[DC-04-035] Spectral Properties of Earth's Surface

Abstract

Spectroscopic remote sensing records the intensity of light in hundreds of different wavelengths to measure the physical and chemical composition of the Earth’s surface. By measuring hundreds of distinct channels simultaneously, spectrometers can uniquely identify the spectral fingerprints of diverse physical processes within a pixel. This can enable more quantitative and accurate physics-based measurements than conventional multiband remote sensing. Spectra are initially measured in radiance units, representing light intensity at the sensor as a function of wavelength. Atmospheric radiative transfer modeling is then used to infer the surface reflectance spectrum, which holds information about the physical and chemical properties of the target pixel. Reflectance spectra provide a wealth of remote sensing information for studies of such diverse topics as vegetation, aquatic ecosystems, the cryosphere, and geology.

Author & citation

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Explanation

1. Introduction

Spectroscopic remote sensing measures light energy as a function of wavelength, a spectrum (plural: spectra), that can be interpreted to characterize the light source and the wavelength-specific absorption, scattering, and emission processes that have acted on the measured photons in their path to the sensor. Spectrometers have long been used for compositional analysis of laboratory samples, or of distant objects in planetary and stellar science. More recently, the increasing availability of imaging spectrometers, which record a spectrum at each location in an image, has enabled spectroscopic measurement of Earth surface properties remotely from airborne and space-based platforms. Imaging spectrometers, also known as hyperspectral imagers, have existed for many decades, and recent improvements in availability, performance, and processing algorithms have made them a practical option for remote sensing practitioners.

Remote spectrometers typically observe photons from one of two sources: either reflected sunlight in the Visible-Shortwave Infrared (VSWIR) range, approximately 380-2500 nm; or emitted thermal radiation in the thermal infrared from 8000-13000 nm. Wavelengths outside these ranges are occasionally used for other specific purposes. Thermal infrared spectroscopy is only rarely used for remote sensing of surface properties, so we will focus this article on the VSWIR interval.

2. Spectroscopic vs. Multiband Measurements

Spectrometers which measure hundreds of discrete channels are a relatively new addition to the remote sensing toolkit. In contrast, multiband sensors measuring a handful of channels have been pervasive for many decades. Multiband instruments include satellites operated by national agencies, such as Landsat 9 which measures 11 channels, or Sentinel-2 which measures 12 channels, and a wide range of commercial providers. In contrast, orbital spectrometers like DESIS (Carmona et al., 2023), EnMAP (Storch et al., 2023), PRISMA (Cogliati et al., 2021), and EMIT (Thompson et al., 2024) have only recently begun collecting orbital data over wide areas.

The shift from multiband to spectroscopic measurement is more than an incremental improvement in performance; it represents a wholly distinct capability enabling an alternative approach to remote sensing. Generally speaking, multiband data is often numerically underdetermined; the spectral channels do not uniquely specify the physical phenomenon of interest. As a result, multiband remote sensing algorithms tend to be qualitative in nature. The majority use unitlesss indices, formed by algebraic operations on the individual channels, to indicate the surface content. These indices’ relation to physical units is generally stochastic, with limited predictive power due to a wide range of unrelated processes which might act on those channels. For example, consider the commonly used normalized difference vegetation index (NDVI), a typical multiband index formed by red and infrared bands. The NDVI suggests the vegetation content of a pixel, but it is influenced by numerous underlying physical factors such as canopy density, the fractional cover of vegetation and substrate, and phenology, making it difficult to derive accurate quantitative information from this index. In contrast, spectroscopy can simultaneously measure multiple independent properties such as plant fractional cover, leaf area, and leaf chlorophyll absorption by teasing apart the spectrally-distinct fingerprints of these processes. This pattern repeats across remote sensing disciplines like hydrology, geology, terrestrial and aquatic ecology.

By measuring hundreds of distinct channels simultaneously, spectroscopy can characterize multiple degrees of freedom in the system to isolate the phenomena of interest. As a result, it can often be more quantitative and accurate than multiband remote sensing. Rather than indices with empirical relations to physical phenomena, spectroscopy enables a well-determined direct inversion of physics-based models for interpreting vegetation, geologic surfaces, and water columns - in essence, applying quantiative laboratory analytical techniques in open air.

3. Radiances

We have described spectra in terms of light energy as a function of wavelength, but quantitative analysis requires more precision. There are many different ways to describe light intensity, and we must know a spectrum's specific physical units to interpret it properly. Analysts studying the Earth surface begin by measuring the light incident at the sensor. This quantity, known as radiance, describes the energy radiated by a surface in the direction of the sensor per unit solid angle. The spectroscopic radiance is the fundamental quantity measured by the sensor, and for an extended surface, is independent of the distance from the sensor to the target.

