

# Global Terrestrial Ecosystem Functioning and Biogeochemical Processes

## Earth System Science Theme:

### III. Marine and Terrestrial Ecosystems and Natural Resource Management

Biogeochemical Cycles, Ecosystem Functioning, Biodiversity, and factors that influence health and ecosystem services

## Description:

A global imaging spectroscopy mission will provide unique and urgent quantitative measurements of vegetation functional traits and biochemistry that are not currently available. Narrowband VSWIR measurements will provide the information necessary to close major gaps in our understanding of biogeochemical cycles and to improve representation of vegetated biomes in Earth system process models.

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## **1. Science and Application Target: Canopy Foliar Traits related to Ecosystem Functioning**

Measurement of the biochemical, physiological, and functional attributes of terrestrial vegetation is required to address Earth Science Theme III: Marine and Terrestrial Ecosystems and Natural Resource Management. An imaging spectroscopy mission is needed to 1) provide new quantitative measurements of biogeochemical cycles, ecosystem functioning, and factors that influence vegetation health and ecosystem services, and 2) advance Earth system models with improved representation of ecosystems. This will result in significantly better understanding of global biogeochemical processes globally to enable more accurate Earth system forecasting.

Terrestrial ecosystems influence the Earth's climate by regulating exchanges of matter and energy between the land and atmosphere (Bonan 2008). On an annual basis, photosynthesis and respiration absorb and release approximately 20% of the total atmospheric carbon (C) pool (Canadell et al. 2007). In recent decades, a net imbalance between these processes, linked to strong C sinks in soils and living vegetation, has offset a substantial fraction of human CO<sub>2</sub> emissions (Le Quéré et al. 2014). The ability of ecosystems to continue sequestering C at such high rates is unclear (Arora et al. 2013, Cox et al. 2013). Addressing this topic is critical to future climate forecasting and will require new tools for characterizing ecosystems and improving models that simulate their response to change. **A key challenge that limits our ability to monitor and model global terrestrial ecosystem functioning, defined as the chemical, biological and physical processes occurring within an ecosystem, is the lack of comprehensive information on the spatial and temporal variability of the critical traits as well as environmental parameters that drive physiological processes in terrestrial vegetation (Jetz et al. 2016).**

Imaging spectroscopy in the solar reflective domain of the electromagnetic spectrum (VSWIR: 380 to 2500 nm) captures multiple absorption features related to plant biochemistry, physiology and the effects of leaf and canopy structure. These spectral features can be used to measure the plant functional traits driving various factors of ecosystem functioning (Table 1). Many of these measurements are required in Earth system models, but most models currently estimate traits from point-based trait data sets (e.g., TRY: Kattge et al. 2011), localized studies, or biome-based lookup tables applied to maps of broad, generalized plant functional types (PFTs), which are insufficient to characterize the spatial and temporal variability in traits both within and among biomes globally (Fisher et al. 2014, Schimel et al. 2015, Jetz et al. 2016). Imaging spectroscopy will provide a vast improvement over existing data used to parameterize dynamic vegetation models (Fisher et al. 2015), most importantly through capturing ecosystem variability that is lost when traits are aggregated by PFT classes (Verheijen et al. 2015).

Global seasonal spectroscopic measurements at the appropriate temporal and spatial scales would provide a transformational change in how we quantify critical variables that are not currently detectable at broad scales using other methods. These new trait measurements obtained via an imaging spectroscopy mission - in combination with ongoing multispectral remote sensing - would enable the full characterization of both vegetation state and ecophysiological processes related to primary productivity as mediated by climate, soils, stress/disturbance and anthropogenic influences. While imaging spectroscopy would provide assessment of functional diversity (e.g., distribution of plant traits among species) in a coherent, continuous fashion, multispectral data that are currently available at high temporal frequency would provide complementary estimates of phenological patterns of green-up and senescence (Garonna et al. 2016), disturbance intensities (Hansen et al. 2013) and land cover change (Gomez et al. 2016). Together with laser scanning and active or passive radar missions to characterize vegetation structure and biomass, these technologies would enable a rich accounting of terrestrial ecosystems' functional dynamics.

**Spatially explicit maps of vegetation functional traits derived spectroscopically are essential to understand the current dynamic state of the Earth's ecosystems, to accurately predict responses to the current high rate of environmental change, and to help to lower the high prediction uncertainties.**

Repeated measurements from a global imaging spectrometer will advance ecosystem and Earth system models (EESMs) that need more explicit treatment of plant traits in both space and time to improve our ability to represent succession and competition (Fisher et al. 2015; Delpierre et al., 2016).

