# Chapter 5 - Applications of Proximal Sensing

Early field spectrometers (1980s - 1990s) were often designed for geologists with the goal of mineral identification, and there is a rich history of proximal remote sensing in geology and soil science for inferring mineral composition via chemical absorption features. Most of these first field spectrometers were large and heavy, and generally lacked appropriate foreoptics for accurate and repeatable sampling of foliage. Additionally, the slow sampling speed of these early field spectrometers made detection of rapid responses (e.g. dynamic physiological responses) difficult.

Over time, due to advances in optics, electronics and computing, the portability and speed of field spectrometers have gradually improved, opening up a wider range of field applications. Proximal remote sensing is now a well-established methodology in areas ranging from agriculture and natural resources management to ecology and Earth system science. This chapter briefly summarizes some of these applications, with a primary focus on vegetation studies.

## *Ground Validation and Calibration*

Historically, proximal remote sensing has often been used as a form of *ground truthing* for airborne or satellite campaigns, and that is still true today. While ground truthing is a misnomer (absolute truth is elusive), proximal sensing can be used for calibration or validation of remote sensing campaigns, often through *vicarious calibration*, which involves simultaneous sampling of ground targets while collecting data from aircraft or satellite) (Thome 2004).  Usually, this involves well-characterized, uniform, calibrated field targets (Figure 1). The empirical line correction (ELC, Conel et al., 1987) is an example of a calibration method employing proximal remote sensing. In this case, a primary goal is to use well-characterized field targets to correct for atmospheric effects, yielding something approximating a true surface reflectance from the radiance detected by the remote sensor.

Figure 1. A field spectrometer being used to sample a uniform painted target during and aircraft overflight.  In this case, proximal remote sensing is being used to obtain surface reflectance and correct for atmospheric effects using the Empirical Line Correction (ELC) method, as described in Wang et al. 2021. Note how the foreoptic (fiber optic mounted on a pole) is held at a distance (to avoid confounding effects of shadows). Dark clothing avoids casting reflected radiation on the calibration target. From Wang et al. 2021

Vicarious calibration allows us to evaluate of the fundamental responses of satellite and aircraft sensors, allowing corrections that enable more accurate or consistent products. Ideally such calibrations would be conducted over the life of an aircraft or satellite sensor to help evaluate changes over time, e.g., due to sensor or orbital drift.

Another example of vicarious calibration involves correction for geometric effects (geometric calibration) on the signals detected remotely. An example of this is the calculation of the bidirectional reflectance distribution function (BRDF), which characterizes the angular reflectance properties of a target (Figure 2). Once the BRDF response of a surface has been characterized, this information can then be applied to satellite or aircraft data to normalize for angular effects in the data. An example of this might involve removing the visible seams where two adjacent images overlap, providing a more uniform appearance in the corrected imagery. While such angular effects are sometimes considered artifacts, they are in fact representations of actual surface responses to sun and view angle and can themselves contain useful information on physical or biological properties that might be of interest. In that case, angular sampling may be used as a source of meaningful information rather than something to be used in a calibration and image correction. BRDF information can be useful in vegetation or soil mapping as different vegetation types tend to have different angular optical properties (Gamon et al. 2004) and different soil types will have different angular responses depending upon soil particle size (Cierniewski 1987)

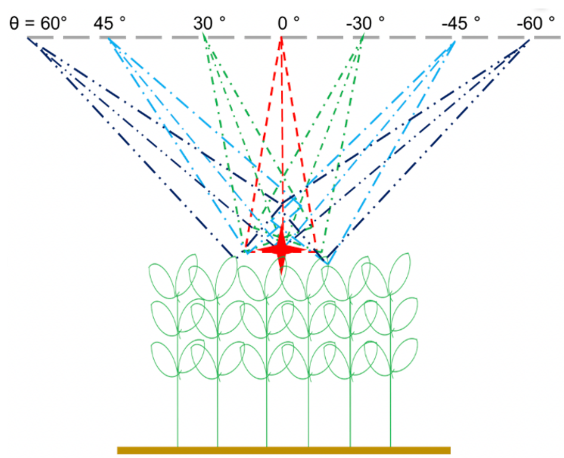


Figure 2 – BRDF sampling, consisting of several measurements at a range of instrument sampling (view) angles to characterize a continuous BRDF function that relates the reflectance signal to the sun and view angle. Different surfaces have different BRDF responses, which can be used in correcting remote images or can be used as a useful source of information about the target. Figure from Bai et al. (in review).

Other types of ground validation and calibration occur at later stages in the data processing stream to evaluate higher-level data products derived from aircraft or satellite sensors and their interpretation. For example, vegetated targets can be sampled on the ground during an overpass, and the agreement of remotely sensed products (e.g. vegetation indices or other derived products) can be compared between field and remote measurements. Such comparisons can reveal errors in the derivation of higher-level satellite products which are not apparent in the basic low-level calibration and validation, and can be used to explore sources of disagreement (Figure 3). These errors can have numerous consequences for downstream products derived from satellite data, and illustrate the value of good ground validation (Cheng et al. 2006).

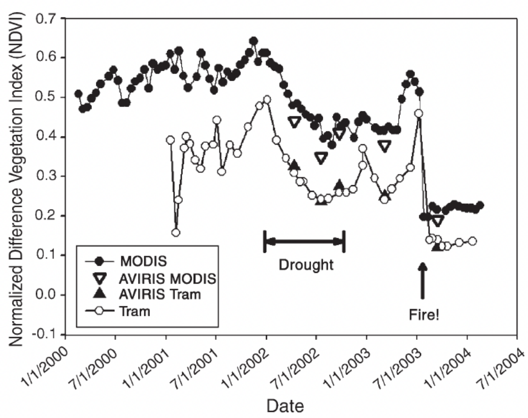


Figure 3 – NDVI measured on the ground using a robotic tram (open circles), aircraft (NASA AVIRIS sensor, triangles) or MODIS satellite (closed circles) for chaparral vegetation at Sky Oaks California. Aircraft data were re-sampled to match the footprint of the tram system (closed triangles) or the MODIS sensor (open triangles) and yielded close agreement with ground data. This analysis revealed several causes of higher MODIS NDVI values. Cheng et al. 2006

Additionally, field measurements can be used in *upscaling* or *downscaling* (see Chapter 1), often involving *empirical*, *mechanistic*, or *statistical models* (e.g., *machine learning*) that extrapolate from local sites to larger areas (upscaling), or to validate an interpretation of a remotely sensed signal with independent ground sampling (downscaling). This level of validation is often very challenging due to the level of data processing required, the dynamics of the biological organisms involved, and due to the differences in sampling scales, and requires careful attention to methodology and effects of sampling scale. Field remote sensing often provides essential information in such scaling activities.