Any light emitted or reflected from a target on Earth's surface experiences atmospheric attenuation and scattering before reaching the sensor. The resulting measurement at the top of the atmosphere contains features due to the surface reflectance, but also the absorption of atmospheric gases and scattering by atmospheric aerosols. Figure 1 (left panel) illustrates some of the key features of a typical radiance spectrum. The radiance has limited utility for understanding Earth's surface properties because it depends on observation conditions, such as the elevation of the sun in the sky, which influences the intensity of light striking the Earth's surface. Moreover, radiance also depends on local atmospheric conditions, such as the amount of aerosols and water vapor in the atmosphere, which can vary measurably over ground distances of a few hundred meters. It is also sensitive to local topography, which influences the thickness of the atmospheric column, and the observer position, which determines the length of the bent photon path through the atmosphere from sun to ground to sensor. Thus, radiance observed at one location can change without any underlying modification to surface properties.

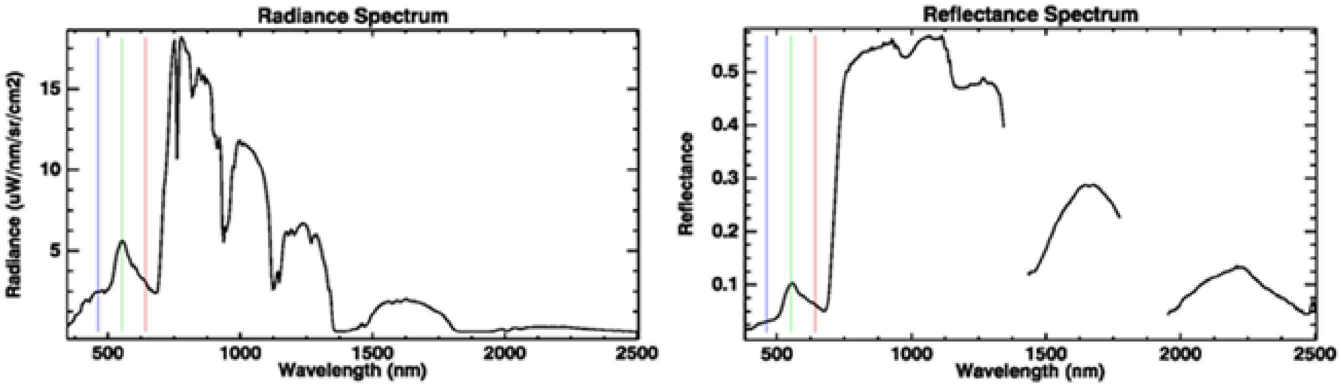

Figure 1. Radiance and reflectance spectra. Red, green and blue lines indicate these visible color channels. Source: author.

4. Reflectance Units

To isolate the signal from the Earth's surface, analysts typically prefer spectra in reflectance units. Roughly speaking, spectral surface reflectance is the fraction of energy falling on the surface which is scattered in a new direction rather than being absorbed. Analysts can infer the surface reflectance from the radiance by estimating and removing the atmospheric influence, a process known colloquially as atmospheric correction. There are a wide range of atmospheric correction approaches, but they generally fall into one of a few categories: empirical methods, which measure atmospheric effects using reference targets introduced into the scene; and physics-based methods, which invert radiative transfer models to infer the surface reflectance. All operational atmospheric correction algorithms currently in use are of the latter type. Physics-based approaches can be further subdivided into sequential methods, that first use rules to infer the atmospheric state and then solve algebraically for surface reflectance (Guanter et al., 2007); and simultaneous methods, which optimize surface and atmosphere together to minimize a cost function (Thompson et al. 2018). With most space missions now producing and distributing reflectance data, most analysts will not need to perform atmospheric correction. However, it is important to recognize this step because these reflectances are seldom perfect; errors in atmospheric correction and underlying instrument calibration can produce artifacts in the resulting reflectance spectra. Systematic errors due to calibration and atmospheric correction inaccuracy still dominate instrument noise as a source of uncertainty in the estimated surface reflectance, especially for data acquired under hazy or humid conditions.

Surface reflectance is a directional quantity, meaning that the probability of scattering is a function of both the arriving photon’s incident angle and also the angle of the observation (Schaepman-Strub et al., 2006). The complete distribution of scattering efficiency as a function of wavelength, incidence and exitance angles is known as the Bidirectional Reflectance Function (BRF). If a surface is Lambertian, it reflects light isotropically, scattering photons equally in all directions independent of their incidence angle, and the BRF is uniform. Real surfaces are seldom Lambertian; they scatter illumination preferentially in certain angles. Thus, no single spectrum can fully capture the BRF in the general case. However, one can measure reflectance spectra by chosing a policy for which incoming and scattering photons are counted.