## 2. Utility of Spectroscopy to Mapping Vegetation Canopy Foliar Traits

Photosynthesis in terrestrial plants is driven by the absorption of light to synthesize the energy needed to convert water and CO<sub>2</sub> to the O<sub>2</sub> and carbohydrates that are the foundation of life on Earth. To maintain a net positive carbon balance during photosynthesis, plants must balance light and water availability, thermal conditions (i.e., climate), and the availability of a range of macro and micronutrients important to both light utilization and the enzymes that catalyze carbon fixation, and to many other biophysical processes in plants. However, variation in the parameters that control physiological functioning in ecosystems is either not known at broad scales, or is highly uncertain spatially and/or temporally (Bloom et al. 2016). For example, global-scale maps of foliar nitrogen (%N) do not exist, despite the fact that N is an essential constituent of several critical compounds necessary for CO<sub>2</sub> assimilation (e.g., chlorophyll and RuBisCo), and – along with a suite of traits such as leaf mass per area (LMA) – has been identified as a key trait describing worldwide variation in foliar function (Wright et al. 2004, 2005a, Poorter et al. 2009).

Imaging spectroscopy can be used to accurately estimate key foliar variables (e.g., chlorophyll, %N, LMA) required to simulate plant physiology and metabolic capacity in enzyme-kinetic ecosystem models (Martin et al. 2008, Asner et al. 2011, Singh et al. 2015, Serbin et al. 2015). **Table 1** provides a list of traits important to photosynthetic capacity and ecological functioning of terrestrial ecosystems that are measureable from imaging spectroscopy. This includes measurements that will fill critical knowledge gaps and reduce uncertainties in the physiological and biochemical parameters that regulate carbon assimilation (i.e., photosynthesis), transpiration (water loss) and decomposition/nutrient turnover under varying climate/environmental conditions (e.g., Cadule et al. 2009). Such measurements will have the added benefit of enabling the quantification of abiotic (e.g. nitrogen, water) and biotic stresses (e.g. pests and diseases) in agriculture (Bhattacharya & Chattopadhyay 2013).

Spectroscopic signals contain information from pigments, nutrients, foliar structure, and/or water content that either drive photochemistry or are a consequence of it. Physiologically, plants generally manage absorbed light in three ways, two of which are addressed directly by new measurements from imaging spectroscopy. These are: 1) physiological processes related to photochemistry in photosystem-II, and 2) the dissipation of energy through non-photochemical quenching (NPQ), which are complemented by 3) chlorophyll fluorescence, an emitted signal providing direct evidence for photosynthetic activity (Damm et al. 2015). As has been shown in recent studies, measurements from spectroscopy are relevant to understanding both traits (Martin et al. 2008, Asner et al. 2011, Singh et al. 2015) and rates (Serbin et al. 2015), as they can be used to map not just fixed biochemical constituents (“traits”), but also physiological parameters that describe exchange of CO<sub>2</sub> and water (“rates”).

The imaging spectroscopy approach includes methods that both a) **identify biophysically critical narrowband features at specific wavelengths caused by known absorption of key indicator molecules or bonds** (Fig. 1), and b) **describe the entire spectrum using their full inherent dimensionality**. Together, these two capabilities are made possible *only* with imaging spectroscopy, and enable measurement of properties important to photosynthesis, as well as others that, while not direct drivers of photosynthesis, either modulate overall ecosystem processes or represent end-products of biological processes. These include the carbohydrate content of plants, as well as constituents such as ligno-cellulose (important structural compounds) that strongly affect decomposition and nutrient cycling) and secondary compounds like phenols that are important to plant defenses and stress responses.

### a) Narrowband Features across the Full VSWIR Spectrum

Dozens of narrowband features associated with **pigment concentrations and activity** occur in the visible wavelengths (400-700 nm), requiring a spectroscopic approach for full characterization. Measurements of pigments provide insights into both light harvesting and plant stress status. Individual pigments have specific narrow absorption features that are the basis for mapping pigment concentration of vegetation (Fig. 2, see Kiang et al. 2007, Ustin et al. 2009, Gitelson 2012), requiring a spectral resolution suitable to discriminating different pigments from each other. Methods have been developed to quantify chlorophylls a and b,

carotenoids (Ferét et al. 2009), including xanthophyll cycle pigments (Harris et al. 2014), and anthocyanin (Gitelson 2012, Ferét, pers. comm.). While coarse estimates of chlorophyll and overall pigment pools are possible from multiple approaches, imaging spectroscopy is required for accessory pigments.