### *Proximal Sensing as an Experimental Tool*

Proximal sensing can improve our understanding of remote sensing particularly when applied in an experimental approach. Remote sensing is generally weak in this regard, largely because the scale and cost of remote sensing campaigns make it hard to apply the traditional *scientific method* involving *treatments*, *controls* and *replication*, classic components of an experimental approach. Because these traditional experimental methods can generally be more easily applied at the finer spatial scale of field sensing than at larger landscape or continental scales, proximal measurement provides a means of testing methods and concepts in a rigorous experimental context involving well-designed treatments and controls with replication and suitable statistical analysis. When used in this way, proximal sampling has often been used as a basis for designing new satellite or aircraft sensors, or for developing new indices or algorithms that are later applied to remote sensing instruments. For example, many of the widely used *vegetation indices* used in remote sensing have had their origins in laboratory and field experiments using proximal sensing. Similarly, the use of spectral reflectance for plant trait analysis has largely begun with proximal measurements derived from chemometric approaches and is now being applied to aircraft and satellite data.

### *Spectroscopic and Chemical Analyses*

Spectroscopy has a rich history in the analysis and quantification of chemical compounds (*analytical chemistry* and *chemometrics*), typically by analyzing chemical absorption features in liquids or dried substances, often under controlled conditions. Such analysis has traditionally been carried out with spectrophotometers on a lab bench. For example, spectral analysis is used to evaluate soil chemistry, the content of dried plant materials, the composition of liquid mixtures, and the quality of food products. In these studies, spectral methods analyzing absorbance (or absorption features in reflectance spectra) are typically compared to independent analytical methods (e.g. elemental analysis or high-performance liquid chromatography, HPLC). Spectrally based analytical methods have emerged as standard methods in analytical chemistry, often replacing older analytical analytical methods as the instruments and related mathematical, statistical and computational methods have improved. It is worth noting that most analytical methods (including HPLC, spectrophotometers, and gas analyzers) are based on optical detection, so are themselves a form of *proximal* optical sensing involving spectroscopy. Field spectrometry takes many of these laboratory approaches and extends them to the outdoors, often by modifying the design and packaging of the instrument and foreoptics to be more portable and rugged.

With the improved design and portability of field spectrometers. chemometric approaches originally designed in the lab have been adapted for vegetation under field conditions. During NASA's Accelerated Canopy Chemistry Program in the 1990s, analytical concepts and methods began to be widely applied to field and airborne spectroscopy for vegetation biochemical analyses, largely inspired by advances in detecting and quantifying canopy nitrogen and lignin (e.g., Wessman et al. 1988). In recent years, further advances have been made in assessing a wide diversity of plant chemical composition from remote sensing, often building on these early successes and a large variety of plant chemical constituents can now be detected and quantified. Chemometric approaches have been greatly assisted by improved computational and statistical methods that facilitate the rapid analysis of large volumes of spectral data. More recently, *plant trait analysis*, *phenotyping*, and *precision agriculture* are examples of applications benefiting from a history of spectroscopic and chemometric methods. These developments, along with the wide availability of open-source code now provides a rich set of tools for statistical analysis of spectral data (see Chapter 6, Data Analysis)

***Biological vs. Physical Targets***

Relative to inanimate targets, vegetation offers several additional sampling challenges. Geological sampling often involves the use of stable absorption features present in reflectance spectra. Geological deposits often display characteristic spectral *signatures* (analogous to fingerprints) that are often the basis for identifying or detecting the presence of a particular mineral feature (Clark et al. 2003). By contrast, in vegetation sampling, the *relative levels* of different compounds (not their actual identity), and their *dynamics* in time and space (not their fixed quantities), are often the relevant topics. While geological materials like soil or minerals change very slowly on a human time scale, living plants are inherently dynamic on multiple time scales ranging from nanoseconds to centuries. This makes vegetation spectroscopy interesting, often challenging and sometimes rewarding, particularly when vegetation's dynamic properties are properly considered and integrated in the study design and analyses.

***Plant Traits and Functional Types***

In recent years, interest in *plant traits* – characteristic features of leaves or canopies that relate to plant function, define functional groups and reveal functional diversity - has expanded rapidly in the ecological literature. Traits offer a way to simplify the enormous complexity of plant features into a few metrics that can be used to identify characteristic plant *functional types*. Plant functional types are broad plant categories (groups of species) that share common properties (Smith et al. 1997). Plant traits reveal different strategies of resource use and are thought to reveal fundamental aspects of the underlying physiological or ecological function of leaves or plants (Wright et al. 2004). Standardized methods for assessing leaf traits (Cornelissen et al. 2003), and standard trait databases (e.g., TRY, Kattge et al. 2011, and Glopnet, Wright et al. 2004) have further expanded the utility of the plant trait concept. Similar to leaf traits, whole-plant traits provide an additional means of categorizing vegetation according to functional characteristics, and are widely used in ecosystem and digital global vegetation models (DGVMs, Bonan et al 2003). Examples of leaf and plant traits are shown in Table 1.

Table 1. Examples of leaf traits (from Cornelissen et al. 2003), along with whole-plant traits.

| Leaf Traits: | Plant Traits: |
|---|---|
| Leaf size | Growth form |
| Leaf thickness | Life form |
| Specific leaf area (or specific leaf weight) | Height |
| N content | Leaf area index |
| P content | Flammability |
| Dry matter content | |
| Leaf lifespan | |
| Photosynthetic pathway (e.g. C3 vs. C4) | |

Since many leaf and plant traits can be related to their corresponding optical attributes, spectral reflectance is increasingly being used to assess traits. To some extent, information on particular plant traits can be associated with specific spectral regions (Figure 4 and Table 2), however some studies have shown plant spectral properties related to traits to be far more complex and dynamic than suggested by a simple mapping of plant traits to plant species (Chavana-Bryant et al. 2017). Because spectral reflectance provides a ready link to remote sensing, plant traits can, in principle, be inferred from satellite or aircraft measurements (Wessman et al. 1988, Asner & Vitousek 2005, Asner et al. 2014, Singh et al. 2015). Such upscaling of plant traits using combined proximal and remote sensing is currently an active area of research.