A typical reflectance quantity for remote sensing is the hemispherical directional reflectance factor (HDRF) representing the fraction of light reflected back in the observer’s direction from the downwelling hemisphere of ambient illumination (Schaepman-Strub et al., 2006). This quantity is closely related to what a remote sensor measures, so many reflectances distributed publicly in mission archives follow this convention. The calculation models the ambient downwelling illumination including both the direct beam from the sun as well as the diffuse illumination by the blue sky. The spectral character of these two sources is different, with the diffuse illumination being much bluer than the direct one.

The directionality of reflectances means that the HDRF measured by sensors is still an observer-dependent property. When comparing multiple HDRFs across different acquisitions of the same target, it is natural to find variability related to the different angles of illumination and observation. This variability typically manifests as a change in the magnitude of the reflectance, though subtle changes in slope may also be observed. Even changes in the atmosphere across different days may subtly affect the measurement by modifying the scattering in the atmosphere, and as a result, the color and intensity of downwelling diffuse illumination on the target. These reflectance differences are appropriate; they are simply the natural behavior of the HDRF, which is specific to ambient illumination conditions and a particular observation geometry. When a more observer-independent quantity is required, analysts will occasionally attempt to transform the HDRF to a standardized illumination and observing angle. This process, which is commonly called a Bidirectional Reflectance Distribution Factor (BRDF) correction, models the complete bidirectional reflectance function of the surface in order to simulate the observation which would have been made from the standard position (typically with the sun and observer both at zenith). BRDF corrections typically rely on modeling assumptions that are specific to scene content, and do not always improve the consistency of downstream products (Vogtli et al., 2023). Consequently, they should be used with care.

When discussing reflectance quantities, it is critical to define the surface being measured. The Earth’s surface within a pixel is a complex three-dimensional structure, containing internal scattering, absorption, and transmission across different objects. For simplicity, many atmospheric correction algorithms define the pixel as a virtual flat surface oriented orthogonally to the local gravity vector. The resulting “pixel reflectance” is a well-defined and allows the downwelling irradiance to be calculated quite easily and accurately. However, an observer on the surface may measure slightly different reflectance due to the local tilt of topography - if one is standing on a slope facing into the sun, that terrain facet recieves relatively more photons from the direct beam because the same solid angle of sunlight falls on a proportionally smaller surface area. At the same time it recieves fewer photons from the isotropic sky irradiance because the terrain obscures part of the downwelling hemisphere. This means that a terrain facet measured in situ may appear to have a slightly different reflectance magnitude and shape than the reflectance of the flat virtual surface. Consequently, analysts will often define reflectance using a virtual surface aligned with a digital elevation model (DEM) of the terrain. This alternative definition sometimes yields reflectance values that are a better match to in situ observations (Carmon et al., 2023). However, it must be used with caution because minor errors in the DEM can cause much larger errors in the downstream analysis (Dozier et al., 2022).

5. Vegetation

Vegetation reflectance spectra are characterized by distinctive spectral features throughout the VSWIR range. These features are formed by the scattering and absorption of photons as they propagate through the tree canopy. The visible range contains features of pigment absorptions such as phycocyanin and carotenoids. Chlorophyll shows a prominent absorption near 690 nm, a feature known as the red edge. Other features in the near and shortwave infrared include features due to the liquid water in leaves and lignin and cellulose features from plant tissues like bark and stems (Kokaly et al., 2017). The broad shapes and relative depths of these absorptions relate to the composition of plant tissues and their distribution throughout the canopy. Leaf density and angular distribution can also have a significant impact on vegetation reflectance. As a result, the reflectance signal contains information about canopy structure and chemistry that can be used to identify vegetation categories and functional types. It can also be used to a limited extent for distinguishing between different species, as in the mapping of invasive species or crop types. Such species signals are not globally unique, but a limited number species can often be reliably classified within a specific domain of interest.

A common approach for modeling vegetated and partially-vegetated spectra in natural scenes is the linear mixture model. Here, the reflectance is a combination of the reflectances of its component materials added together in proportion to their surface area within the pixel (Roberts et al., 1998). For example, pixels in most natural terrain are some combination of green vegetation, senesced vegetation, and soil. The pure spectra used in the model are known as endmembers, and can be drawn from the scene itself or from spectral libraries. The linear mixing model is accurate for the single-scattering case, i.e. where photons do not bounce between objects within the same pixel. In practice, the linear mixing assumption works well for modeling a wide range of spectral mixtures observed in the field, and is common across many domains. However, the proprtions that are estimated are most physically accurate for flat single-scattering surfaces.