Gamon et al. (1992) introduced the **Photochemical Reflectance Index (PRI)**, which exploits a narrowband absorption feature at 531 nm that, in relation to specific reference bands, varies on short time scales with xanthophyll pigment conversions (Gamon et al. 1997) and on seasonal time scales with overall pigment ratios (Wong and Gamon 2015ab, Gamon 2015), and correlates strongly with radiation use efficiency and CO<sub>2</sub> uptake. Stylinski et al. (2000) also demonstrated the sensitivity of PRI to photosynthetic capacity, while Peñuelas et al. (2013) found that PRI could be used to estimate ecosystem-level isoprenoid emissions from vegetation canopies, enabling further reduction of uncertainties in estimates of carbon fixation. With over 1,000 literature citations, PRI is the most widely used remote sensing index directly related to plant physiology.

The position, steepness and inflection point of the **red edge**, the long wavelength edge of the chlorophyll absorption feature (680-750 nm), is a strong indicator of vegetation status and performance (Horler et al. 1983ab, Rock et al. 1988). While NDVI calculated using reflectance on both sides of the red edge is a useful indicator of overall vegetation greenness, the shift of the position and shape of the red-edge across this wavelength interval is a more explicit metric of chlorophyll amount, activity and change (Vogelman et al. 1993).

Numerous narrowband features associated with vibrations in chemical bonds occur in the rest of the NIR-SWIR spectral range (700-2500 nm) and are used to estimate biochemical constituents and other vegetation properties important to physiological functioning, such as water, nitrogen, starches, sugars, lignin, cellulose, and secondary constituents (Curran, 1989, Elvidge 1990, Kokaly et al. 2009). Curran (1989) listed 42 narrowband features, 38 in the 900-2500 nm region. Kokaly & Skidmore (2015) report the presence of a narrowband feature at 1656-1660 nm that can be used to accurately estimate phenolic concentrations in vegetation canopies, important to plant defenses against both herbivory and excess light absorption in young leaves. Detection and mapping of recalcitrant compounds such as lignin and cellulose is important to characterizing decomposition rates and nutrient availability. Additional work shows the ability to use SWIR wavelengths to map condensed tannins (also important to plant defense), as well as non-structural carbohydrates in foliage like sugars and starches (Asner & Martin 2015), and elements important to metabolism, like P and K (Asner et al. 2015).

Finally, water content, which typically represents about half of fresh leaf weight, exerts a primary control on vegetation physiology. Water in vegetation exhibits broad absorptions across the NIR and SWIR, but also narrow water absorption features, notably at 970 and 1200 nm, that are widely used to estimate equivalent water thickness (Ustin et al. 2012, Casas et al. 2014) and subtle changes in canopy water content due to drying (Cheng et al. 2014a), drought impacts (Asner et al. 2016) and mortality (Stimson et al. 2005).

#### b) Methods Exploiting the Full VSWIR Signal

Since the first Decadal Survey, the most significant advances in the use of imaging spectroscopy to characterize ecosystem function have entailed use of the full VSWIR spectrum (380-2500 nm) to map ecosystem properties. While numerous methods exist to exploit the full spectrum, the most common used in spectroscopy are statistical and/or empirical approaches, such as partial least squares regression (PLSR, Wold et al. 2001) and continuum removal (Kokaly & Clark 1999), along with physical approaches such as radiative transfer models, RTMs).

**Radiative Transfer.** RTM approaches include both leaf optical and canopy reflectance models, and have gradually evolved from using 1D to 3D schemes, as well as from two-stream to four-stream approximations. Jacquemoud & Ustin (2008) provide a comprehensive treatment of the range of leaf model types, which include plate models such as PROSPECT (Jacquemoud et al. 2009) or LEAFMOD (Ganapol et al. 1998), compact spherical particle models such as LIBERTY (Dawson et al. 1998), and less-used stochastic (Maier et al. 1999) and ray tracing models (Govaerts & Verstraete, 1998). Canopy reflectance modeling is achieved by

coupling soil and leaf scattering regimes to include canopy scale reflectance and transmittance. Such coupled models (SAIL, PROSAIL, SLC; e.g. Jacquemoud et al. 2009, Verhoef & Bach 2007) are inverted with relatively low prior informative requirements and yield good results of some key traits (chlorophyll, dry matter, leaf mass per area (LMA), water content, leaf area index (Jacquemoud et al. 2009)), retrieval of carotenoids (Ferét et al. 2008) and anthocyanins (Ferét, pers. comm.). While those models cannot capture all biochemical sources of variation in foliage (Asner et al. 2011), they are critical to a physically based understanding of the drivers of spectral variation in foliage (Ustin 2013, Knyazikhin et al. 2012). VSWIR imaging spectroscopy provides the information needed to improve our mechanistic prediction of plant traits through RTM approaches by helping to identify key relationships between plant properties and spectral reflectance.