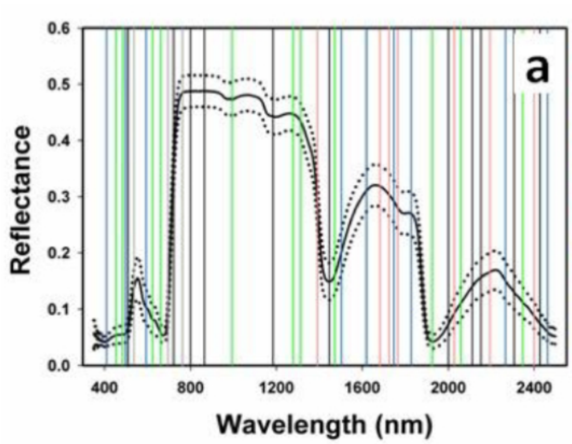


Figure 4.

Vegetation reflectance spectrum, with vertical bands indicating spectral regions having strong statistical associations with particular plant traits listed in Table 2. Figure by A. Singh and J. Couture, as reported in Townsend et al. (2016)

Table 2. Plant functional traits detectable with spectral reflectance (Figure 4). Townsend et al. (2016)

| Functional characterization[1] | Trait | Example of functional role | Example Citations |
|---|---|---|---|
| Primary | Foliar N (% dry mass or area based) | Critical to primary metabolism (e.g., Rubisco), | Johnson et al. 1994, Gastellu-Etchegorry et al. 1995, Mirik et al. 2005, Martin et al. 2008, Gil-Perez et al. 2010, Goekkaya et al. 2015, Kalacska et al. 2015, Singh et al. 2015 |
| | Foliar P (% dry mass) | DNA, ATP synthesis | Mirik et al. 20015, Mutangao & Kumar 2007, Gil-Perez et al. 2010, Asner et al. 2015 |
| | Sugar (% dry mass) | Carbon source | Asner & Martin 2015 |
| | Starch (% dry mass) | Storage compound, carbon reserve | Matson et al. 1994 |
| | Chlorophyll-total (ng $g^{-1}$) | Light-harvesting capability | Johnson et al. 1994, Zarco-Tejada et al. 1999, 2000a, Gil-Perez et al. 2010, Zhang et al. 2008, Kalacska et al. 2015 |
| | Carotenoids (ng $g^{-1}$) | Light harvesting, antioxidants | Datt 1998, Zarco-Tejada et al. 1999, 2000a |
| | Other pigments (e.g., anthocyanins; ng $g^{-1}$) | Photoprotection, NPQ | van den Berg & Perkins 2005 |
| | Water content (% fresh mass) | Plant water status | Gao & Goetz 1995, Gao 1996, Thompson et al. 2016, Asner et al. 2016 |
| Physical | Leaf mass per area (g $m^{-2}$) | Measure of plant resource allocation strategies | Asner et al. 2015, Singh et al. 2015 |
| | Fiber (% dry mass) | Structure, decomposition | Mirik et al. 2005, Singh et al. 2015 |
| | Cellulose (% dry mass) | Structure, decomposition | Gastellu-Etchegorry et al. 1995, Thulin et al. 2014, Singh et al. 2015 |
| | Lignin (% dry mass) | Structure, decomposition | Singh et al. 2015 |
| Metabolism | Vcmax (μmol $m^{-2}$ $s^{-1}$) | Rubisco-limited photosynthetic capacity | Serbin et al. 2015 |
| | Photochemical Reflectance Index (PRI) | Indicator of non-photochemical quenching (NPQ) and photosynthetic efficiency, xanthophyll cycle | Gamon et al. 1992; Asner et al. 2004 |
| | Fv/Fm | Photosynthetic capacity | Zarco-Tejada et al. 2000b |
| Secondary | Bulk phenolics (% dry mass) | Stress responses | Asner et al. 2015 |
| | Tannins (% dry mass) | Defenses, nutrient cycling, stress responses | Asner et al. 2015 |

[1]Categories of functional characterization are for organizational purposes only: ***Primary*** refers to compounds that are critical to photosynthetic metabolism; ***Physical*** refers to non-metabolic attributes that are also important indicators of photosynthetic activity and plant resource allocation; ***Metabolism*** refers to measurements used to describe rate limits on photosynthesis; and ***Secondary*** refers compounds that are not directly related to plant growth, but indirectly related to plant function through associations with nutrient cycling, decomposition, community dynamics, and stress responses.

### *Plant traits are dynamic*

Unlike minerals with their unique, stable chemical signatures, most plants or plant species show similar spectral patterns that represent variations on a common set of absorbing compounds in a scattering medium. The levels and activity of these compounds vary over time due with conditions, leading to reflectance spectra that are far more complex and dynamic than those of inanimate surfaces. This make vegetation spectroscopy fundamentally different from many other fields of spectroscopy. Most plants contain variations of the same basic chemical compounds, which include pigments (chlorophylls, carotenoids, and anthocyanins), water, and structural materials (sometimes called "dry matter," and comprised of biochemical compounds like cellulose, hemicellulose, and lignin) (Figure 5). Depending upon environmental conditions and functional states, individual plants or species often differ slightly in the detailed structure or *relative levels* of these biochemical compounds, and it is often these subtle differences in content or activity of these chemical constituents that are of interest. Changing biotic or abiotic environmental conditions can alter plant physiology and biochemistry in ways that affect leaf or canopy reflectance spectra.

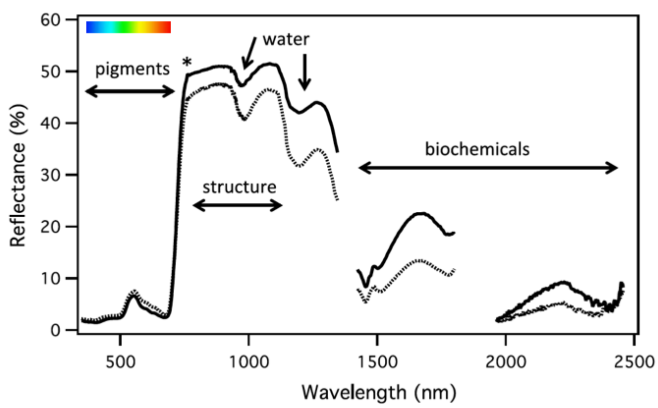


Figure 5. Canopy reflectance spectra for deciduous (*Populus balsamifera* solid line) and evergreen (*Picea glauca*, dotted line) tree canopies, showing spectral regions associated with detection of pigments, water, and structural biochemicals. The rainbow color bar indicates spectral regions of visible light (blue to red). The asterisk (*) indicates a region used for detecting chlorophyll fluorescence, a measure of photosynthetic activity and plant stress. Gaps indicate spectral regions where signal-to-noise is poor due to atmospheric absorption

