Light interacts with physical matter by being either absorbed by it, reflected from it, or passed through it, depending on the structural and chemical composition of the object’s surface. Measuring the radiant flux reflected from an object, relative to the radiant flux received by it therefore allows conclusions about the chemical or structural composition. Earth science has long used this principle for characterizing earth surface properties through optical remote sensing. However, light received by satellite sensors orbiting our planet has passed through Earth’s atmosphere twice before it is being recorded. Reflectance measured at the top of the atmosphere (TOA) is therefore a function not only of the composition of the earth surface, but also the earth’s atmospheric conditions as well as the geometric configuration of sun, earth, and observing instrument. This is because surface properties are typically not Lambertian, thus the reflectance measured at the sensor will depend on the angle with which the reflected light beam hits the target. Disentanglement of the contributions of both aerosol properties and surface bidirectional reflectance effects is not trivial and can form major obstacles for accurate inference of surface properties.

### 3.02.1 Atmospheric Effects

Radiation passing through the atmosphere interacts with atmospheric gases and particles, affecting light through scattering and absorption. Scattering describes the interactions of radiation with particles or large gas molecules causing a redirection of radiation from its original path. The amount of scattering depends on the abundance and size of particles or gases, the wavelength of the electromagnetic radiation and the distance it travels through the atmosphere. Particle size mostly affects the type of scattering, classified as Rayleigh scattering (when particles are small compared to the wavelength of the radiation), Mie scattering (when the particles are about the same size as the wavelength of the radiation), and nonselective scattering (when particles are larger than the wavelength of radiation). In addition to particle abundance, the distance that radiation travels through the atmosphere, also referred to as atmospheric path length, affects the probability of a photon hitting a particle or gas molecule. Atmospheric path length is largely determined by the sun-sensor geometry (Fig. 1) because radiation entering the atmosphere at a low angle needs to travel through the atmosphere longer in order to reach the surface.

In addition to scattering, the atmosphere also absorbs electromagnetic radiation of specific wavelengths. In contrast to scattering, absorption causes molecules in the atmosphere to absorb energy thereby typically causing an increase in the molecule’s temperature and consequently its thermal emission. Absorption is mainly caused by atmospheric ozone, carbon dioxide, and water vapor. Some portions of the electromagnetic spectrum are almost entirely absorbed, other portions of the spectrum that are less or not affected by atmospheric absorption. These are the “atmospheric windows” we use for remote sensing.

Effects of the atmosphere on satellite measured reflectance need to be corrected in order to allow accurate inference of earth surface properties. Steps of atmospheric correction include (1) the retrieval of atmospheric conditions, most notably the aerosol optical depth and the column water amount, (2) correction of atmospheric influences through modeling the radiative transfer for the given aerosol and column water vapor, and (3) computation of surface reflectance.

Various techniques for correction of atmospheric effects on spectral reflectance have been developed, from empirical linear methods to more sophisticated algorithms based first-principles methods (Matthew et al., 2002). In general, atmospheric correction algorithms may be classified into pixel-based and time series-based approaches. Among the most commonly applied pixel-based techniques for estimating aerosol optical depth is the Dark Target method (Kaufman et al., 1997; Remer et al., 2005; Levy et al., 2007). This approach uses an empirical spectral regression coefficient (SRC) to define the relationship between visible and shortwave IR (SWIR, 2.1 μm) surface reflectance on a per pixel basis. The dark target method is based on the recognition that shortwave IR light can pass through the atmosphere almost unaffected by aerosol content; its relationship to the more heavily affected, visible light therefore allows determination of the aerosol optical depth. Two separate Dark Target algorithms exist, one for the retrieval of aerosol information over oceans and one for the retrieval of aerosol information over vegetated land surfaces. The Dark Target

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1Deceased.
A fundamental limitation of pixel-based algorithms such as the Dark Target method is that these techniques only use a single observation to characterize multiple unknowns, that is, aerosol properties, surface bidirectional effects, and surface properties. As a result, a priori assumptions are required to describe their relationship. For instance, the SRC is typically prescribed, often using a relationship optimized for vegetated (dark) land surfaces. Consequently, aerosols are retrieved with higher accuracy over most vegetated areas, but the technique is limited to brighter surfaces, such as nonvegetated or urban areas (e.g., Remer et al., 2005; Gao et al., 2015). The consistent surface reflectance products from the Landsat sensors provide a reliable medium resolution data source for data fusion.

