class.

Spectral information from training pixels of the IKONOS image was extracted (Fig. 4-2). The spectral pattern of each class varied enough to discriminate the classes. Dry grass had higher reflectance, and evergreen trees had lower reflectance, compared to flowering SY. However, the spectral pattern and magnitude of soil and evergreen trees were almost identical. Therefore, we conducted a spectral separability test to determine the distinctness of each class.

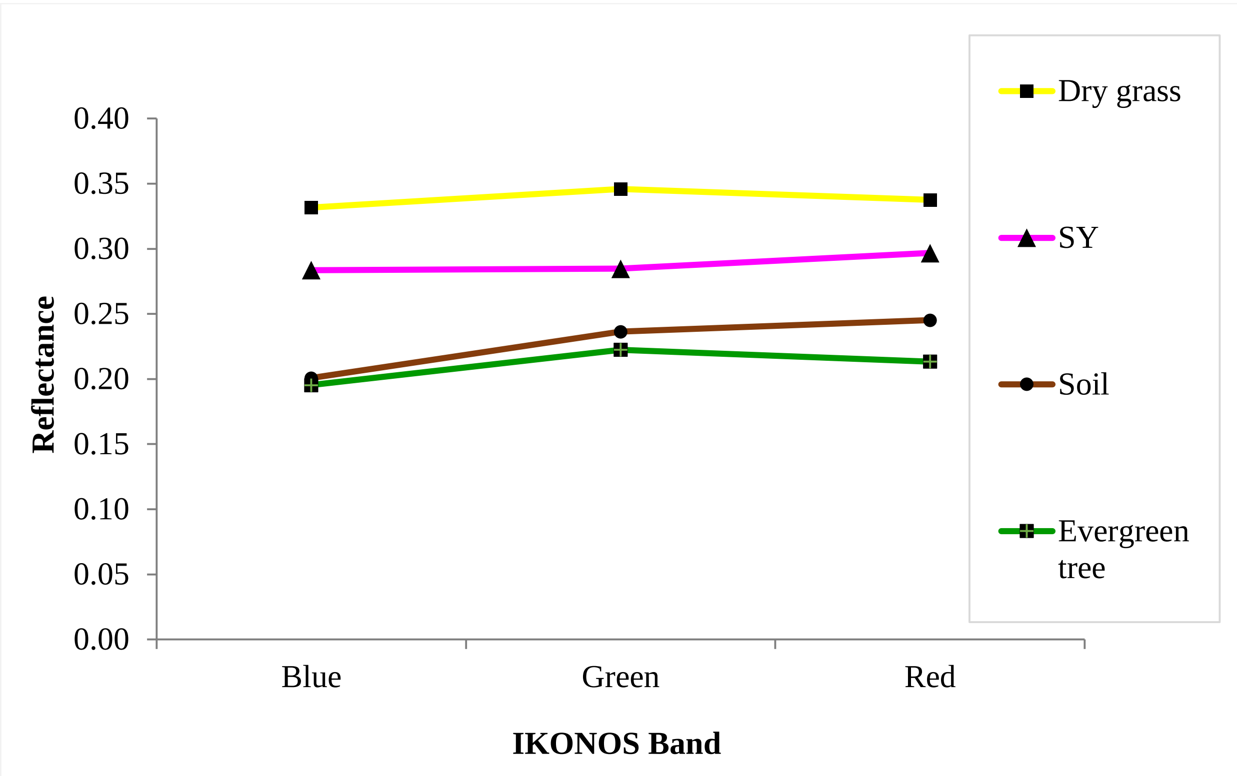


Figure 4-2: Mean spectral signature of the IKONOS image used to select training areas for each class.

Transform Divergence (TD) was applied to the IKONOS image to select the features with the greatest degree of statistical separability. TD is used to evaluate spectral variability among classes of training areas. A TD value of 1.90–2.00 indicates good to excellent separation between classes, while a value <1.70 indicates poor class separation (Jensen 2005). The TD results demonstrated good class separability (TD = 2.00) between flowering SY, soil, dry grass, and evergreen trees. However, the TD value was 1.73 for flowering SY and dry grass and 1.83 for flowering SY and evergreen trees, indicating weak separabililty of these classes. Soil and evergreen trees had even lower separability, with a TD value of 1.65. However, classes with lower separability were able to distinguish based on spatial evaluation (Fig. 4-1). Therefore, flowering SY, soil, dry grass, and evergreen trees was used as the training classes for ML classification. To obtain optimal accuracy of the ML classification, the four spectral bands of the IKONOS imagery was supplemented with four bands of local texture information (variance). Thus, a total of eight bands were used in this classification.

2.3.1.2 Mixture Tuned Matched Filtering

MTMF is a linear process of unmixing that is widely used to identify plant species (Dehaan et al. 2007; Parker Williams and Hunt 2002; Mitchell and Glenn 2009). There are two phases in the MTMF algorithm: the Matched Filter (MF) calculation to estimate abundance, and the Mixture Tuning (MT) calculation to identify false-positive results.

MT assesses the probability of an MF estimation error for each pixel based on mixing feasibility. Abundances in MTMF must obey two critical feasibility constraints: (1) they must be non-negative, and (2) the abundances for each pixel must sum to one. Calculated infeasibility represents the distance of the pixel from the line connecting the target spectrum and the background mean, measured in terms of standard deviations using the appropriate mixing distribution for the MF score of that pixel. MT and MF scores can be jointly interpreted to provide good sub-pixel detection and false-positive rejection (Boardman and Kruse 2011).

The endmember of MTMF is a spectrum representing ground surface materials (Adams and Gillespie 2006). In this study, we assigned a single endmember for MTMF classification of flowering SY by selecting ten pure pixels of flowering SY. We averaged the spectral data from the IKONOS imagery for these ten data points to create a single composite target spectra that was used as the endmember for MTMF classification.

2.3.2 Infeasibility scores

Infeasibility scores are used to confirm the classification of flowering SY from the MTMF classifier. The best match is indicated by an MF score close to one and an infeasibility score close to zero (Sugumaran et al. 2007). However, according to Brelsford and Shepherd (2014), certain spectral signatures can generate large positive MF scores that are indicated as false positives in MTMF. In this study, the cumulative distribution function (CDF) was used to identify an infeasibility score for 36 points where flowering SY was confirmed by GPS ground-truthing. These 36 points were distributed across 40 pixels in the IKONOS imagery. The MF scores of these 40 pixels was assigned to five groups to identify the best infeasibility score, which lies between 0.01 and 0.1 and represents the highest MF score ($0.8 \leq MF \leq 1.2$) (Fig. 4-3).