An example of dynamic plant spectral responses involves the rapid induction of protective chemicals in response to insect attack (Couture et al. 2013). Another example of subtle spectral dynamics involves adjustments in photosynthetic pigment levels, which occur both diurnally and seasonally, and with a leaf's position in the canopy due to varying illumination. A schematic of the relevant photosynthetic regulatory processes associated with plant pigments is shown in Figure 6, along with the corresponding spectral patterns in Figure 7. These photosynthetic regulatory processes cause specific spectral features to increase or decrease slightly, primarily in the visible region of the spectrum. Because some of these changes involve biochemical processes, they tend to be temperature sensitive, adding further complexity to the sampling. These changes in physiological state that influence reflectance spectra often occur very rapidly (over time frames of seconds to minutes), as illustrated in Figure 7, requiring different sampling approaches than those used for more static (e.g., geologic) features.

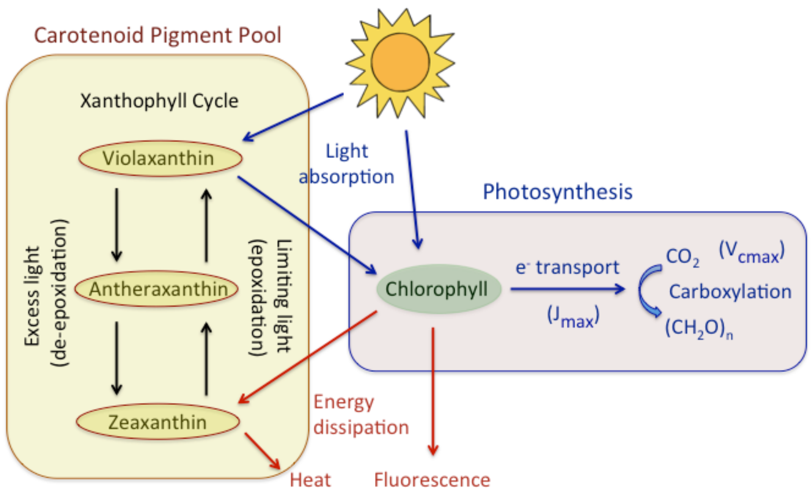


Figure 6 – Pathways of absorbed energy (arrows) in a leaf tied to photosynthetic regulatory pigments and processes leading to spectral dynamics shown in Figure 7. Energy dissipation and heat production (red arrows) are ways that plants can safely dissipate excess absorbed energy under stress. (Gamon, 2015)

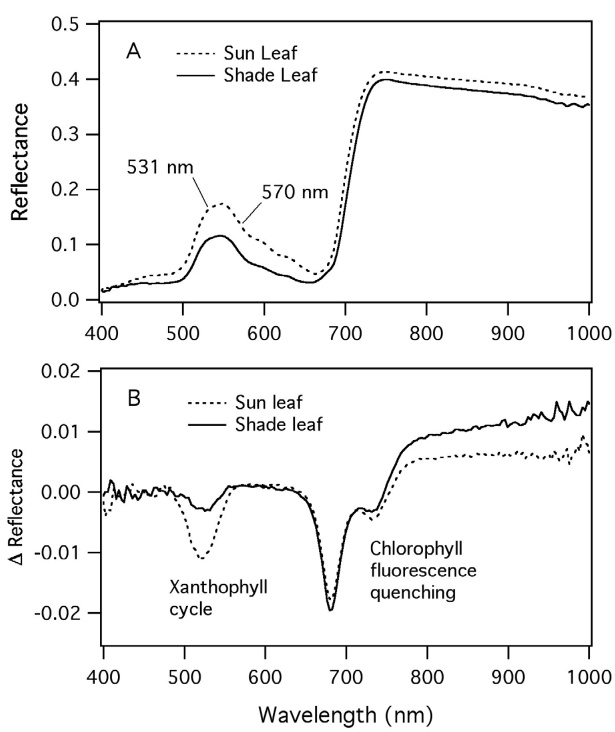


Figure 7. Spectra for jack pine (*Pinus banksiana*) leaves in sun and shade (top panel) and difference spectra (Δ reflectance, calculated as dark minus light state), of the same leaves after exposure to 10 minutes of bright light. The difference spectra exhibit dips centered at 531 nm due to conversion of the xanthophyll cycle pigments from violaxanthin to zeaxanthin, and a double dip near 685 and 740 nm due to declining chlorophyll fluorescence (non-photochemical quenching, NPQ) (Figure 6). The larger green hump (panel A) and greater dip at 531 nm (panel B) for the sun leaf indicates a greater investment in photoprotective carotenoids and xanthophyll cycle pigments for the sun leaf exposed to high irradiance relative to the shade leaf exposed to a lower growth irradiance. (Gamon and Berry 2012).

Sampling these subtle pigment dynamics require specialized instruments with rapid, accurate and repeatable measurement capabilities, good signal-to-noise, and specialized foreoptics. Specialized portable spectrometers and leaf clips have been developed to sample the pigment dynamics shown in Figure 7. An example of a leaf clip for sampling pine needle reflectance is shown in Figure 8.

Figure 8 – leaf clip used for sampling pine needle reflectance (see Figure 7). The clip contains a bifurcated optical fiber that can measure reflected radiation on samples less than 1mm diameter within five seconds and is an example of specialized spectrometer foreoptics developed for capturing dynamic regulatory processes even in narrow plant leaves.

Plant chemical constituents are present in a complex, 3-dimensional scattering medium, comprised of leaves and canopies, which are also dynamic over a day or growing season, causing further spectral variation. For example, in addition to the photoregulatory processes depicted in Figures 6-7, many plants have active chloroplast and leaf movements and that, along with wind, changing sun angles and dynamic sky conditions, cause canopy spectral signatures to vary within a day (figure 9). Plants also undergo large structural changes with ontogeny, growth and senescence, adding further dynamism over longer, seasonal or interannual time frames (figure 9).

The presence of water in living plant tissues makes it hard to detect or quantify many of the important biochemical and structural compounds that are masked by overlapping water absorption features, particularly in the infrared regions (Figure 5). These water absorption bands can be useful indicators of vegetation water status, which, like pigments, can be very dynamic over daily or seasonal time scales.

The complexity and activity of living tissues provides particular challenges and opportunities for proximal remote sensing, requiring careful attention to sampling methods and context. This context includes not only the particular question at hand, but also issues of sampling scale, including temporal, spatial, spectral scale, and angular (see also Chapter 4 – Sampling).