A variation of the code has also been applied for atmospheric correction of Landsat (Gao et al., 2015). MODTRAN is implemented for instance in the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) algorithm for atmospheric correction in the visible through shortwave infrared (Vis-SWIR) spectral region (Berk et al., 2002). The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm uses the MODIS 6S technique for atmospheric correction of Landsat TM, ETM+, and OLI shortwave images. The algorithm obtains aerosol thickness from the imagery itself at a coarse resolution (Masek et al., 2013). LEDAPS was first developed at NASA Goddard Space Flight Center (GSFC) for mapping forest disturbance and was later adopted and modified to produce the Landsat surface reflectance product at the USGS EROS center (Gao et al., 2015). The consistent surface reflectance products from the Landsat sensors provide a reliable medium resolution data source for data fusion.

Fig. 1 Dependence of atmospheric path length on solar zenith angle.
3.02.2 Cloud Masking

From a perspective of land surface remote sensing, clouds are a hindrance for observing earth surface properties as they obstruct view of satellites operating in the visual and infrared spectrum (Lisens et al., 2000). Aerosol and surface retrievals depend on the identification of cloud-free pathways by cloud masking algorithms (Martins et al., 2002). Cloud screening is therefore a major step in deriving surface reflectance from spaceborne remote sensing (Martins et al., 2002). Different cloud mask algorithms have been developed, typically based on thresholds of visible, NIR, and thermal reflectance, and sometimes also using polarized light (Breon et al., 1999). Ackerman et al. (1998) developed a cloud mask using the combination of 14 wavelengths from the MODIS instrument to discriminate clear-sky cases from clouds. Challenges for large scale detection of cloud contaminated pixels include difficulties separating between clouds and heavy aerosol loading due to similarities between the spectral reflectance of large aerosol particles (e.g., dust) and clouds (Martins et al., 2002). Furthermore, reflectance thresholds are sensitive to physical changes in cloud form, and cloud temperature, as well as the aerosol condition in above cloud layers (Martins et al., 2002). Regionally, cloud masking errors can have significant impacts on the quality of surface reflectance, for instance, for the Amazon basin, up to 80% of uncertainties in surface reflectance stem from inaccuracies in threshold-based cloud retrieval (Hilker et al., 2012). Cloud masking in tropical regions is particularly challenging, partly because of persistent cloud cover, and partly because of relatively warm cloud temperatures rendering thresholds based on thermal reflectance less effective.

Moderate resolution cloud masking algorithms are routinely implemented in the MOD35 product for MODIS (Ackerman et al., 2006, 1998) based on the decision tree analysis combined with limited ancillary information such as a land/ocean and snow/no snow flags. At finer spatial resolution (30 m), a large number of algorithms is available, including Fmask, an object-based cloud detection algorithm integrated into the Landsat surface reflectance Climate Data Record (CDR) provided by U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (Zhu and Woodcock, 2012). Fmask uses a series of rules to identify clouds and clear-sky pixels. These include cloud physical properties, temperature probability, spectral variability probability, and brightness probability (Zhu and Woodcock, 2012). Potential cloud shadows are identified using the view angle of the satellite sensor and the illuminating angle. The average Fmask overall cloud accuracy is as high as 96.4% (Zhu and Woodcock, 2012).

As with the atmospheric correction, time-series approaches of cloud masking have been developed in addition to pixel-based, threshold-only algorithms. Time-series cloud screening takes advantage of a priori knowledge about the specific cloud-free reflectance to better distinguish between cloudy and clear-sky observations (Yang and Di Girolamo, 2008). Unless disturbed, consecutive images in cloud-free conditions have a highly reproducible spatial structure, which can be identified by a high covariance between images. Clouds randomly disturb this pattern reducing the time-series’ covariance. The knowledge of reference clear-sky reflectance by keeping a history of the previous surface state in addition to spectral and thermal reflectance tests (Ackerman et al., 1998) can therefore substantially improve cloud detection regionally (Hilker et al., 2012; Lyapustin et al., 2008). Time-series approaches require frequent overpasses, as the assumption of reproducibility of spatial patterns is only valid over relatively short periods of time. As such, time-series techniques are less applicable for medium and high resolution imagery with less frequent overpasses. An examples for a time series-based cloud masking algorithm is implemented in the MAIAC cloud mask (CM) algorithm and the MAIAC surface reflectance product (Lyapustin et al., 2011a, 2012).