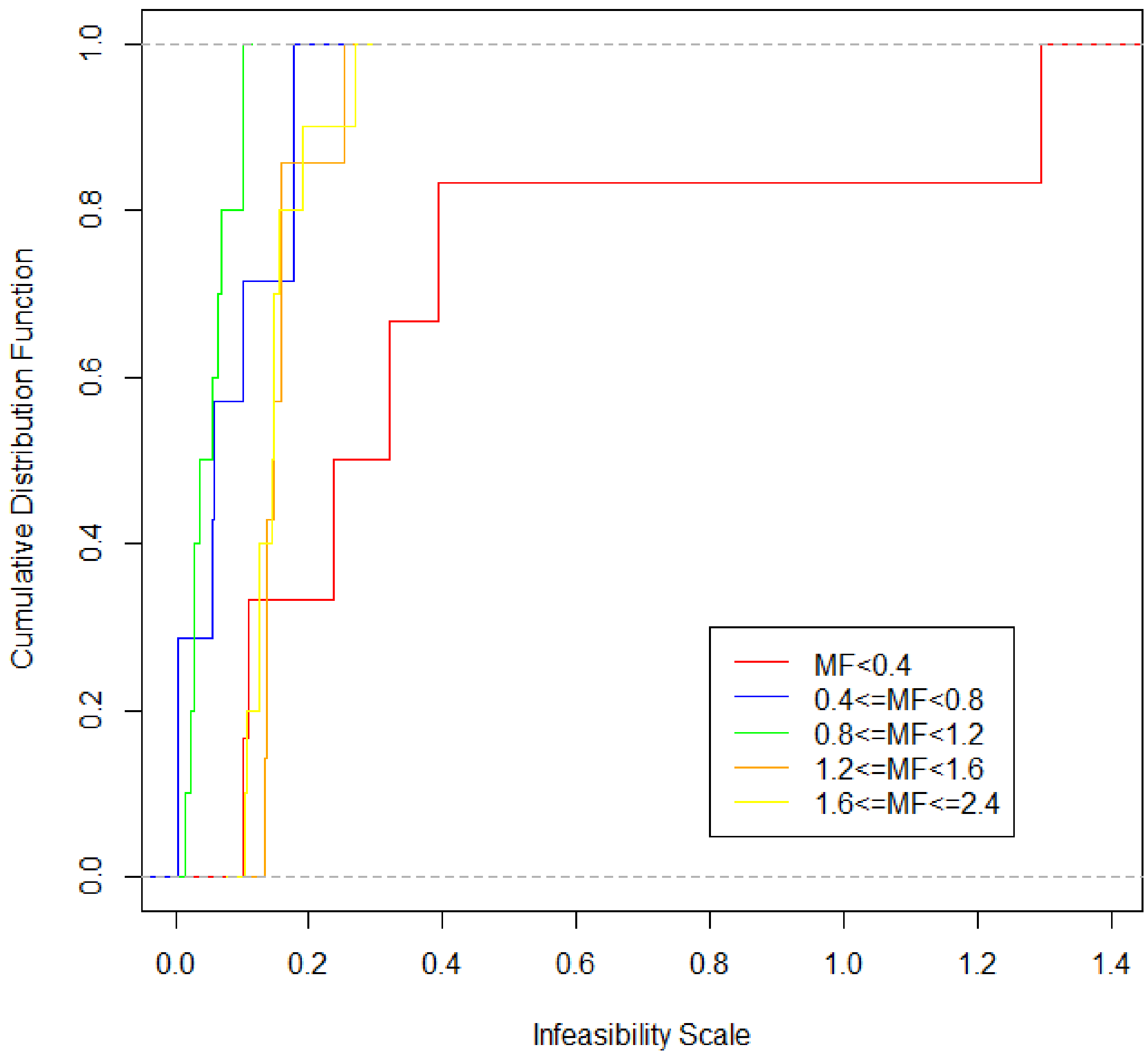


Figure 4-3: Best infeasibility scores for 36 points of flowering SY used to identify the feasibility of Matched Filter (MF) scores.

2.3.3 Accuracy assessment

The accuracy of MTMF and ML classification of flowering SY was assessed by comparing to ground-truthed data. Both user's and producer's accuracy for both classification methods was calculated. According to Congalton (1991), producer's accuracy is the ability of the IKONOS imagery to classify a certain target (number of individual classes correctly classified / total number of reference data), while user's accuracy is the probability that a classified pixel actually represents that category (number of pixels classified on the map / number of pixels in the image that actually represent that category). The percentage of all classes correctly classified was evaluated using overall accuracy and the kappa coefficient, which measures the level of agreement of the overall accuracy. The overall accuracy and kappa coefficient was calculated as in Eq. 4-1 and 4-2:

$$\boldsymbol{OA} = \frac{\sum_{k=1}^{q} \boldsymbol{n_{kk}}}{\boldsymbol{n}}$$

(4-1)

$$\hat{K} = \frac{n \sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q} n_{k+} \times n_{+k}}{n^2 - \sum_{k=1}^{q} n_{k+} \times n_{+k}}$$

(4-2)

where q is the number of rows in the matrix, n_{kk} is the number of observations in row k and column k of the error matrix, n_{k+} and n_{+k} are the marginal totals of row k and column k, respectively, and n is the total number of observations.

The number of flowering SY trees in Yanagisawanoike Park is limited by the presence of a lake. This made it impossible to take a random sample of at least 50 plots for each land cover class, which is ideal. Laba et al. (2010) had a similar problem due to the limited areas of certain vegetation classes, and suggested using the largest possible number of plots. The numbers of training and test pixels used for each class in ML and MTMF classification are shown in Table 4-1.

Table 4-1: Number of training pixels and test pixels for each class for ML and MTMF classification.

	ML classification		**MTMF classification**
	Training pixels	**Test pixels**	**Test pixels**
Flowering SY	10	36	36
Soil	12	40	40
Dry grass	18	40	40
Evergreen trees	15	40	40

4.3 Results

The percentages of each land cover feature in the IKONOS image of the park were: 19% SY trees, 19% asphalt roads, 18% deciduous trees, 17% evergreen trees, 15% pedestrian roads, 8% grass areas, and 4% lake (Fig. 4-4a).

The MF scores, which represent the abundance of pixels in each category, ranged from -2.698 to 2.947 (Fig. 4-4b). Pixels representing masked asphalt road and lake had negative MF scores. Thus, the MF scores were interpreted as zero target abundance, similar to previous studies (Sankey et al. 2010; Mundt, Streutker, and Glenn 2007; Robichaud et al. 2007). The 36 points of flowering SY were distributed across 40 pixels with $0.8 \leq MF \leq 1.2$ (Fig. 4-4b), indicating more than 80% flowering SY per pixel. Pixels with MF scores < 0.8 represented bare soil and MF scores > 1.2 represented dry grass and evergreen trees. Infeasibility scores from the MTMF classification ranged from 0.01 to 16.854. Each MF score in the MTMF classification had its own infeasibility score that indicated the class to which the pixel belonged. Pixels identified as flowering SY had infeasibility scores ranging from 0.001 to 0.1.

The IKONOS image used in this study had high variation and contrast among the training classes. Therefore, we supplemented the image with four grey level co-occurrence (variance) bands for the ML classification. However, the TD showed that separability of flowering SY, dry grass, and evergreen trees was poor. The ML classification identified most of the soil pixels as evergreen trees (Fig. 4-4c), even though texture analysis was conducted before ML classification.

The MTMF classification had 62.2% overall accuracy and a kappa coefficient of 0.507, compared to 48.7% overall accuracy and a kappa coefficient 0.321 for the ML classification. User's accuracy of the MTMF classification of flowering SY (48.1%) was higher than that of ML classification (39.4%). The poor overall accuracy of the ML classification was primarily due to misclassification of soil (user's accuracy: 37%, producer's accuracy: 25%). ML misclassified 60.6% of flowering SY as dry grass or evergreen trees (Fig. 4-4c). However, the producer's accuracy of the MTMF classification (72.2%) was lower than that of the ML classification (77.7%). MTMF tended to misclassify flowering SY as dry grass or soil.