**PLSR Retrievals.** Foliar nitrogen content (%N) is a widely used surrogate measure for photosynthetic capacity (Evans 1989). Nitrogen in proteins is central to photosynthesis, with higher %N suggesting a greater foliar RuBisCo and thus higher capacity for carbon assimilation. As such, maps of %N derived from imaging spectroscopy have been used in a modeling framework to predict net primary productivity (Ollinger & Smith 2005). Most approaches to foliar trait mapping utilize chemometric approaches such as PLSR as a function of the full 400-2500 spectrum, excluding atmospheric water absorption bands (Fig. 3). Martin et al. (2008) showed that %N could be accurately mapped using PLSR models built from VSWIR Hyperion and AVIRIS imaging spectroscopy data sets from numerous sites around the world. Likewise, both Asner et al. (2015) and Singh et al. (2015) have shown the capacity to estimate a range of traits from imaging spectroscopy collected in multiple environments across many images. In addition to %N, these authors and others (e.g., Casas et al. 2013, Cheng et al. 2014b, Homolová et al. 2013) have also mapped LMA. LMA is important to vegetation physiology, as it represents a plant's trade-off between leaf longevity (high LMA) and high productivity (low LMA) (Reich et al. 2004, Poorter & DeJong 1999, Wright et al. 2005b, Poorter et al. 2009). Research has shown that both %N (Kattge et al. 2009) and LMA (Green & Kruger 2001) can be used to infer photosynthetic capacity. In addition to inferring photosynthetic capacity from imaging spectroscopy maps of %N and LMA, recent studies have shown the capability to directly map  $V_{\text{cmax}}$  (Serbin et al. 2015), a measure of photosynthetic capacity that is used in all enzyme-kinetic ecosystem models employing the widely used Farquhar model of photosynthesis.

Both Asner et al. (2015) in the tropics and Singh et al. (2015) in mid-latitude ecosystems show the capacity of full VSWIR methods to map a range of additional canopy traits that are important to overall ecosystem function, including phenolics, condensed tannins, cellulose and lignin. Asner & Martin (2015) also demonstrate the utility of VSWIR spectroscopy to estimate non-structural carbohydrates, the more soluble carbon-containing compounds in foliage, as well as a range of other elements important to metabolism.

### 3. Performance and Coverage Specifications for VSWIR Imaging Spectroscopy

At a global scale, terrestrial ecosystem modeling is limited by the lack of data on vegetation functional traits. Only a small portion of the taxa and functional trait space has been characterized either through traditional field methods (Schimel et al. 2015, Jetz et al. 2016) or by imaging spectroscopy. No global coverage of imaging spectroscopy data or other relevant method to retrieve biochemistry/foliar traits currently exists, and the ground-based methods (field sampling, analytical chemistry, gas exchange measurements) that would be needed to fully characterize spatial and temporal variation in biochemistry on Earth are impractical to impossible (Jetz et al. 2016). Global imaging spectroscopy is therefore needed to fill these critical data gaps. Sampling data from the forthcoming EnMAP mission (Guanter et al. 2015) and data from airborne missions such as AVIRIS-C (Green et al. 1998) and AVIRIS-NG (Hamlin et al. 2011), the NEON Aerial Observation Platform (Kampe et al. 2010), the Carnegie Aerial Observatory (Asner et al. 2012) and the APEX instrument (Schaeppman et al. 2015) are not of sufficient spatial coverage or temporal resolution to characterize the dynamic drivers of vegetation physiology across global ecosystems. Moreover, these sampling missions often cannot deploy to ephemeral or "hot-spots" of change (e.g., short but intense drought events) which, if imaged, could provide critical missing information needed to better understand plant responses to short-term perturbations or the ability to capture previous conditions and post change.

Based on existing algorithms that have been developed primarily from aircraft studies (e.g., Singh et al. 2015), the physical requirements of the mission include atmospherically corrected surface reflectance covering 450-2450 nm at a minimum 10 nm intervals (see Science Traceability Matrix, Table 2). Identification of narrowband features associated with foliar absorption features requires signal-to-noise (SNR) commensurate with the depth of spectral features (Fig. 4). Spatial resolution  $\leq 40$  m is necessary to retrieve foliar parameters at scales that balance capturing the natural variability in vegetation across landscapes while minimizing intra-canopy effects (i.e., the pixel is a canopy, not part of a canopy). Because vegetation physiology and biochemistry change across the growing season, seasonal measurements of foliar traits are required to fully characterize annual dynamics of biogeochemical cycles and their variability between and among biomes. The baseline requirement is at least one cloud-free measurement in the peak of the growing season for  $\geq 90\%$  of the Earth's terrestrial surface per year, with multi-seasonal measurements for  $\geq 90\%$  of the Earth's terrestrial surface collected over the mission lifetime. Geometric surface location requirements include a maximum of two times the instantaneous field of view using global high resolution DEM data. This will also enable correction for directional effects due to volumetric and geometric scattering (i.e., BRDF, Lucht et al. 2000).