3.02.3 Bidirectional Reflectance Effects and Bidirectional Reflectance Modeling

Surface reflectance is dependent on the sun-sensor geometry, because of surface and atmospheric scattering effects. Surface scattering describes the way how a light beam is reflected from a surface and is dependent on the size, shape, and structure of the reflector as well as wavelength and angle of the incident radiation. Atmospheric scattering describes the scattering of light as it passes through the atmosphere and depends on particle size, density, and wavelength. Fig. 2 shows an illustration of such directional reflectance effects obtained from a tower-based camera system at a mature Douglas-Fir site in Vancouver Island, Canada.

A common way to account for directional scattering effects is through models that describe the directional reflectance properties, so called BRDF (e.g. Gao et al., 2003; van Leeuwen et al., 1999; Bryant et al., 2003; Liang and Fang, 2004) (Fig. 3). BRDF describes how radiation is reflected at an optically thick surface (Nag et al., 2016) and provides reflectance as a function of illumination and viewing geometry. The BRDF is dependent on wavelength as well as structural and optical properties of the surface, such as shadow-casting, multiple scattering, mutual shadowing, transmission, reflection, absorption, and emission by surface elements, facet orientation distribution, and facet density (Schaaf et al., 2002). While it can never be measured directly, BRDF accuracy serves as a main metric in multiangle remote sensing (Gatsef et al., 2003; King et al., 1986). BRDF of a ground spot can be estimated from multiple images of that spot taken at multiple angles of solar incidence and reflection simultaneously. Prominent features in bidirectional reflectance modeling are hotspot and dark-spot effects (Lucht et al., 2000). Hotspot describes a reflectance peak around a viewing direction that is exactly opposite the solar illumination direction. As a result, hotspot effects appear when light is backscattered from the earth surface to a recording sensor. The size of the hotspot depends on the relative sizes of scatterers for instance in a tree canopy (leaves, branches, twigs, etc.) and the wavelength of the radiation (Jupp and Strahler, 1991; Chen and Leblanc, 1997). Opposite to the hotspot, the so-called dark-spot describes a completely shaded area with the source of illumination located opposed to the observer. BRDF should not be confused with the Bidirectional reflectance factor (BRF), which is defined as the ratio of the reflected spectral radiance from the surface in the direction $\theta, \phi$ to the directional spectral irradiance in the surface in the direction $\theta_s, \phi_s$, where $\theta$ describes the zenith angle and $\phi$ describes the azimuth angle (Liang and Fang, 2004).
Early BRDF models, such as the Minnaert Function (1941), were developed for astronomy purposes. These models did, however, not incorporate any azimuthal dependencies and were therefore not suitable for reflectance measurements in structured terrain (Liang and Fang, 2004). One of the first semiempirical models that have been used for canopy reflectance modeling was proposed by Walthall et al. (1985). Originally developed for soil surfaces, the model is dependent on the viewing zenith angle \( q_v \) and the relative azimuth angle \( \phi \) and is therefore comparatively easy to apply. A lack of a hotspot effect, however, makes it less suitable for highly structured surfaces, such as forest canopies (Liang and Fang, 2004).

A first geometric optical model to describe the bidirectional effects of conifer forest canopies based on physical principles was the Li and Strahler (1985) model. The algorithm uses parallel ray geometry to describe the illumination of tree crowns which are modeled as a three dimensional, randomly located, green cones (Li and Strahler, 1985). The original algorithm has been extended by Li and Strahler (1992) to account for the hotspot effect and mutual shadowing of trees at larger zenith angles (Li et al., 1992). Because physical approaches like the Li and Strahler model try to precisely describe geometric reflectance properties, they usually suffer from a large number of complex input parameters, limiting its application and inversion from remote sensing data.

In an effort to reduce model complexity and allow an application over large areas from space, semiempirical models retain some physical interpretation, through approximations made from complex BRDF models, yet offer the advantage of being versatile and rapidly inverted (Roberts, 2001). A first, nonlinear analytical approach to model BRDF was described by Liang and Strahler (1993). In this analytical model, BRDF is expressed as a sum of the single scattering, the unscattered sunlight reflectance, the incident radiation and an estimation of a multiple scattering component (Liang and Strahler, 1993). More recently, linear kernel-driven BRDF models were designed to ease the difficulties of inverting nonlinear physical models. Kernel-based BRDF models represent angular reflectance distribution as linear superposition of a set of basic BRDF shapes based on relative sun position and simple measures of the canopy structure (Wanner et al., 1995). Their simple character allows acquisition of model parameters from mathematical inversion of relatively few reflectance observations, thereby facilitating applications over a wide range of spatial scales. Semiempirical
Kernel driven models for the BRDF of vegetated land surfaces consist of a linear combination of three kernels describing isotropic, geometric, and volumetric scattering effects (Roujean et al., 1992). Isotropic scattering refers to the reflectance properties of an isotropic, Lambertian surface, and, assuming random leaf distribution, can be seen as aggregate property of the sum of leaves. Geometric scattering describes scattering effects due to crown shape (Roujean et al., 1992), while volumetric scattering models dispersion effects due to vertical and horizontal distribution of vegetation elements inside the tree canopy. A series of different mathematical kernels can be selected to optimize BRDF models for various kinds of vegetation cover. Among the most commonly applied functions are Ross and Li kernels (Schaaf et al., 2002; Wanner et al., 1995) with the Ross kernels (Roujean et al., 1992) based on the radiative transfer theory of Ross (1981), whereas the Li kernels are geometric-optically based (Li and Strahler, 1986). In temperate climatic zones and when observing discontinuous, stacked canopies (e.g., conifer stands), the bidirectional reflectance distribution is most commonly represented by the so-called Li-sparse (LS) and Ross-thick (RT) kernels, yielding the LSRT BRDF model as (Los et al., 2005).