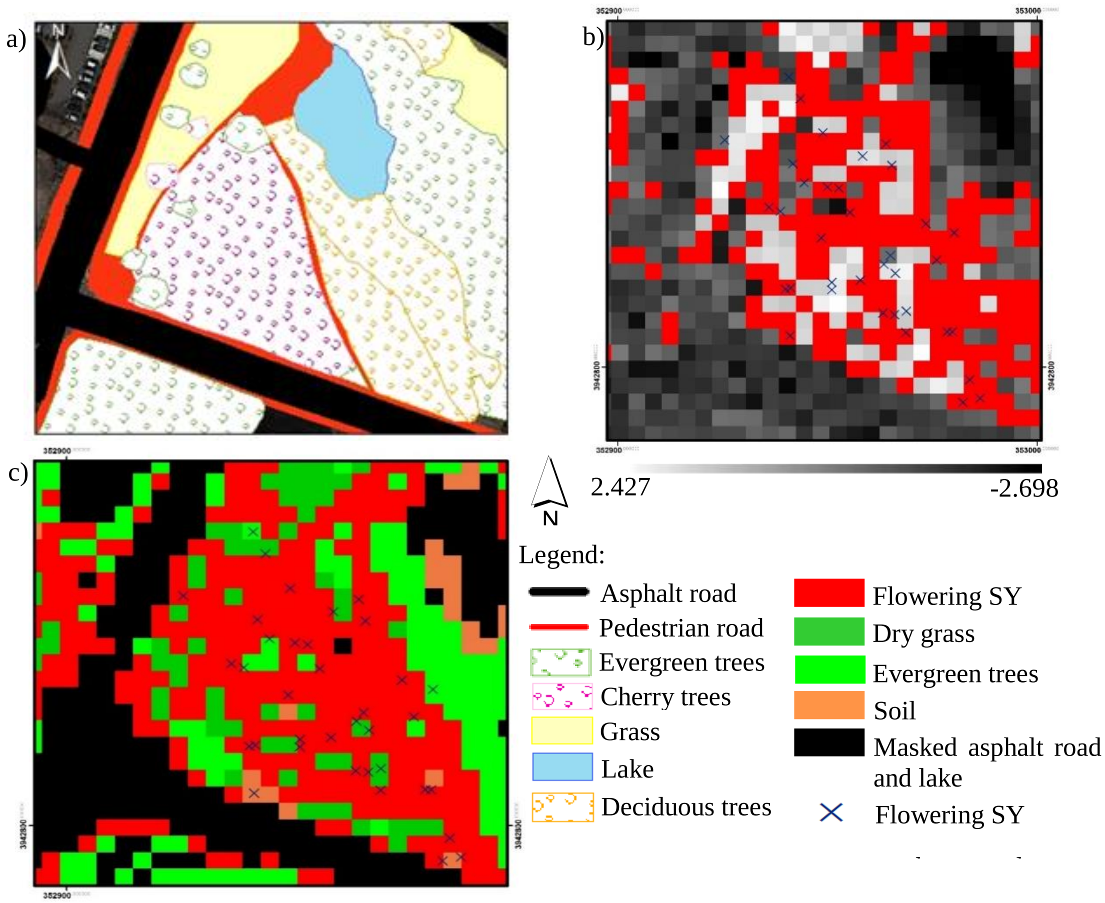


Figure 4-4: Land classification and identification of flowering SY in Yanagisawanoike Park. (a) Dominant features of the study area, (b) MF scores of MTMF classification (red colour represents flowering SY with MF scores ranged from 0.8 to 1.2), and (c) ML classification of the IKONOS image.

4.4 Discussion

Results obtained indicate that, in terms of overall accuracy and Kappa coefficient, MTMF classified flowering SY in an urban park more accurately than ML. However, the producer's accuracy of the MTMF classification was slightly lower than the ML due to misclassification of flowering SY pixels as soil or dry grass (Table 4-2). This may be due to the limited number of available bands for ML (four bands for IKONOS). MTMF can achieve higher classification accuracy by using hyperspectral data. William and Hunt (2002) demonstrated that MTMF classification worked well to identify leafy spurge in hyperspectral Airborne Visible Infrared Imaging Spectrometer (AVIRIS) images. In addition, the existence of an endmember with a stronger signal than flowers, such as dry grass in this study, may have limited the user's accuracy of MTMF classification. Therefore, additional endmembers may be needed to improve the performance of MTMF for classifying flowering SY trees.

In contrast, the ML classifier identified flowering SY with relatively high producer's accuracy (Table 4-2). However, misclassification of soil as evergreen trees may be the cause of the low overall accuracy. Most of the pixels representing soil were assigned as evergreen trees, and pixels of deciduous trees were often assigned as soil. Cherry blossoms precede the leaf flushing of other deciduous trees, which had no leaves at the time of the imagery. Because soil has higher reflectance than branches or trunks, deciduous trees were often misclassified. Therefore, adding a training class for deciduous trees could improve the accuracy of ML classification.

Plant leaves, rather than flowers, have often been used (Zhang et al. 2003; Delbart et al. 2006; Ahl et al. 2006) to observe plant phenology from remotely sensed data because the spectral signal of flowers is generally weaker than that of leaves. We confirmed that cherry blossoms of SY have weaker spectral signals than dry grass (Fig. 4-1), but MTMF classification has considerable potential in terms of enabling their accurate separation (Fig. 4-4).

4.5 Summary

Results suggest that MTMF classification is more accurate than ML classification for identifying plant flowering phenology in a highly heterogeneous urban landscape. However, the number of spectral bands can limit the producer's accuracy of MTMF classification. Therefore, utilisation of hyperspectral data with high spatial resolution such as AVIRIS might be useful to identify flowering phenology in urban ecosystems.

Table 4-2: Accuracy assessment for Maximum Likelihood (ML) and Mixture Tuned Matched Filtering (MTMF) classifications of flowering SY trees. The values for each class represent the number of ground-truthed points used to evaluate the accuracy of classification.

ML Classifier

Class	Label	Reference A	Reference B	Reference C	Reference D	Sum	User's accuracy (%)	Overall accuracy (%)	Kappa coefficient
Somei Yoshino	**A**	**28**	7	20	16	71	39.4	**48.7**	**0.321**
Soil	**B**	1	**10**	2	2	22	37		
Dry grass	**C**	5	3	**18**	2	28	64.2		
Evergreen Trees	**D**	2	20	0	**20**	42	47.6		
Sum		36	40	40	40	156			
Producer's accuracy (%)		77.7	25	45	50				

MTMF Classifier

Class	Label	Reference A	Reference B	Reference C	Reference D	Sum	User's Accuracy (%)	Overall accuracy (%)	Kappa coefficient
Somei Yoshino	**A**	**26**	10	10	8	54	48.1	**62.2**	**0.507**
Soil	**B**	5	**26**	5	5	41	63.4		
Dry grass	**C**	5	4	**25**	5	39	64.1		
Evergreen Trees	**D**	0	0	0	**20**	20	100		
Sum		36	40	40	40	156			
Producer's accuracy (%)		72.2	65	62.5	50				

Chapter 5

Inter-Specific Differences in Spectral Properties of Flowers among 45 Cherry Cultivars

5.1 Introduction

Cherries (members of the *Prunus*) are the most popular ornamental trees in Japan and have been cultivated for more than 1000 years (Flower Association of Japan 1982; Kuitert 1999). There are 200 traditional cultivars that are known in Japan (Kobayashi 1992), and they show diverse floral characteristics (Kato et al., 2014). The long history of cultivation has caused significant confusion over the origins of these cultivars, and Kato et al. (2014) suggested that morphological variations among flowering cherry cultivars may arise through a complex sequence of hybridizations.

Hyperspectral imagers, currently available on airborne platforms, provide increased spectral resolution over existing space-based sensors that can document detailed information on the distribution of vegetation community types, and sometimes species (Zomer et al. 2009). Current efforts using today's remote sensing satellites may not have sufficient resolution, either spatially or spectrally, to monitor flowering cherries conditions. For example, within a Landsat image (30 m resolution) a majority of pixels are mixtures of several plant species or spectral response from others. Increasing the number of ‘‘pure pixels’’ through improved spatial resolution removes a large source of error in the remote sensing analysis.

Spectral matching techniques can be used to identify species or vegetation types based on spectral data collected in the field (Underwood 2003), through laboratory analysis (Schmidt and Skidmore 2003), or extracted directly from the images (Underwood et al., 2006). Developing spectral libraries is the key to improving our capacity to utilize the full mapping potential from these new sources of data provided by airborne and advanced space-borne hyperspectral imagers.

Moreover, the spectral reflectance signature of living organisms provides important information to evaluate their biological characteristics and physiological status. Hyperspectral imaging techniques have been recently focused due to improvement of usability. Therefore, several studies have been conducted to examine the effectiveness of the hyperspectral techniques in biological sciences (Matsuda et al. 2012). Some studies attempt to measure leaf pigments such as chlorophyll, carotenoid, and anthocyanin in identification of biological and physiological status of plant (Ustin et al. 2009, Lichtenthaler 1987). Commonly, identification of biological and physiological status of plant in most studies utilized hyperspectral sensing at landscape and canopy levels using remotely sensed satellite data. However, there are few studies on plant materials except leaves.