#### 4. Affordability of Required Measurements

The measurement of vegetation traits from imaging spectroscopy can be achieved affordably in the decadal timeframe, due to investments by NASA in response to global terrestrial/coastal coverage missions outlined in the 2007 NRC Decadal Survey (NRC 2007), the NRC Landsat and Beyond report (NRC 2013) and other efforts. This builds on a legacy of air and space instruments, which have validated the feasibility of these measurements, including airborne: AIS (Vane et al. 1984), AVIRIS (Green et al. 1998), and AVIRIS-NG (Hamlin et al. 2011); and space: NIMS (Carlson et al. 1992), VIMS (Brown et al. 2004), Deep Impact (Hampton et al. 2005), CRISM (Murchie et al. 2007), EO-1 Hyperion (Ungar et al. 2003, Middleton et al. 2013), M3 (Green et al. 2011) and MISE, the imaging spectrometer now being developed for NASA's Europa mission.

NASA-guided engineering studies in 2014 and 2015 show that a Landsat-class VSWIR (380 to 2510 nm @  $\leq 10$  nm sampling) (Fig. 5) imaging spectrometer instrument with a 185 km swath, 30 m spatial sampling and 16-day revisit with high SNR and the required spectroscopic uniformity can be implemented affordably for a three-year mission with mass (98 kg), power (112 W), and volume compatible with a Pegasus class launch or ride share (Fig. 6). The telescope can be scaled for higher orbits.

The key for this measurement is an optically fast spectrometer providing high SNR and a design that can accommodate the full spectral and spatial ranges (Mouroulis et al. 2016). A scalable prototype F/1.8 full VSWIR spectrometer (van Gorp et al. 2014) with full spectral range CHROMA detector array has been developed, aligned, and is being qualified (Fig. 6).

Data rate and volume challenges have been addressed by development and testing of a lossless compression algorithm for spectral measurements (Klimesh et al. 2006, Aranki et al. 2009ab, Keymeulen et al. 2014). This algorithm is now a CCSDS standard (CCSDS 2015). With compression and the current Ka band downlink offered by KSAT and others, all terrestrial/coastal measurements can be downlinked (Fig. 7).

Algorithms for calibration (Green et al. 1998) and atmospheric correction (Gao et al. 1993, 2009, Thompson et al. 2014, 2015) of large diverse data sets have been benchmarked as part of the HypSIIRI preparatory campaign (Lee et al. 2015) as well as for the AVIRIS-NG India and Greenland campaigns and elsewhere. Algorithms for vegetation trait retrievals have been tested extensively in a range of ecosystems including the tropics, temperate and boreal zones, as well as in agriculture (see Table 1, e.g., Martin et al. 2008, Asner et al. 2015, Singh et al. 2015, Serbin et al. 2015).

To enhance affordability and accelerate measurement availability, there is good potential for shared launches, spacecraft, and international partnerships.

## TABLES AND FIGURES

Table 1. List of key foliar functional traits that can be estimated from imaging spectroscopy.

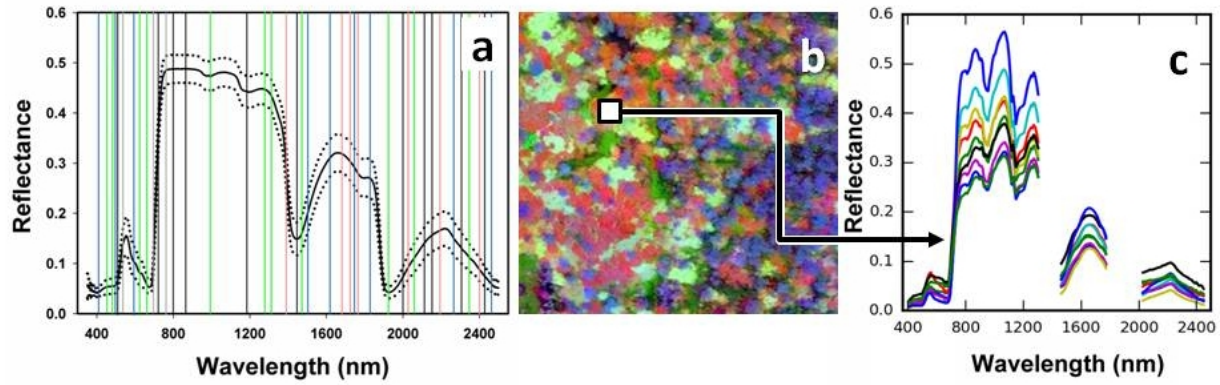
Functional characterization <sup>1</sup>	Trait	Example of functional role	Example Citations
<b>Primary</b>	Foliar N (% dry mass or area based)	Critical to primary metabolism (e.g., Rubisco),	Johnson et al. 1994, Gastellu-Etcheberry et al. 1995, Mirik et al. 2005, Martin et al. 2008, Gil-Perez et al. 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 <sup>-1</sup> )	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 <sup>-1</sup> )	Light harvesting, antioxidants	Datt 1998, Zarco-Tejada et al. 1999, 2000a
	Other pigments (e.g., anthocyanins; ng g <sup>-1</sup> )	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
<b>Physical</b>	Leaf mass per area (g m <sup>-2</sup> )	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-Etcheberry et al. 1995, Thulin et al. 2014, Singh et al. 2015
	Lignin (% dry mass)	Structure, decomposition	Singh et al. 2015
<b>Metabolism</b>	Vcmax (μmol m <sup>-2</sup> s <sup>-1</sup> )	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
<b>Secondary</b>	Bulk phenolics (% dry mass)	Stress responses	Asner et al. 2015
	Tannins (% dry mass)	Defenses, nutrient cycling, stress responses	Asner et al. 2015