***Plant Photosynthesis***

Good examples of the dynamism associated with vegetation sampling lie in the many processes related to plant photosynthesis and gross primary productivity (GPP), which unfold over multiple time scales. Some photosynthetic features change seasonally, while others respond rapidly with light environment, adjusting in seconds to minutes with changing conditions (Figures 7 & 9). For this reason, the sampling procedure should be adjusted to match the spatial, temporal, and spectral scale of the process of interest (refer to Chapter 4 to review sampling scales). Here we briefly consider the dynamic processes related to photosynthesis and the different time scales involved.

Specific examples of highly dynamic plant biochemical responses accessible with proximal sensing include the diurnal dynamics related to photosynthetic light regulation, including the xanthophyll cycle and non-photochemical quenching (NPQ) of chlorophyll fluorescence, along with related regulatory processes (Gamon et al 1990, 1997), which are depicted above (Figures 6-7). At longer time scales, the seasonal pigment shifts associated with ontogeny and changing environmental conditions (Gitelson & Merzlyak 1994, Gamon & Surfus 1999, Gamon et al. 2016), and the gradual development of water stress or nutrient stress (Peñuelas et al. 1994) are examples of more gradual vegetation responses related to photosythesis. Depending upon the particular question and time frame involved, sampling methodology needs to be adjusted to best capture the process(es) of interest.

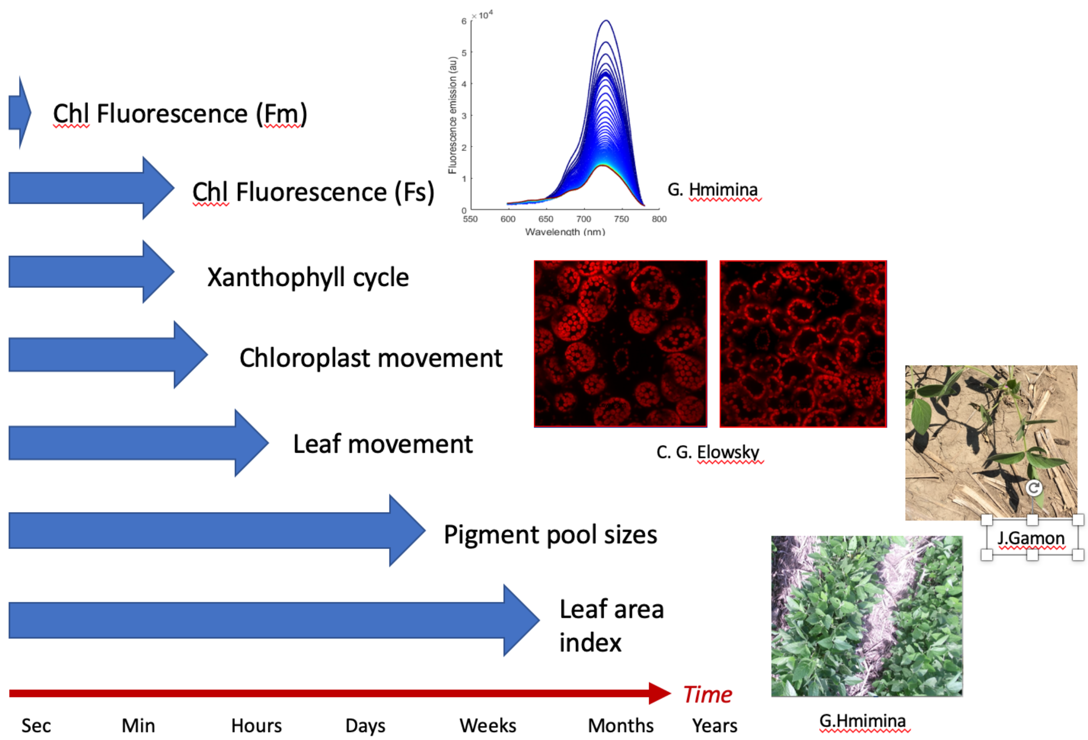


Figure 9. Time constants for various physiological and structural responses related to photosynthetic regulation. Some *chlorophyll fluorescence* processes (e.g., the attainment of peak fluorescence, *Fm*, upon light exposure) occur in nanoseconds, whereas *steady-state fluorescence* (*Fs*, analogous to *solar-induced fluorescence*) may be reached in minutes, a time scale approximating that of the operation of the *xanthophyll cycle*, which is tied to the regulation of photosynthesis and chlorophyll fluorescence (Figures 6-7). *Chloroplast movement* and *rapid leaf movements* (as occur with legumes) often occur on diurnal time scales (hours), whereas leaf *pigment pool sizes* (and the relative levels of chlorophyll and carotenoid pigments) adjust over many days to weeks (e.g. seasonal time scales). Finally, growth and senescence responses that alter *leaf area index* occur over many weeks to months (i.e., over seasonal time scales).

Consideration of this dynamism at different time scales is an essential difference between sampling dynamic biological targets like vegetation as opposed to relatively stable physical targets like soil or minerals. These dynamic processes are often best detected at different spatial and temporal scales (Figure 9) using different spectral scales (e.g., by using different wavelengths or bands), illustrating the benefit of hyperspectral sensors for vegetation studies.

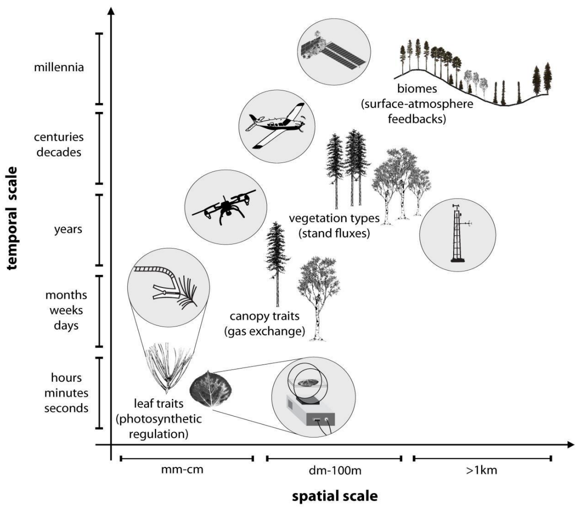


Figure 10. Remote sensing is used to sample different aspects of photosynthesis at different spatial and temporal scales. Because photosynthetic activity can be studied across such a wide range of scales and processes (figure 9), sampling methods must be matched to the process and scale of interest, or integrated across scales for a more complete understanding. From Gamon et al. 2019.