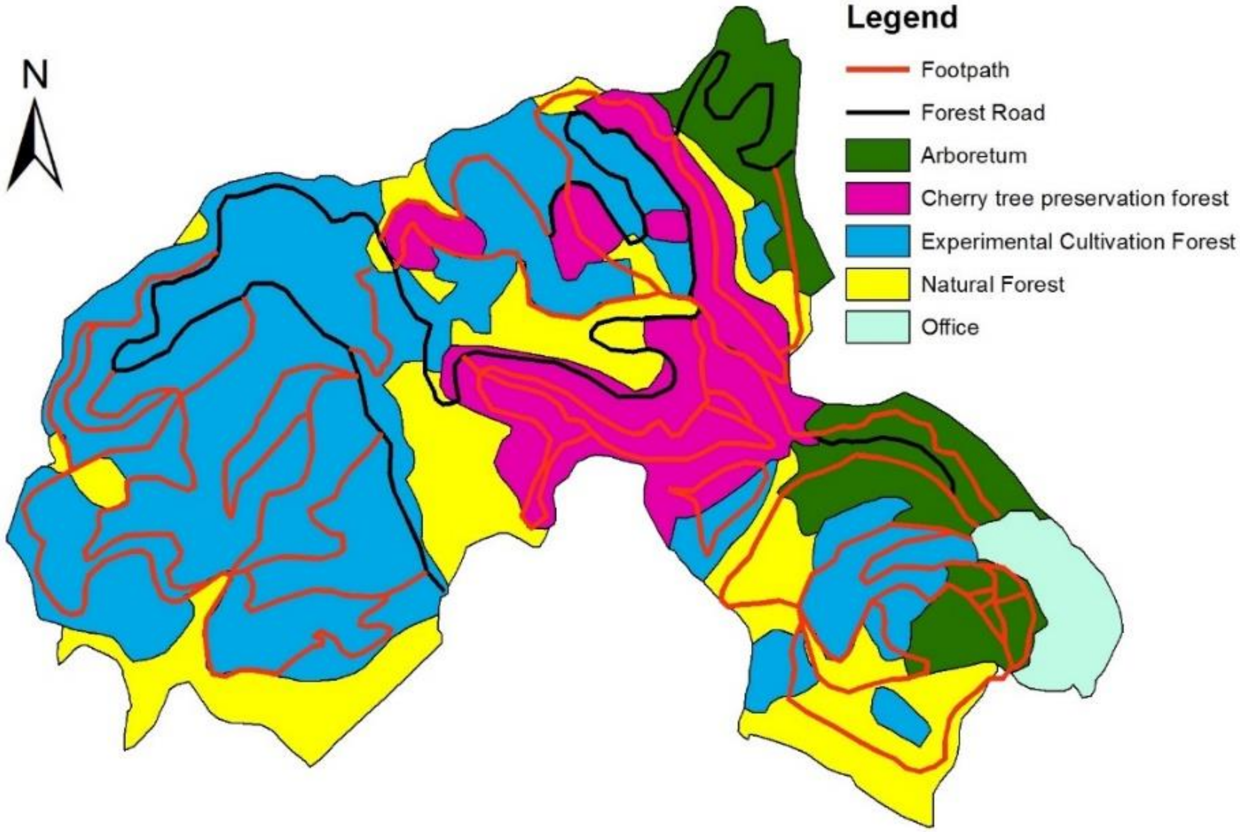
In-situ hyperspectral measurement is needed to evaluate spaceborne or airborne hyperspectral information especially identifying biological and physiological status of urban flowering plant like cherry blossoms. Therefore, detail in-situ hyperspectral measurement is needed to obtain concrete spectral data of plant materials such as flower, leaves, buds and branch. Thus, two types of spectral measurements of flowering cherry blossoms were carried out in this study by using (1) plant probe and (2) pistol grip methods. Initial hypothesis of using these two different methods can be made where the measured spectral reflectance at petal level were consistent with actual cherry blossoms flower colour than that of branch level.

In this study, the relationship between spectral properties of cherry cultivars and visual characteristics was identified. Colours of cherry blossoms flowers were evaluated using hyperspectral radiometer and spectral properties of flowering cherry cultivars were determined. Then, colours of cherry blossom flowers were evaluated using established vegetation indices.

5.2 Materials and Methodology

5.2.1 Study Site

Forty five cherry blossoms cultivars samples were collected in Tama Forest Science Garden (TFSG) managed by Forestry and Forest Products Research Institute (FFPRI) (Figure 5-1). TFSG was located at the foot of Mount Takao, Hachioji, Tokyo, Japan (35°38'46.41''N, 139°16'44.06''E, altitude 3.6 km). TFSG is comprised of cherry tree preservation forest, arboretums and experimental forest. The size of cherry tree preservation forest in TFSG is around 8-ha. This cherry tree preservation forest contains over 1,600 cherry trees gathered from all over Japan. These include cultivated varieties handed down from before the Edo Era and clones of cherry trees designated as protected species (Outline of Tama Forest Science Garden, 2013).



(Map not to scale)

Figure 5-1: Tama Forest Science Garden, Hachioji managed by FFPRI Tama.

5.2.2 Materials

5.2.2.1 Sample collection

Forty five cherry cultivars samples were collected in TFSG and one cultivar was collected near Tokyo Metropolitan University campus (Table 2-1). Those cultivars have been classified into twelve taxonomic groups as listed in Table 2-1 (Kato et al. 2014). Those cultivars are comprised of wild and cultivated cherry blossoms. Spectral properties of all cultivars were measured and morphological effects of cherry cultivars were investigated.

5.2.2.2 Spectral data acquisition

Two approaches were used to acquire spectral data of forty five flowering cherry cultivars: (1) by using plant probe (Figure 5-2a) and (2) pistol grip (Figure 5-2b). One or two petals of each cultivar spectra were acquired by using plant probe where the petal was placed within the clip of the plant probe. The sensor of plant probe were calibrated using Spectralon panel. Spectral of each cultivar was recorded ten times and the average spectral was used in further analyses. The purpose of acquiring spectral data of petal for each cultivar using plant probe is to estimate the chemical contents in each cultivar petal.

a) b)

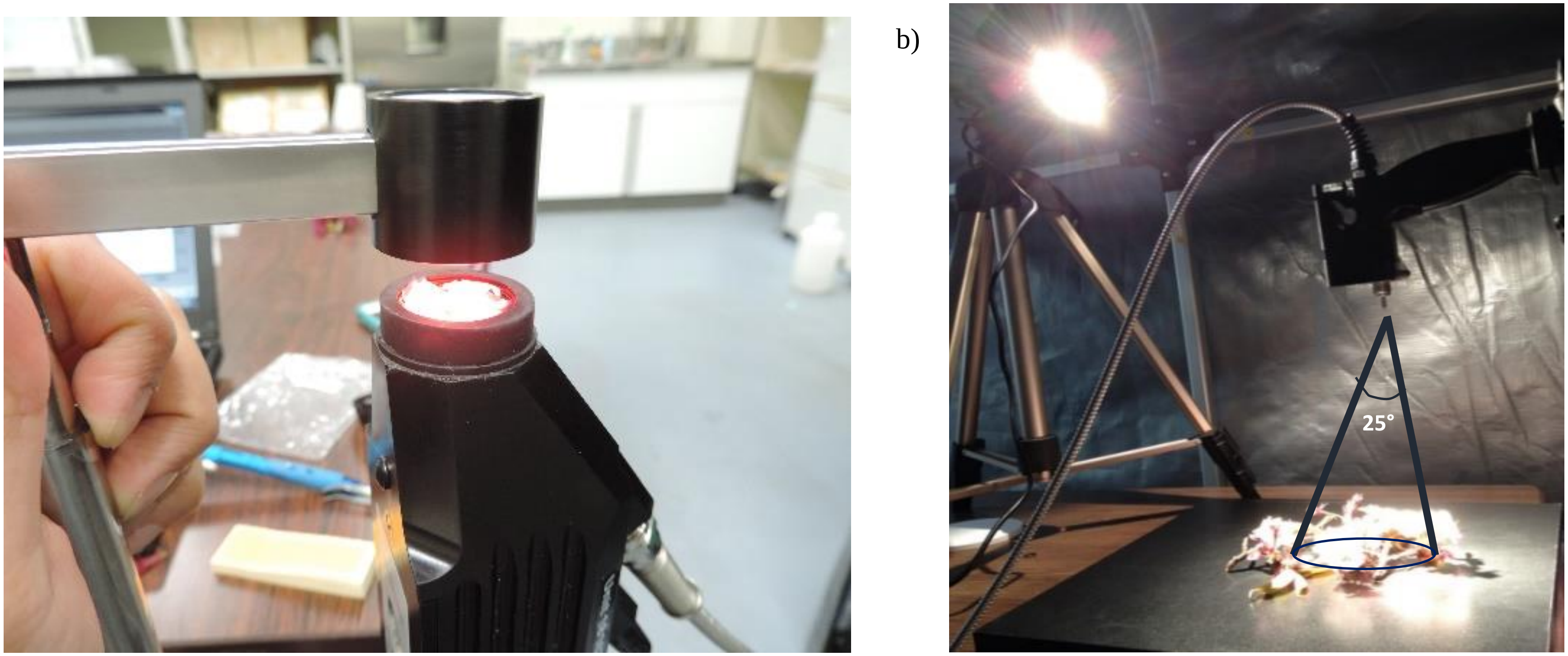


Figure 5-2: Spectral data acquisition of forty five flowering cherry cultivars using (a) plant probe and (b) pistol grip.