6. Rocks and Soils

Rocks are crystalline materials with very well-defined absorption features indicating their unique chemical composition. Today, the gold standard library for the reflectance of minerals in the visible to shortwave infrared is the USGS spectral library (Kokaly, et al. 2017). Mineral identification was one of the first applications of imaging spectroscopy, where it continues to be used widely for prospecting and other geologic studies. Many minerals have unique distinuishing features in the shortwave infrared, including clay minerals and carbonates. Iron oxide minerals like hematite and goethite have distinctive absorptions in the visible wavelength region of the spectrum. Rare earth elements like neodymium are also uniquely identifiable by their near infrared fingerprints. The unique features of these minerals enables identification of their presence and also gives some ideas about their relative abundance. However, measuring the physical mass abundance of the minerals based on their signatures alone is much more challenging because the minerals are often embedded in an intimate mixture, a matrix of grains with multiple internal scattering events. As a result, the depths of these features changes not just with mass, but also with particle size and the properties of other scattering grains in the matrix of the rock. Radiative transfer formulations such as Hapke modeling (Shepard and Helfenstein, 2007) are commonly used to analyze intimate mixtures.

Soil properties are subtler than mineral signatures, since typical soils include a wide range of organic and nonorganic material. However, a growing community of soil spectroscopists has started using spectroscopic data to analyze properties such as organic carbon content, water content, degradation, and swelling (Ben-Dor et al., 2009). Techniques range broadly from spectral signature matching, to radiative transfer modeling, to machine learning methods.

7. Water and Benthos

The aquatic community uses a different convention for reflectance quantities than the unitless HDRF described above. In ocean optics it is more common to use the remote sensing reflectance (R_{rs}), a directional quantity in units of inverse steradians, i.e. the reflected energy per unit solid angle. One can convert a directional R_{rs} to a unitless reflectance quantity by integrating over the hemisphere of upwelling illumination, weighting each direction proportionally to the cosine of exitance following Lambert’s Cosine Law. This is not as difficult as it sounds - one simply multiplies by π to translate R_{rs} to a unitless quantity. Another critical feature of R_{rs} in the aquatic domain is that it excludes surface glint. The light leaving the water surface includes components due both to mirror-like specular reflections from the surface (think sunlight glinting on wave facets), but also to the upwelling light from beneath that has entered the water column and undergone one or more scattering events before exiting. Only the second is included in R_{rs}; any other signals, such as glint or foam whitecaps on the ocean, are excluded.

R_{rs} contains rich information about the properties of the water column. In an optically deep case, such as a large lake or open ocean, the bottom is not visible. There are two main spectroscopic categories for deep water. Case I waters, which dominate in the deep ocean, have optical properties that are determined primarily by the abundance and type of phytoplankton in the water column. Different phytoplankton can impart different pigment absorption signatures, allowing functional types to be mapped (Werndell et al., 2014). Case II waters, generally observed in coastal and inland settings, often contain phytoplankton as well as measurable quantities of other materials like Coloured Dissolved Organic Matter (CDOM), or suspended minerals. This leads to a more optically complex water column (Kondratyev et al., 1998). Spectroscopy, with the ability to identify the spectral fingerprints of these constituents, is well-suited to measuring Case II water.

When the bottom is visible, the bottom surface, or benthos, can also be measured spectroscopically. This generally requires accounting for both water column and benthic reflectance properties. Key ecosystems, like coral reefs, seagrass, and kelp beds, contain unique spectroscopic fingerprints that permit them to be mapped remotely. Other bottom materials, such as algae and sand can also be observed. Methods for benthic mapping include fitting physics-based models of the water column and benthic reflectance, as well as machine learning approaches.

8. Snow and Ice

Snow has enormous spectral variability across the VSWIR range. The observed spectral reflectance of the snow’s surface is caused by the multiple scattering and absorption of photons within the matrix of snow crystals. Ice absorption features are visible in the near infrared. In the shortwave, absorption is so strong that the total reflectance is very low. Snow reflectance is strongly anisotropic, with a significant forward scattering component that can occasionally yield HDRFs greater than unity in visible wavelengths. The observed variability in snow reflectance carries a wealth of information about its microphysical properties. For example, the depth and shape of ice absorption features in the infrared can be used to estimate grain size (Painter et al., 1998) from which albedo can be derived. Light absorbing particles on the snow surface, such as dust or algae, also impart unique signals in the visible range. Snow reflectance properties are important for understanding its affects on climate. It also influences melt rates, impacting water resource management in regions dependent on mountain snowpack for freshwater.

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