## *Ecosystem function*

Because plant chemistry and plant traits can be detected optically, and because these features are important to ecosystem processes (e.g. photosynthesis and biogeochemical cycles), remote sensing can provide a useful way to study ecosystem function. Ecosystem topics like productivity, phenology, disturbance, biogeochemical cycling and hydrology can be readily informed by proximal remote sensing, often in combination with airborne or satellite data. If a clear connection can be established between a key ecosystem process and detectable plant optical properties, then remote sensing can be a useful data source for ecosystem process studies. Multi-scale measurements can be potent tools for upscaling and developing new remote sensing methods (Chapter 1). Good examples include the tracking of seasonal patterns of gross primary production (photosynthesis), or timing of budburst (phenology) or gradually changing water status (hydrology) or nutrient status (biogeochemistry). These can be inferred from plant spectra for example via changing pigment content, water content, and canopy structure. Experiments of photosynthetic pigment dynamics at leaf and stand scales (Figures 6-7, 9-10) have led to new remote sensing approaches for monitoring plant photosynthesis from proximal remote sensing as well as from aircraft and satellite platforms (Gamon 2015, Gamon et al 2016). Other less visible plant constituents (e.g. water or nitrogen) and related biogeochemical cycles are becoming increasingly studied with remote sensing (Wessman et al., 1988, Asner & Vitousek 2005, Asner et al. 2015). Many of these methods were first developed or refined with studies involving proximal remote sensing, but then are later applied to aircraft or satellite data (e.g., Asner et al. 2014, Gamon et al. 2016) (figure 11).

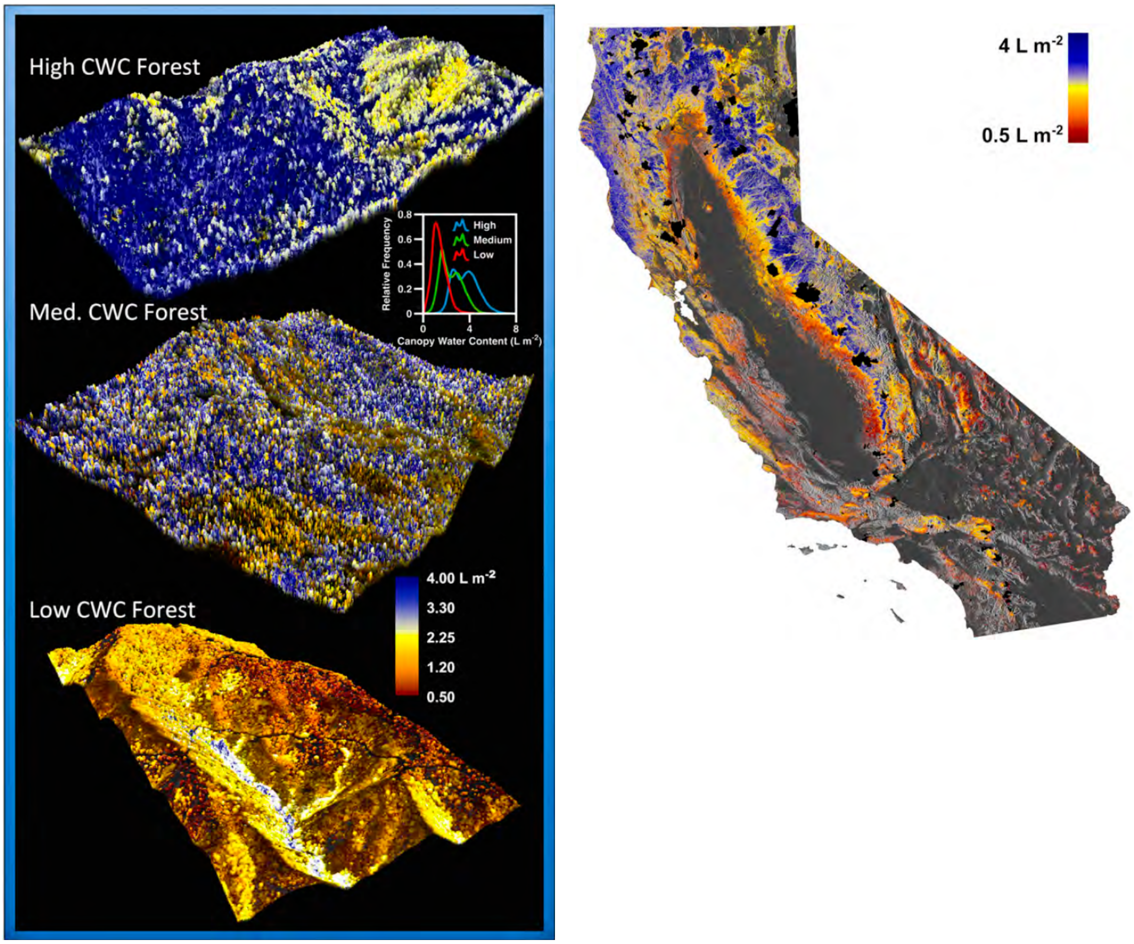


Figure 11. Canopy water content determined using water absorption features detected with airborne imaging spectrometry (left) and upscaled to the state of California using satellite data and machine learning. Asner et al. 2015

Plant *stress*, including its underlying causes and its effects on overall vegetation and ecosystem function (e.g., productivity), is increasingly studied with remote sensing. This is an important topic both in ecology and global change studies, and in practical applications like precision agriculture. Many *stressors* lead to photosynthetic downregulation (Figure 6), which can be detected with optical methods (Figure 7). Spectral reflectance is commonly used for stress detection, and can readily reveal conditions of nutrient stress or water stress (Peñuelas et al. 1994). Additional methods, including chlorophyll fluorescence (Figures 6, 7, & 8) or thermal remote sensing offer powerful stress detection tools, particularly when combined with reflectance (Schickling et al. 2016). Studies of plant stress are important in many fields including agriculture, ecology, energy balance, and global carbon cycle studies.

***Vegetation Biodiversity Assessment***

The rapid rate of biodiversity loss and the importance of biodiversity to ecosystem function, along with the challenge of sampling biodiversity over large, remote and inaccessible areas, has spurred interest in using remote sensing to assess biodiversity (Jetz et al. 2016, Cavender-Bares et al. 2020). While there is growing interest in this topic, there is currently little agreement of *how* to use remote sensing for biodiversity assessment, and many methods are currently used (Wang and Gamon 2019). Similarly, while knowledge of this topic is rapidly expanding, there is only a partial understanding of *why* remote sensing even works as a biodiversity assessment tool. Proximal remote sensing, particularly in experimental field plots Figures 12 and 13), is providing useful answers to these questions.