Meanwhile, pistol grip was used to measure spectral reflectance of flowering cherries branch. Spectral data of each cultivar was generated in the laboratory under dark conditions by using pistol grip mounted at a nadir position with a 25° field of view and height of 20 cm above the target with a single 75W halogen lamp as a source of energy (Figure 5-2b). For each cultivar, 10 readings were recorded. Before the recording of each sample, the sensor was calibrated using a white Spectralon panel (Dian et al. 2013).

5.2.2.3 Morphological data

To measure effect of morphological characteristics, all cultivars were classified into four main colours of cherry flower which are light pink, pink, white and green based on published book by Parks and Open Space Association of Japan and Sakura database provided by FFPRI, Japan (http://db1.ffpri-tmk.affrc.go.jp/sakura/home.php). The amount of flowers, leaves and twigs were calculated for each colour group (Figure 5-7). Pearson's chi-square test used to identify the relationship between flowers, leaves and twigs compositions for each colour group.

To identify the relationships of cherry cultivars spectral properties with other cherry cultivar biological properties (i.e. chemical content in the petal), few vegetation indices were used in order to obtained information on chemical content in the flower petal that represents colour of cherry blossoms flower by using spectral information.

5.2.2.4 Colour extraction using cherry blossoms spectral properties

Before develop a new vegetation index for distinguishing cherry flower colours, established vegetation indices (VIs) were first used to test the ability of flower spectral signal to provide flower colour information. This is due to weak flower spectral signal (Chen et al. 2009). Thus, to identify cherry blossoms colour using spectral properties of cherry flower established VIs in Table 5-1 were used. Each vegetation index represent colour of cherry blossoms colours; green represents Modified Chlorophyll Absorption Index (MCARI) represent green colour, pink represents Modified Anthocyanin Index (MARI) and yellow represents Carotenoid Reflectance Index (CRI). Vegetation indices used in this study were just used to evaluate colour estimation using spectral properties of cherry blossoms flower and not to measure chemical in the flower.

Table 5-1: Vegetation indices used in this study to identify cherry blossoms colours.

	Vegetation index expression	Reference
Modified Chlorophyll Absorption Index (MCARI)	$\frac{1.5\,[2.5(\rho_{800}-\rho_{670})-1.3\,(\rho_{800}-\rho_{550})]}{\sqrt{(2\times\rho_{800}+1)^2-(6\times\rho_{800}-5\times\sqrt{\rho_{670}})-0.5}}$ (1)	(Haboudane 2004)
Modified Anthocyanin Index (MARI)	$\rho_{800}\left(\frac{1}{\rho_{550}}\right)-\left(\frac{1}{\rho_{700}}\right)$ (2)	(Gitelson et al. 2001)
Carotenoid Reflectance Index (CRI)	$\left(\frac{1}{\rho_{510}}\right)-\left(\frac{1}{\rho_{550}}\right)$ (3)	(Gitelson et al. 2002)

5.2.2.5 Statistical Analyses

Statistical analyses were performed using the software ‘‘R’’ (R Development Core Team 2012). Spectral reflectance differences at petal and branch levels were evaluated using one-way ANOVA. Meanwhile, relationship among colours was estimated using VIs and were examined using Pearson’s correlation test.

Colours estimated using VIs were evaluated using generalized linear mixed models (GLMMs) with log-link functions and gaussian error distributions using the R package, *lme4* (Bates et al., 2013). Actual cherry blossoms flower colour groups were treated as fixed effects, while cherry cultivars were treated as a random effects. *Post hoc* tests of pairwise differences among colour groups were carried out using multiple comparisons for general parametric models with the R package, *multcomp* (Hothorn, Bretz, and Westfall 2008).

5.3 Results

5.3.1 Spectral properties of 45 cherry blossoms cultivars

Raw spectral reflectance of cherry blossoms cultivar ranging from 350 nm to 2500 nm obtained by plant probe and pistol grip approaches shown in Figure 5-3. Figure 5-3a shows spectral signature of cherry blossoms petal by using plant probe that is also known as petal level measurement. Most of cherry blossoms cultivars absorb ultraviolet reflectance (350nm-380nm). Spectral pattern of flowers of each cultivar varies at visible wavelength (400nm to 700nm) and spectral pattern at infrared wavelength is similar. Meanwhile, spectral reflectance pattern collected using pistol grip that also known as branch level are slightly different with plant probe among cherry blossom cultivars because at pistol grip level, spectra of the whole branch that contain flowers, leaves and branch of cherry blossoms was collected as shown in Figure 5-3b. Spectral patterns of cherry blossoms cultivars has high variations among cultivars at visible wavelength (400nm – 700nm) (Figure 5-3b). However, spectral absorption at both plant probe and pistol grip measurements are the same which is around 1350nm and 1850nm.

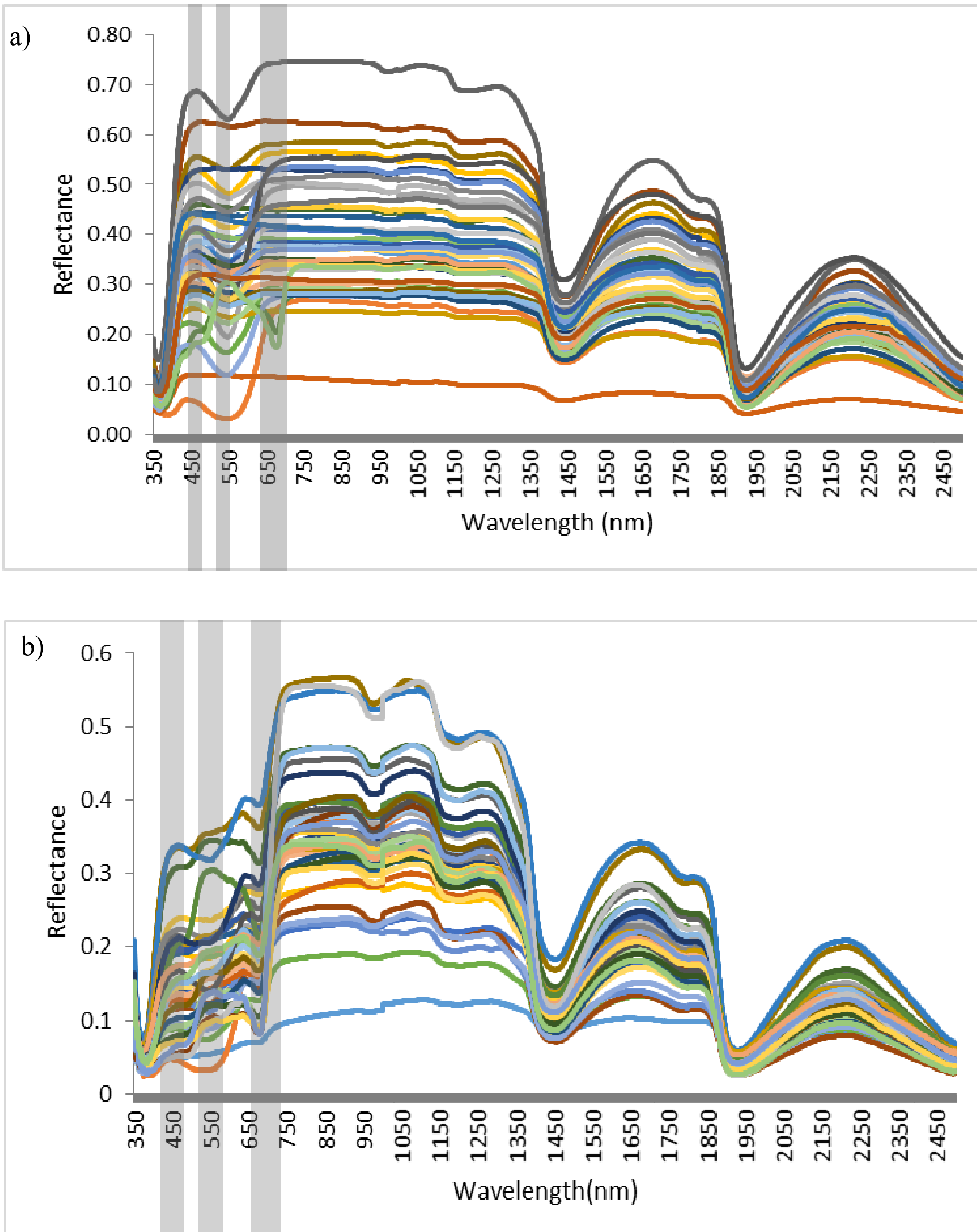


Figure 5-3: Spectral properties of forty five cherry blossoms cultivars at (a) petal and (b) branch levels.