<sup>1</sup>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.

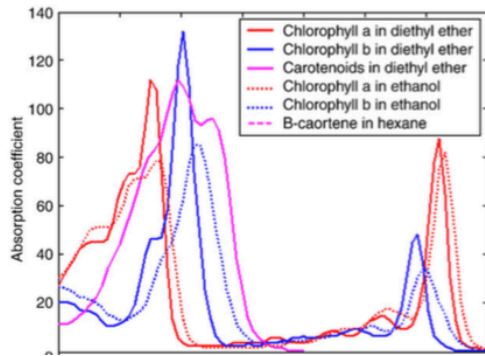
Table 2. Traceability matrix for a global imaging spectroscopy mission for terrestrial ecosystem functioning and biogeochemical processes.

Science Target	Science Objectives	Functional characterization <sup>1</sup>	Trait	Spectral Range and Sampling	Other Measurement Characteristics	Example Citations
Theme III: Marine and Terrestrial Ecosystems and Natural Resource Management	O1. To deliver new quantification of biogeochemical cycles, ecosystem functioning, and factors that influence vegetation health and ecosystem services.	Primary Biochemical Content	Foliar N (% dry mass or area based)	450 to 2450 nm @ ≤15 nm	Seasonal cloud free measurement for ≥ 80% terrestrial vegetation areas.  Radiometric range and sampling to capture range of vegetation signals from tropical to high latitude summers.  Signal-to-Noise Ratio consistent with tropical to high latitude vegetation (e.g., red region, >500:1).  At least three years of measurement to capture inter-annual variability and seasonally as robust baseline for ≥80 of the terrestrial ecosystems.	Johnson et al. 1994, Gastellu-Etchegorry et al. 1995, Mirik et al. 2005, Martin et al. 2008, Gil-Perez et al. 2010, Goekka et al. 2015, Kalacska et al. 2015, Singh et al. 2015
			Foliar P (% dry mass)	450 to 2450 nm @ ≤15 nm		Mirik et al. 2005, Mutangao & Kumar 2007, Gil-Perez et al. 2010, Asner et al. 2015
			Sugar (% dry mass)	1500 to 2400 nm @ ≤15 nm		Asner & Martin 2015
			Starch (% dry mass)	1500 to 2400 nm @ ≤15 nm		Matson et al. 1994
			Chlorophyll-total (mg g <sup>-1</sup> )	450 to 740 nm @ ≤ 10 nm		Johnson et al. 1994, Zarco-Tejada et al. 1999, 2000, Gil-Perez et al. 2010, Zhang et al. 2008, Kalacska et al. 2015
			Carotenoids (mg g <sup>-1</sup> )	450 to 740 nm @ ≤ 10 nm		Datt 1998, Zarco-Tejada et al. 1999, 2000
			Other pigments (e.g., anthocyanins; mg g <sup>-1</sup> )	450 to 740 nm @ ≤ 10 nm		van den Berg & Perkins 2005
			Water content (% fresh mass)	980 nm ±40, 1140±50 @ ≤ 20 nm		Gao & Goetz 1995, Gao 1996, Thompson et al. 2015, Asner et al. 2016
		Physical/Structural Content	Leaf mass per area (g m <sup>-2</sup> )	1100 to 2400 nm @ ≤20 nm		Asner et al. 2015, Singh et al. 2015
			Fiber (% dry mass)	1500 to 2400 nm @ ≤20 nm		Mirik et al. 2005, Singh et al. 2015
	Cellulose (% dry mass)		1500 to 2400 nm @ ≤20 nm	Gastellu-Etchegorry et al. 1995, Thulin et al. 2014, Singh et al. 2015		
	Lignin (% dry mass)		1500 to 2400 nm @ ≤20 nm	Johnson et al. 1994, Gastellu-Etchegorry et al. 1995, Thulin et al. 2014, Singh et al. 2015		
	Metabolism	Vcmax (μmol m <sup>-2</sup> s <sup>-1</sup> )	450 to 2450 nm @ ≤15 nm	Serbin et al. 2015		
		Photochemical Reflectance Index (PRI).	450 to 650 nm @ ≤ 10 nm	Gamon et al. 1992, Asner et al. 2004		
		Fraction of absorbed photosynthetically active radiation by chlorophyll, fAPARchl.	450 to 800 nm @ ≤ 20 nm			
	Secondary Biochemical Content	Bulk phenolics (% dry mass)	1100 to 2400 nm @ ≤ 10 nm	Asner et al. 2015		
		Tannins (% dry mass)	1100 to 2400 nm @ ≤ 10 nm	Asner et al. 2015		
	Required for Atmospheric Correction	Water vapor	980 nm ±50, 1140±50 @ ≤ 20 nm	Thompson et al. 2015, Gao et al. 1993		
		Cirrus clouds	940 nm ±30, 1140±40 @ ≤ 20 nm			
		Aerosols	450 to 1200 nm @ ≤ 20 nm			