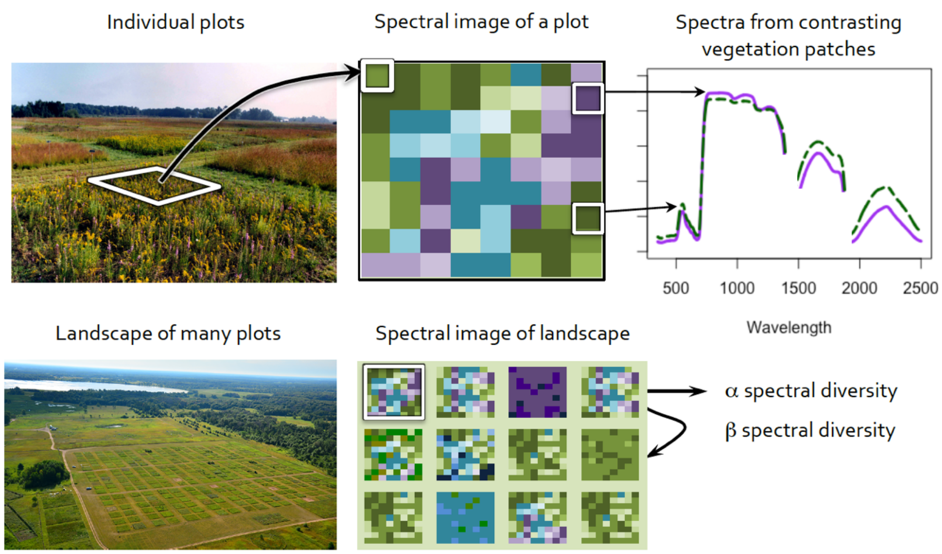


Figure 12. Experimental plots at Cedar Creek Reserve (operated by the University of Minnesota) used for biodiversity studies at different scales. Figure: Cavender-Bares et al. 2017.

Figure 13. Field measurements of spectral diversity and biodiversity by airborne (a) and field (b) spectrometry, along with leaf-level measurements of reflectance and plant traits (c) at Cedar Creek, Minnesota. Figures: J. Gamon

The history of remote sensing of biodiversity goes back several decades, and covers very different methods, often tied to the type of sensor and sampling scale(s) involved. Most of the early studies of biodiversity using remote sensing involved mapping habitat or quantifying habitat loss (e.g. Westman et al. 1989). Other studies have employed remote sensing to map specific species or traits themselves, and from this infer the diversity of species or functional types. More recently, remote sensing has been used to infer spectral variation in space (Rocchini et al 2010). According to the *Spectral Variation Hypothesis* (Palmer 2000*)*, the variation in optical properties can be used to infer the variation in species or types, providing a remote metric of biodiversity. In this case, the *information* *content* of spectra becomes a proxy for biodiversity. Recent summaries of remote sensing of biodiversity can be found in Wang and Gamon 2019 and Cavender-Bares et al. 2020

Revealing why spectral diversity works as a proxy for biodiversity remains an active area of research. The *optical diversity hypothesis* (Ustin and Gamon 2010), essentially a refinement of the *Spectral Variation Hypothesis*, states that diversity in leaf traits, plant structure, and phenology lead to variation in spectral properties (Figure 14). The underlying reason for this appears to be that variation in resource use and evolutionary history among species cause variation in plant traits that affect plant optical properties. In this sense, *spectral diversity* (sometimes called *optical diversity*) is analogous to species diversity and provides a useful proxy for field measurement of biodiversity. While much work remains to be done to refine these emerging remote sensing methods and to understand the links between spectral diversity and biodiversity, remote sensing is increasingly being used as a tool to explore biodiversity, and studies using proximal remote sensing are leading to a greater understanding of the underlying principles guiding the biodiversity-optical diversity relationship.

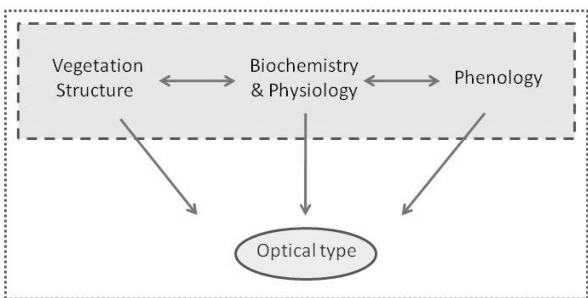


Figure 14.

The optical diversity hypothesis states that plant optical types, detectable with spectral reflectance, are a function of canopy structure, leaf traits (tied to biochemistry and physiology) and phenology. After Ustin & Gamon 2010.

***Phenotyping and Precision Agriculture***

Just as optical sampling of biodiversity can reveal contrasts in underlying plant traits between species, optical sampling can also be used to detect differences in individual plant species that might confer desired traits, such as productivity, disease resistance, stress resistance, and water- or nutrient-use efficiency. The emerging field of plant *phenotyping* makes heavy use of proximal remote sensing in greenhouses, chambers (Figure 15), and field plots (Figure 16), both on the ground and from the air (typically using UAVs or aircraft). A good understanding of spectral reflectance and proximal sensing is essential to this newly emerging field.

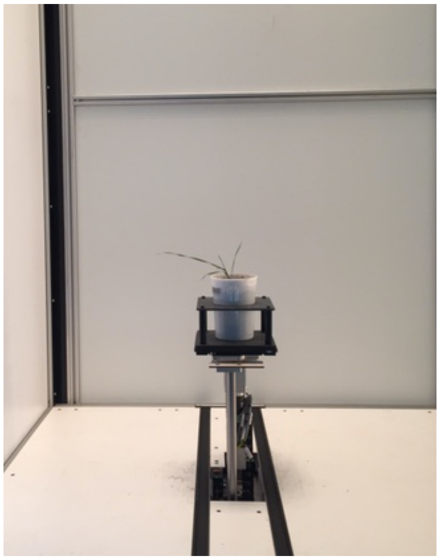

Figure 15. A potted plant in a chamber, where reflectance and fluorescence can be sampled automatically, as part of a high-throughput phenotyping facility at the University of Nebraska – Lincoln. In this case, potted plants are moved automatically along a track from a greenhouse to a sampling chamber for optical measurements under controlled lighting. The artificial conditions of this sampling method can make it difficult draw meaningful conclusions about plants under more natural, field conditions.