5.3.2 Spectral reflectance differences at petal level and branch level

The significant relationship between colours estimated at petal and branch levels was evaluated using Pearson's correlation test. Figure 5-4 show the correlation test result of pink, green and yellow elements at petal and branch levels. Results indicate that pink element estimated using MARI is significantly correlated at two different types of measurements. This is because all cultivars have pink element at petal and branch levels. Meanwhile, green and yellow elements estimated using MCARI and CRI, respectively are not correlated at petal and branch levels because only two cultivars have green elements and one cultivar have yellow elements at petal level.

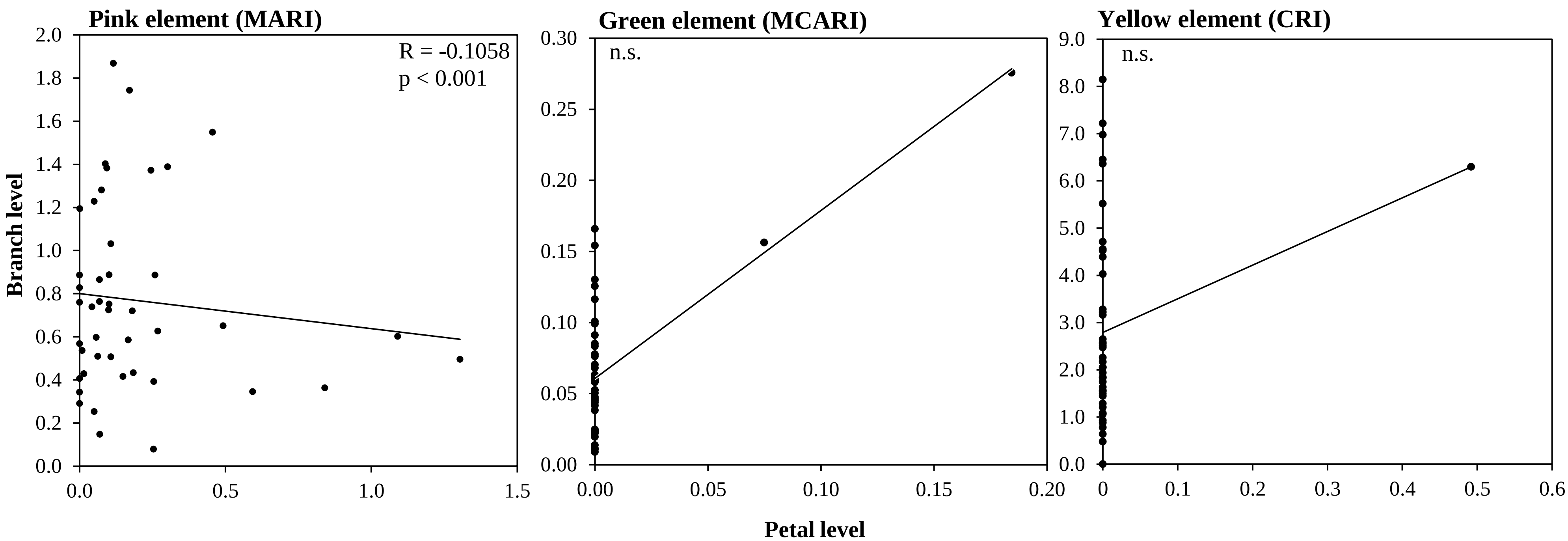


Figure 5-4: Relationship identification between spectral reflectance measured using pistol and plant probe for pink, green and yellow elements.

5.3.3 Differences among colours estimated using vegetation indices

Three types of colours were estimated using established VIs at petal and branch levels. Significant relationship between colours estimated were identified using Pearson's correlation test at both petal and branch levels. Results showed that there are no significant different among colours estimated at petal level. This is due to low pigments concentrations in flower petal especially chlorophyll and carotenoid. Conversely, colours estimated at branch levels were significantly different among them due to the existence of other plant organs s leaves and twig (Figure 5-5).

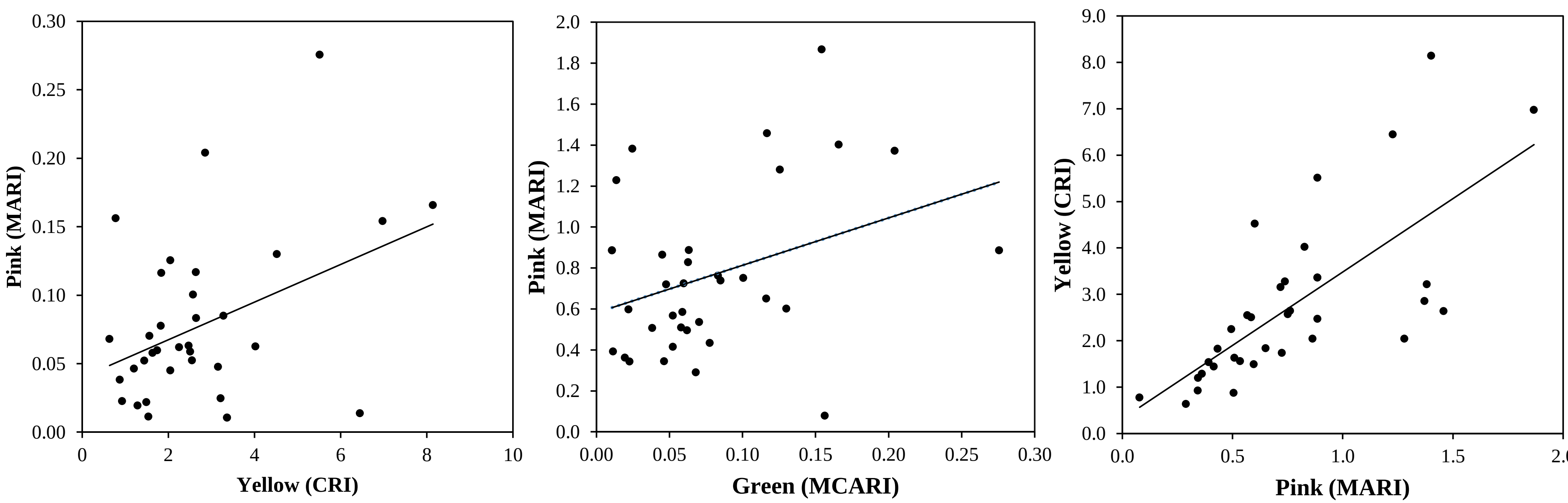


Figure 5-5: Relationship among colours estimated using VI at branch level.

5.3.4 Evaluation of Cherry blossoms colours using vegetation indices

Forty five cherry cultivars were divided into four types of colours based on published book by Parks and Open Space Association of Japan and FFPRI databased. The colours estimated using VIs were evaluated. Results showed that spectral radiometer evaluation of pink element was inconsistent from petal to branch level (Figure 5-6). Meanwhile, green and yellow elements were consistent at petal to branch levels. In addition, results showed that spectral radiometer evaluation was consistent with the human visual evaluation of cherry flower colour at petal level. Estimated green element at petal level was significantly different ($z = 66.23$, $P < 0.001$, GLMM) with human visual evaluation where green element was higher in green colour cherry blossom flower than other colours ($z = 22.45$, $P < 0.001$, multiple comparison for GLMM). While pink element was significantly different with human visual evaluation ($z = 61.95$, $P < 0.001$, GLMM) where pink element was significantly higher in pink ($z = 34.23$, $P < 0.001$, multiple comparison for GLMM) than other colors. Conversely, yellow element did not significantly different with the actual cherry blossoms flower colours (Figure 5-6a).