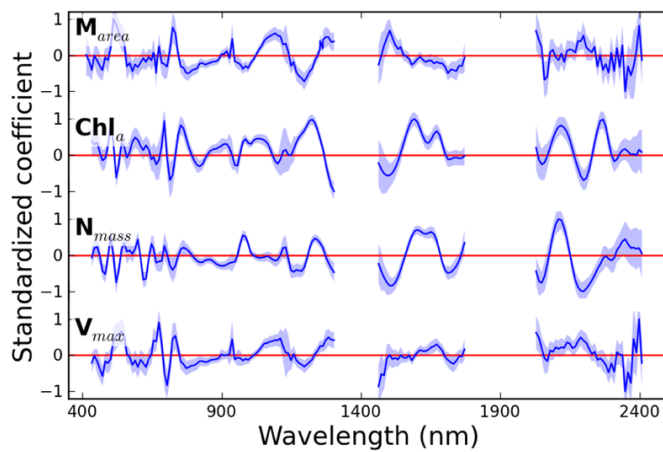




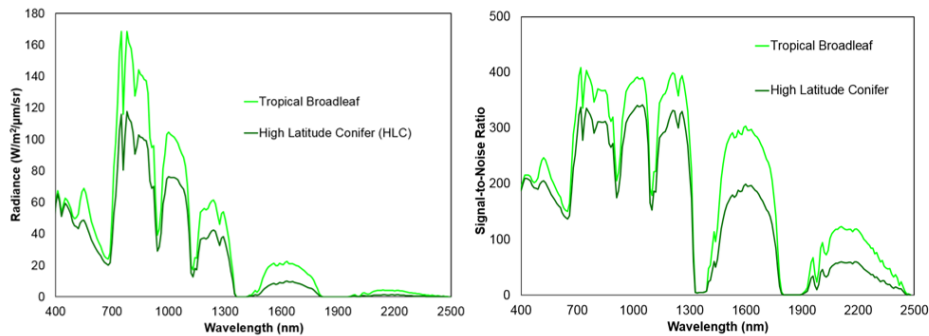
**Fig. 1.** a) Narrowband features associated with vegetation functional traits in Table 1 and reported in the literature; b) minimum noise fraction of imaging spectroscopy data from Florida; and c) example spectra from b) showing narrowband variations across spectra. Figure courtesy of A. Singh and J. Couture.



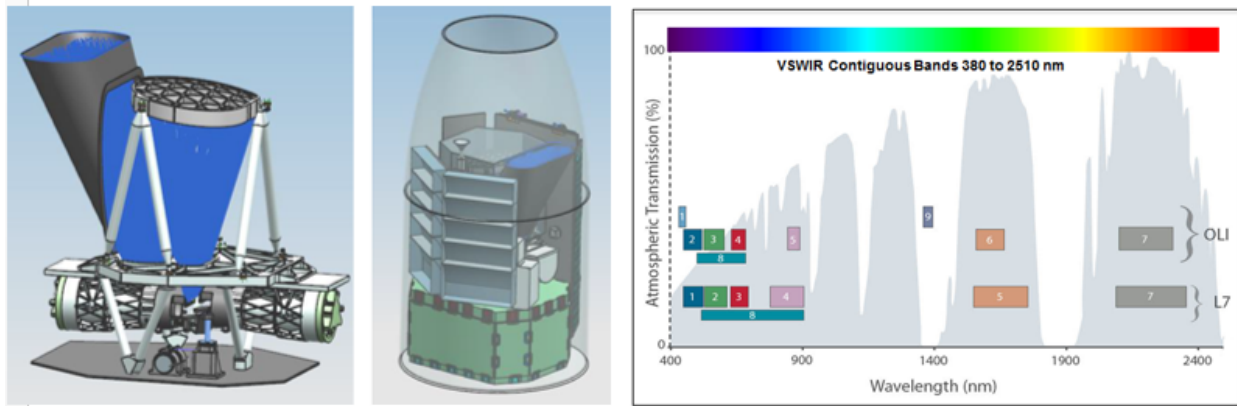
**Fig. 2.** Differences in absorption spectra of chlorophyll a, chlorophyll b and  $\beta$ -carotene. From Ustin et al. (2009).