\[ \rho(\theta_v, \theta_i, \Delta \phi) = k_i + k_g K_L \left( \theta_v, \theta_i, \Delta \phi, \frac{h}{b}, \frac{h}{r} \right) + k_v K_R(\theta_v, \theta_i, \Delta \phi) \]  

where

- \( k_i \): isotropic scattering component
- \( k_g \): geometric scattering component
- \( K_L \): Li-Sparse kernel
- \( k_v \): volumetric scattering component
- \( K_R \): Ross-Thick kernel
- \( \theta_v \): view zenith angle
- \( \theta_i \): solar zenith angle
- \( \Delta \phi \): azimuth angle

\( h \) = crown relative height = 1 (Wanner et al., 1995; Justice et al., 1998) 
\( s \) = crown relative shape = 2 (Wanner et al., 1995; Justice et al., 1998)

\( k_i, k_g \), and \( k_v \) are the empirical components (kernel weights) derived from the least squares solution of the linear model using multangular radiation observations. For a surface that behaves in a more Lambertian manner (e.g., a smooth nonlayered surface), the magnitude of the isotropic kernel coefficient \( k_i \) of equation is relatively larger than \( k_g \) and \( k_v \). For a continuous layered canopy, \( k_i \) and \( k_v \) dominate since the RT function better describes the directional observations. For a discontinuous coniferous canopy the LS function better matches the observations hence, \( k_g \) is expected to be the larger component. The LSRT model as shown in Eq. (1) has been applied to global satellite reflectance observations for a range of vegetation canopy structures thereby permitting a semiempirical reconstruction of the full canopy BRDF from satellite acquisitions for a limited number of view and illumination angles (Wanner et al., 1995).

### 3.02.4 Summary and Discussion

Atmospheric correction, cloud screening, and modeling of the bidirectional reflectance distribution are essential requirements for accurate inference of surface properties from optical satellite remote sensing. With the advent of MODIS, satellite data provision has moved away low level, top of atmosphere processing to comprehensive, high level surface reflectance products that facilitate data handling and processing even for nonremote sensing experts (Liang et al., 2002). This, together with free and open access to satellite imagery has revolutionized earth system science and contributed to the huge success of satellite remote sensing over recent years. For instance to date, cloud screened, BRDF corrected surface reflectance products are available at different spatial resolutions globally and free of charge.

While increased product availability opens a whole range of opportunities for earth system science, it also creates certain “bottlenecks” as high level scientific results based on remote sensing data will depend upon the accuracy of the remote sensing products provided with end users not always being capable of assessing the plausibility and quality and limitations of the product obtained. As a result, constant validation and improvement of surface reflectance products and their derivatives is more important than ever to assure the quality and correctness of remote sensing-based findings. Such validation requires networks of ground validation, such as from AERONET stations (Holben et al., 1998), eddy flux networks (Baldocchi et al., 2001), or other ground networks (Gamon et al., 2006), but can also be accomplished from cross sensor and cross algorithm comparisons.

New developments, such as MAIAC provide exciting opportunities for exploring remote sensing-based techniques in regions for which remote sensing has previously been difficult as such tropical ecosystems or high arctic regions. The potential for increasing the number of cloud-free observations through less conservative, but more accurate cloud masking in combination with improved surface reflectance algorithms will allow more timely and accurate predictions of the status of global ecosystems.

See also: 1.04. The Joint Polar Satellite System. 1.09. Japanese Space Program. 5.06. Land Surface Albedo. 5.07. Sea Surface Albedo.
References


Further Reading