Contrary to results at petal level, spectral radiometer evaluation at at branch level was inconsistent with human visual evaluation (Figure 5-6b). Results showed that green element was significant ($z= 23.53$, $P < 0.001$, GLMM) where green element in green cherry blossoms flower at branch level was significantly higher than other cherry blossoms flower colours ($z = 5.63$, $P < 0.001$, multiple comparisons for GLMM). Spectral radiometer evaluation of pink element did not significantly different with human visual evaluation (z = 3.762, P = 0.288, GLMM). This result was inconsistent with pink at petal level as pink element estimated using VI able to show pink colour of cherry flower. Spectral radiometer evaluation of yellow element also did not show any significant different with human visual evaluation (z = 0.606, P = 0.8951). This result was consistent with yellow element estimated at petal level.

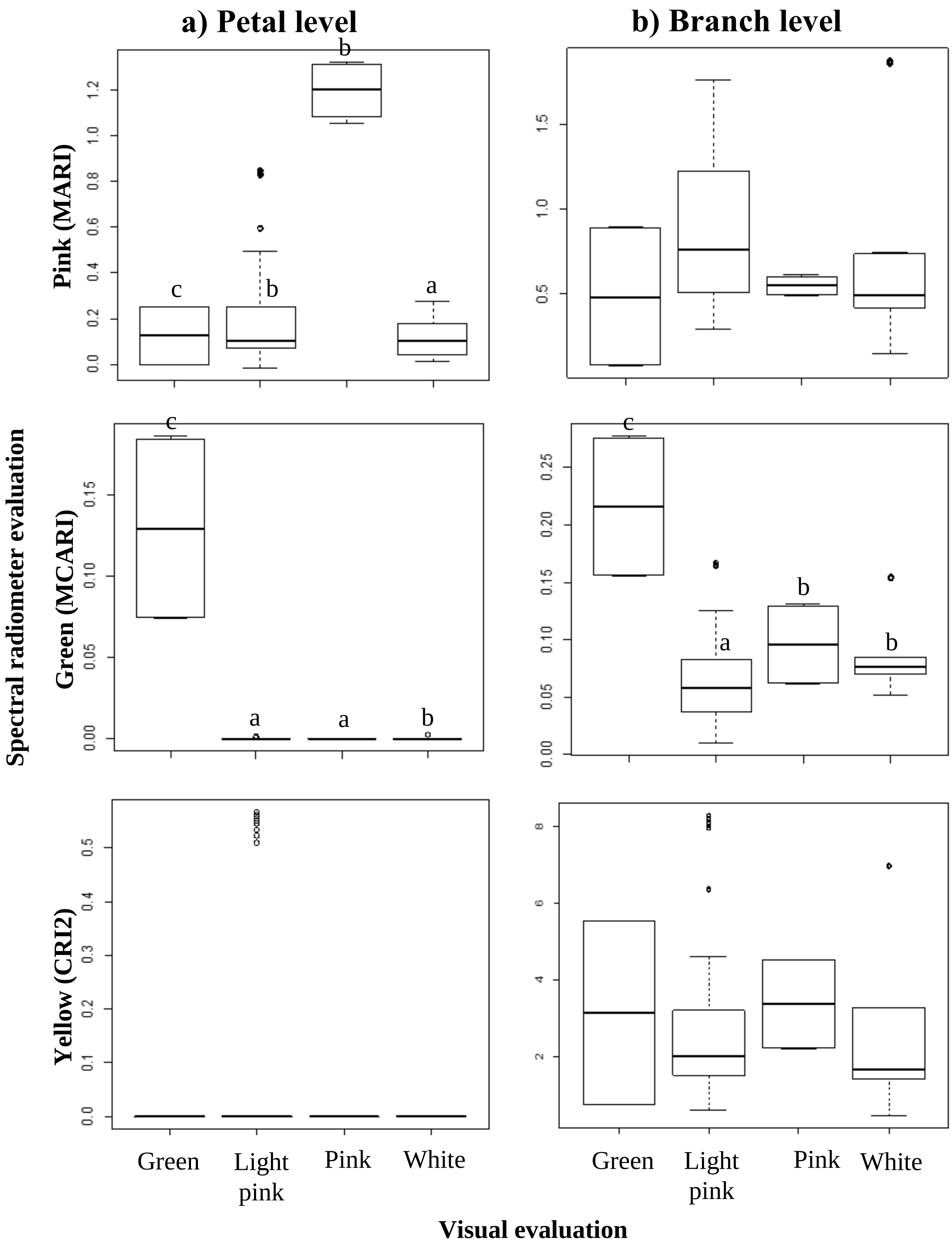


Figure 5-6: Cherry blossoms colour estimation using spectral properties for green, light pink, pink and white cherry cultivars measured at (a) petal level and (b) branch level. Different lowercase letters indicate significant differences in means among colours ($p < 0.05$, multiple comparisons for GLMM).

5.4 Discussion

5.4.1 Spectral properties of 45 cherry cultivars

All cherry blossoms cultivars are absorbing ultraviolet signals for both plant probe (at 360nm – 380nm) and pistol grip (at 350nm – 380nm) measurements. Chittka et al. (1994) stated that generally flower spectral reflectance have high ultraviolet absorption than the one with ultraviolet reflections. In addition, spectral variations at petal and branch level are different. This is may be due to spectral measurement condition. At petal levels, only spectral reflectance of flower petal was measured. Contrary to petal level, spectral reflectance of whole branch was collected. Thus, multiple spectral responses were recorded by hyperspectral radiometer sensor and caused higher spectral variations than at petal level measurement. However, spectral absorption at both plant probe and pistol grip measurements are the same which is around 1350nm and 1850nm. These absorptions are due to water content in both flowers and leaves at petal and branch levels measurement (Allen and Richardson 1968; Knipling 1970).

5.4.2 Evaluation of Cherry blossoms colours using spectral properties

Results indicated that spectral radiometer evaluation of pink element was inconsistent from petal to branch level (Figure 5-6). This is because of weak spectral signal of flower petal at petal level and high spectral contributions of high amount of leaves and twigs at branch level (Figure 5-

7). Meanwhile, green and yellow elements were consistent at petal to branch levels (Figure 5-6). This is because at both petal and branch levels, green element is high in flower petal at petal level and leaves at branch level. Moreover, yellow element is consistent from petal to branch level because flower petal at petal level do not have any yellow pigment or contain less yellow pigment.

In addition, results showed that spectral radiometer evaluation was consistent with the human visual evaluation of cherry flower colour at petal level (Figure 5-6a). Pink and green elements are consistent with human visual evaluation because flower petal has pigment that is sensitive to the vegetation indices used. In addition, no other spectral contribution in spectral properties of flower at petal level as it has been measured using plant probe with 0° instantaneous field of view. Contrary to results at petal level, results showed that spectral radiometer evaluation of pink element at branch level was inconsistent with human visual evaluation. This may be due to leaf amount is higher in light pink at branch level (Figure 5-7)**.** However, the amount of leaves and flowers are slightly different but pink element unable to show the actual flower colour at branch level. This is because cherry blossoms flower spectral signals are weaker than leaves spectral signals (Chen et al. 2009).

Conversely, spectral radiometer evaluation of green element was consistent at branch level because in the green groups, all attributes (leaves and flower) was green in colour. Even light pink group has the highest amount of leaves (Figure 5-7), light pink group do not have highest green element because in light pink group, some leaves was red in colour and some flower’s sepals are also red in colour. In addition, there are spectral contribution from light pink and white flower that mixed at branch level as the spectral reflectance was measured using pistol grip with 25° instantaneous field of view. Meanwhile, results of yellow element at branch level was consistence with results at petal level. This may be due to flower and leaves colour which may be have slightly low of yellow element.