Figure 16.

Sampling reflectance from the "SpiderCam" platform at a field phenotyping facility operated by the University of Nebraska. In this case, spectrometers and cameras are mounted on a moving platform attached to towers via cables. The entire instrument package can be readily moved and repositioned over any part of the field plot. This has many features of airborne sensing (e.g. UAVs), but with the added stability and control provided by the tethered cables. This method also has the benefit of sampling plants under a more natural environment than chamber methods (depicted in Figure 15), so provides a more realistic assessment of plant responses to natural environmental conditions.

In agriculture and forestry, early detection of stress, often in the pre-visual stage, is desirable. If drought, nutrient stress, insect infestation or other disease can be detected early, corrective measures may be more effective and less costly. With early detection, the external costs (e.g. environmental damage) of extreme correction methods involving extensive pesticide spraying, over-irrigation, or overuse of nitrogen fertilizer can be minimized or avoided. Many tests of these methods have involved airborne remote sensing, sometimes combining methods that have first been developed in proximal applications (e.g. Zarco-Tejada et al. 2018, Sapes et al. 2022) Particularly with the onset of mobile sensors and sensor platforms (e.g. aircraft or unmanned aerial vehicles, UAVs), along with low-cost wireless sensors or sensor networks, early detection becomes feasible.

A strong program in phenotyping or precision agriculture requires a truly interdisciplinary approach, drawing not only on technical advances, but also on conceptual advances in a number of fields ranging from engineering, computing science, informatics, plant physiology and plant ecology. As in all complex areas of research, understanding the full context of measurement is important.

***Emerging Opportunities***

Many of the topics discussed in this chapter represent areas where proximal remote sensing is not only being used, but has emerged as a primary experimental tool. Progress in each of these areas requires a good understanding of plant spectra, which requires knowledge of biology (e.g., photosynthesis and plant pigments) and physics and chemistry (e.g., optics and spectroscopy). The rapid development of methods and applications is leading to some new challenges. Often practitioners are given a new sampling tool without understanding its basic principles, inner workings, or sampling context, making effective usage difficult. Experts in one field often lack relevant knowledge from another field. The rapid expansion of computerized data acquisition and storage is greatly expanding our ability to collect data, often faster than our understanding of how best to use the data. A key challenge emerging from the rapid development of proximal remote sensing applications lies in informatics, the tools for collecting, storing, analyzing, visualizing and sharing data.

Unfortunately, many efforts in proximal remote sensing are primarily focused on one aspect of the problem while ignoring other aspects. For example, in developing a new instrument or sampling platform such as a UAV, the issues of flight control or power management often take priority over understanding the basic principles of remote sensing or optical sampling required to obtain useful results. In the rush to employ new technology, basic knowledge of the key biological processes involved and their scale dependence (Figures 9-10) and appropriate sample design are often overlooked. Efforts in one field such as phenotyping or precision agriculture could be better informed by parallel advances in other science domains such as chemometrics, ecology and plant physiology. Along with a knowledge of basic sampling principles (discussed in Chapter 4), reintegration of separate disciplines is needed.

To address these challenges, cultural change is needed. Scientist and technologists often work in narrow disciplines, but much can be gained by interdisciplinary interactions and collaborations. It is likely that ecological trait theory, along with knowledge of plant physiology and biochemical dynamics will lead to a more useful conceptual framework for guiding progress in areas like high throughput plant phenotyping or precision agriculture, two emerging fields where large amounts of resources are being spent on automated proximal sampling. Similarly, technological advances likely to occur in phenotyping or precision agriculture could yield advances in ecological studies, and contribute to the larger imperative of reducing greenhouse gas emissions or maintaining diverse, resilient cropping systems. A common informatics framework for exchanging and analyzing spectral data, along with contributions from statisticians and informatics experts, could help facilitate advances in many applications of proximal sensing and spectral analysis.

We now live in an interconnected world where technological advances, including a diversity of remote sensing methods, provide a new view of the planet as a whole, and proximal sensing can help us interpret what we are seeing. Methods in field spectroscopy can often readily be transferred to new aircraft or satellite instruments or platforms. Space agencies, including NASA, the European Space Agency and others, are developing a dizzying array of new satellite sensors for monitoring the health of the entire planet. Multi-scale remote sensing will surely play an important role in this emerging global monitoring system (Figure 17).

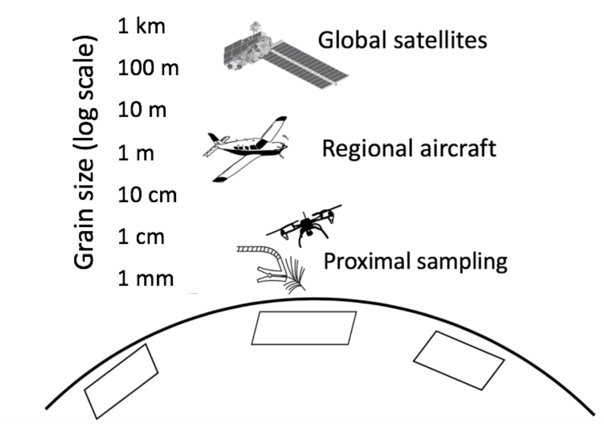


Figure 17 – Proximal sampling will play an important role in global systems for monitoring the health of the planet Earth. From Gamon et al. 2020.

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<u>Terms to know</u>:

ground validation
ground truthing
calibration
vicarious calibration
empirical line correction
scientific method
experimental method
vegetation index (plural: indices)
chemometrics
absorption features
spectrophotometer
high performance liquid chromatography (HPLC)
spectrometry
spectrometer
spectroscopy
foreoptic
plant [functional] trait
plant trait analysis
phenotyping
precision agriculture
spectrum (plural: spectra)

spectral signature
spectral reflectance
scattering
chlorophyll
carotenoid
anthocyanin
pigment pool size
cellulose
hemicellulose
lignin
fluorescence
chlorophyll fluorescence quenching
non-photochemical quenching
xanthophyll cycle
energy dissipation
photosynthesis
electron transport
carboxylation
excess light
chloroplast movement
leaf clip
leaf area index
plant functional type/trait
ecosystem model
ecosystem function
biogeochemical cycle (cycling)
digital global vegetation model (DGVM)
phenology
disturbance
hydrology
biodiversity
spectral variation (hypothesis)
optical diversity (hypothesis)
information content
proxy
phenotyping
precision agriculture
informatics
scale (dependence)

*[note other key terms in italics]*