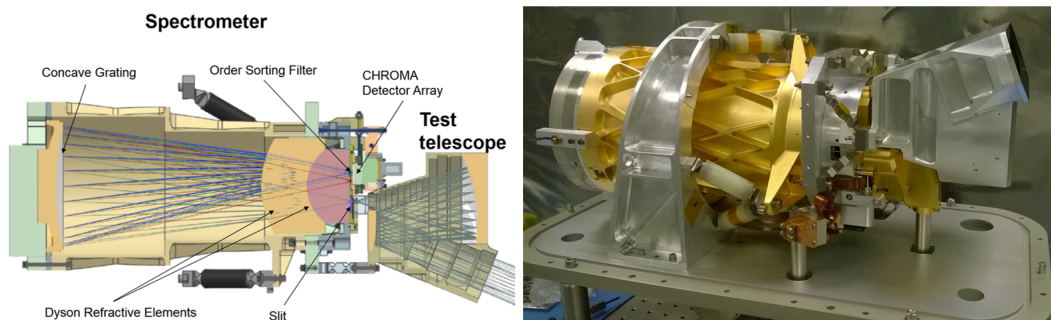
**Fig. 3.** Example PLSR coefficients by wavelength for mapping functional traits from imaging spectroscopy: chlorophyll and nitrogen from Asner et al. (2015), LMA ( $M_{area}$ ) from Singh et al. (2015), and  $V_{cmax}$  from Serbin et al. (2015).



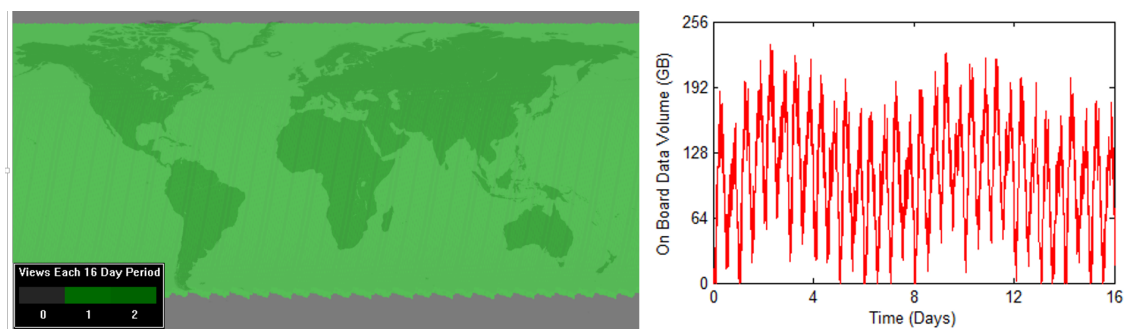
**Fig. 4.** Left: Top of atmosphere radiance for a reference tropical broadleaf and a high latitude conifer. Right: Corresponding SNR that is consistent with the measurements by AVIRIS-C and other airborne imaging spectrometers that have been used to retrieve the plant parameters of interest. This SNR is a factor of 4 higher than EO-1 Hyperion that has been used with some success for trait mapping.



**Fig. 5.** Left: Opto-mechanical configuration for a high SNR VSWIR imaging spectrometer with 185 km swath a 30 m sampling providing full terrestrial and coastal coverage every 16 days. Center: Imaging spectrometer with spacecraft configured for launch in a Pegasus shroud for an orbit of 429 km altitude, 97.14 inclination to provide 16 day revisit for three years. Right: Contiguous spectral coverage from 380 to 2510 with comparison to Landsat bands.



**Fig. 6.** Left: Design of F/1.8 VSWIR Dyson covering the spectral range from 380 to 2510 nm. Right: Developed, aligned and qualified Dyson with CHROMA full range VSWIR detector array.



**Fig. 7.** Left: Global illuminated surface coverage every 16 days. Right: On-board data storage usage for illuminated terrestrial/coastal regions with downlink using Ka Band ( $<900$  mb/s) to KSAT Svalbard and Troll stations. Oceans and ice sheets can be spatially averaged for downlink.

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