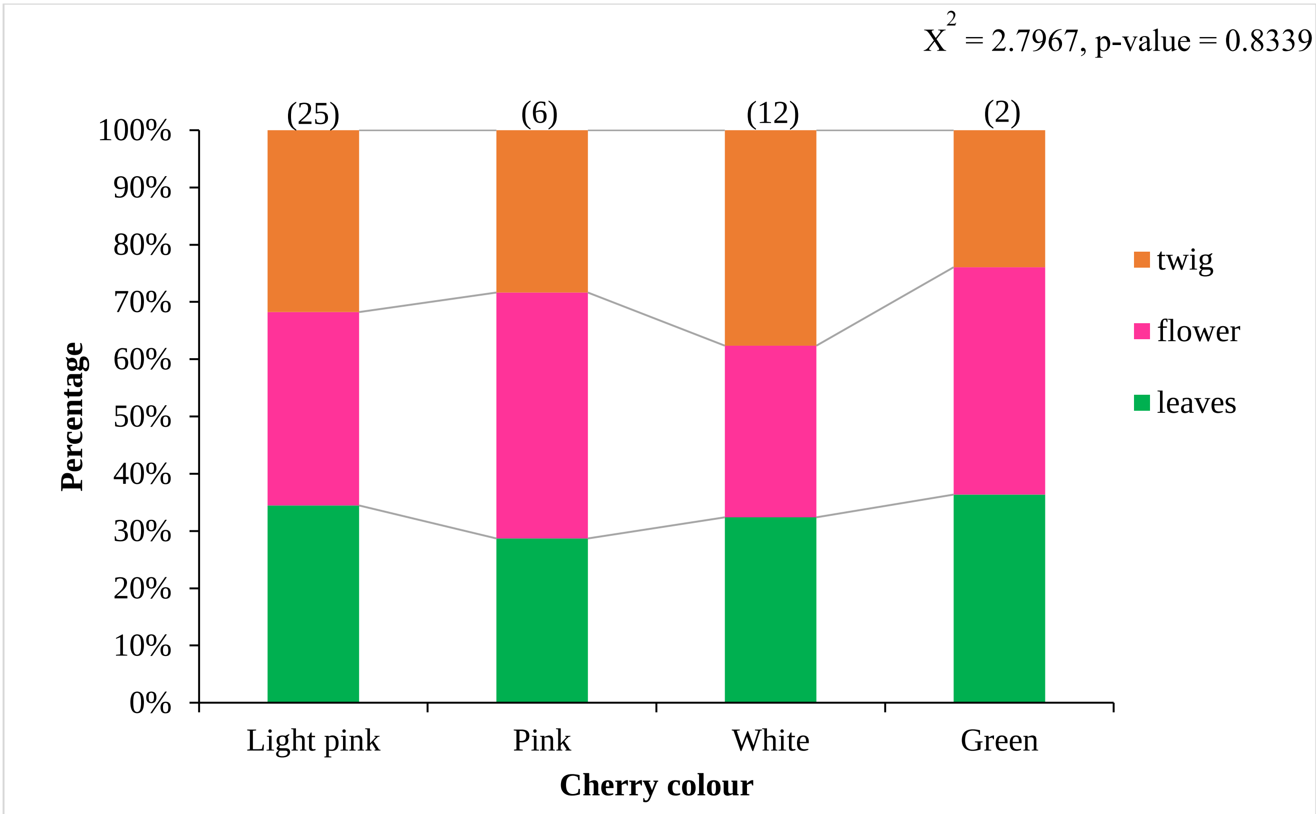


Figure 5-7: Characteristics of each colour group that represents cherry cultivars proportions and compositions of twigs, flowers and leaves.

5.5 Summary

Results suggest that spectral properties of cherry cultivars can be used as an endmember in image classification approach to obtain more accurate cherry cultivars identification. Besides that, results suggest that spectral radiometer evaluation of pink element at petal level was inconsistent with the evaluation at branch level. While spectral radiometer evaluation of green and yellow elements at petal level was consistent with evaluation at branch level. However, spectral radiometer evaluation of pink and green element was consistent with human visual evaluation. Contrary to petal level, spectral radiometer evaluation of pink element was inconsistent with human visual evaluation. While spectral radiometer evaluation of green element was consistent with human visual evaluation.

Chapter 6

General Discussion and Conclusion

6.1 Issues on urban plant monitoring using remotely sensed data

As discussed in Chapter 3, urban plant monitoring using remotely sensed data might face mixed pixel problem due to complex urban ecosystems. Therefore, remote sensing experts have carried out a big number of studies focused on spectral mixture analysis (SMA) to identify and monitor urban plant phenology from leaf, branch to canopy scale. However, a few studies focused on a plant reproductive organ and most of studies are focused on leaves and structure of the tree. This is most probably because most of the urban plant that been focused on was non-flowering plant or evergreen plant.

Conversely, the situation in Japan is relatively different as the flowering plant is the dominant plant planted in urban area and flowering cherry is the most common ornamental plant that can be found in urban area. This is because flowering cherries are of interest and one of the source of social and economic benefits. In addition, ecologists in Japan has used flowering cherries phenological cycle information as one of the indicators in monitoring long-term impacts of climate change in Japan. Thus, monitoring flowering cherries is vital.

Nevertheless, it is believed that flowering cherries identification and monitoring in urban area using remotely sensed data might face the same problem as monitoring evergreen and non-flowering plant in urban area. Thus, Chapter 3 was suggested that spectral properties of reproductive organ at flower, branch and canopy level must be identified as it can be used as endmember in SMA.

6.2 Identification of flowering cherry at landscape level

Urban plant status identification is vital to perpetuate urban ecosystems sustainability. Therefore, it is important to monitor them frequently. However, monitoring flowering plant in urban ecosystems using satellite remotely sensed data is a challenge due to high heterogeneity of urban features and weak spectral signal of flowering plant especially flowering cherries. Many studies has been carried out in identifying and monitoring urban plant using satellite remotely sensed data. Remote sensing experts have examined numerous of methods to identify and monitor urban plant such as by using image classification methods and vegetation indices.

Nevertheless, most of studies on urban plant monitoring using those methods are focused on evergreen and non-flowering plant. Therefore, study on flowering plant identification using satellite remotely sensed data was carried out as in Chapter 4. In this chapter, hard and soft classifiers were used which is Maximum Likelihood classification (MLC) as hard classifier and

Mixture Tuned Matched Filtering (MTMF) as soft classifier. This study was carried out to identify the ability of hard and soft classifiers in identifying flowering cherry trees in an urban park.

Results of this study indicate that soft classifier identify flowering cherry tree more accurate than hard classifier. This is because limited number of bands of IKONOS image has limit the accuracy of classification. Moreover, low accuracy achieved due to the existence of dry grass in study area. Therefore, additional endmember is needed to achieve higher accuracy. However, hyperspectral image is needed in order to add number of endmember.

In addition, results of this study also suggest that further study on spectral properties of flower at flower, branch and canopy level is important to be carried out as suggested in Chapter 3 since this study has proven that flower spectral signal can be mixed with other spectral signal.

6.3 Spectral properties difference of 45 cherry blossoms cultivars

Hyperspectral sensing is able to provide information on physiological status of flowering plant. Commonly, physiological status of evergreen or non-flowering plant was carried out. Thus, we believed that hyperspectral sensing is able to provide physiological status of flowering plant like flowering cherry. Flowering cherries have a unique characteristics as it have been cultivated since long time ago and have caused morphological and phylogenetic diverse characteristics (Kato et al., 2014).

In Chapter 5, the investigation on spectral properties of flowering cherry has been carried out. Results of this study indicate that all colours estimated at petal level was consistent with actual cherry blossoms flower colours (Figure 5-6a). Conversely, only green and yellow elements were consistent with actual cherry blossoms colour at branch level due to leaves existence (Figure 5-6b). While pink element are not significantly different with actual cherry blossoms colours due to weak spectral signals of flowers at branch level. However, only pink element was inconsistent from petal to branch levels. While green and yellow elements is consistence at petal to branch levels (Figure 5-6) .This is because some of cherry cultivars flower were green in colour and at branch level, some cherry cultivars have leaves which contain pigment that represent green element. As a conclusion, spectral properties of cherry blossoms flowers at petal level can be used as endmember to improve soft classification accuracy while monitoring flowering cherry.

As a conclusion, results obtained in this thesis strongly suggest that remote sensing techniques may have the potential to monitor and estimate urban flowering plant spring phenology event although urban landscape is highly occupied by numerous land cover types. Results in this thesis might be useful to monitor spring phenological event of flowering plant in urban area as it could improve cherry blossoms management especially in highly heterogeneous areas as cherry blossoms could provide social and economic benefits towards nature-based tourism. Besides that, this study would be important input to improve satellite development in future.

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