A review of Selected MODIS Algorithms, Data Products, and Applications

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1. INTRODUCTION

The Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the key instruments designed as part of NASA's Earth Observing System (EOS) to provide long-term global observation of the Earth's land, ocean, and atmospheric properties (Asrar and Dokken, 1993). The development of MODIS was built upon the experiences of Advanced Very High Resolution Radiometer (AVHRR) and the Landsat Thematic Mapper (TM). It was designed not only for providing continuous global observations, but also as a new generation of sensor with an increased combination of spectral, spatial, radiometric, and temporal resolutions. In addition to advances in sensor instrument, the MODIS mission also emphasized the development of operational data processing algorithms to generate global remote sensing spectral datasets and a variety of value added products spanning both the optical and biophysical domains. The motivation was to provide MODIS standard products to the general scientific community to support both theoretical and applied applications. Two MODIS instruments were initially scheduled for launch on the EOS-AM and EOS-PM platforms in June 1998 and December 2000, respectively (Running et al., 1994). The actual launch dates were December 18, 1999 (EOS-Terra) and May 4, 2002 (EOS-Aqua). Terra MODIS data have been available since February 2000. Subsequently, numerous scientific papers have been published on topics of MODIS data, algorithms, validation, and applications.

This chapter provides a review of selected MODIS data products and algorithms. We reviewed a large number of MODIS algorithm theoretical basis documents (ATBD) developed by individual MODIS science teams and scientific papers published over the last 10–15 years. It is of our main interest to review MODIS algorithms to increase the understanding of the standard data products, document advances and limitations, and identify data quality and validation issues. The general organization of this chapter is as follows. We first briefly describe the MODIS sensor characteristics. We then review selected MODIS data products and algorithms for land, atmosphere, and ocean disciplines. Our focus is on the MODIS land product because its relatively wider use among the three. Finally, we review a wide range of applications and research activities that emphasize broad range of MODIS product applications.

1.1 MODIS sensor characteristics

Both EOS-Terra and EOS-Aqua are polar orbiting sun-synchronous platforms. The orbit height of EOS platforms are 705 km at the Equator. Terra's equatorial crossing time (descending) is at 10:30am local time; approximately 30 minutes later than the Landsat 7 satellite. Aqua crosses (ascending) the equator at approximately 1:30 pm. Each MODIS instrument has a two-sided scan mirror that operates perpendicular to the spacecraft track. The mirror scanning extends 55° at either side of nadir, providing a nominal swath of 2330 km. The wide swath allows the nearly global coverage to be obtained by each instrument every 1–2 days.

In addition to the high temporal resolution, the MODIS sensor has high spectral, spatial, and radiometric resolutions; compared to previous sensor systems such as the AVHRR. A total of 36 spectral bands were carefully positioned across the 0.412–14.235 μm spectral region. Among the 36 spectral bands, the first two bands are located in the red (0.648 μm) and near-infrared (0.858 μm) with a spatial resolution of 250 m. There are five additional bands (bands 3–7: 0.470 μm, 0.555 μm, 1.240 μm, 1.640 μm, and 2.13 μm) with a spatial resolution of 500 m located in the visible to short-wave infrared (SWIR) spectral regions. The remaining 29 spectral bands (bands

8–36) have 1000 m spatial resolution, and are located in the middle and long-wave thermal infrared regions (TIR). The MODIS instrument also has a 12-bit radiometric resolution and an advanced onboard calibration subsystem that ensures high calibration accuracy (Guenther *et al.,* 1998; Justice *et al.,* 1998). The sensor characteristics are considered to be substantially improved over other similar observation systems (Townshend and Justice, 2002). Unlike the AVHRR (mainly designed for monitoring the atmosphere), the MODIS sensor, is well suited for a wide range of research applications intended to improve the understanding of land, ocean and atmospheric processes, domain interactions, and the impacts of human activity on the global environment. Table 1 shows MODIS technical specifications including primary use, band numbers, band widths, spectral radiance, spatial resolutions, and signal-to-noise ratio.

1.2 Data Products and Algorithms

The MODIS instrument calibration, algorithm development, and standard data products are provided by the MODIS science team. The science team consists of over 70 American and international scientists, divided into four discipline groups for: calibration, land, atmosphere, and ocean. Each discipline group has clearly defined scientific responsibilities, and close interactions between the groups are maintained throughout the algorithm development, data processing, evaluation and product distribution.

MODIS data products are broadly categorized into five levels from level-0 to level-4. MODIS level-0 data is the initial dataset automatically converted from instrumental raw format. The level-0 data is subsequently split into granules and an earth location algorithm is employed to add geodetic position information to each MODIS granule. This creates the MODIS level 1-A product that contains geodetic information such as latitude, longitude, height, satellite zenith/azimuth and solar zenith/azimuth angles (Nishihama *et al.,* 1997). The level-1A data is further processed to generate level 1-B product (calibrated radiance for all bands and surface reflectance values for selected bands). Additional information such as data quality flags and error estimates are also provided. The MODIS level-1B data is still considered to be instrument data. It is used primarily as input to derive higher order MODIS geophysical products (levels 2–4). For example, MODIS level-2G is a gridded product that stores level-2 data in an earth-based uniform grid system. level-3 data provides an estimation of optical or biophysical variables for each grid element for predefined spatial and temporal resolutions (*e.g.,* daily, eight-day, and monthly). The algorithms for the level-3 products often include spatial re-sampling, averaging, and temporal composition. Finally, level-4 data is generated through a variety of algorithms, models, and statistical methods. Generally, additional ancillary data are required to generate level-4 data (*e.g.,* MODIS Net Primary Production product).

MODIS data products are also labeled by collection version. Each collection version indicates a complete set of MODIS files corresponding to a specific data updating or re-processing stage. At the time of chapter preparation, the MODIS science team had completed the processing of the "Collection 5" data. The MODIS team anticipates that another round of data processing will be conducted in 2010, subject to the availability of new MODIS algorithms. The distribution of MODIS land, atmosphere and ocean data are primarily supported by three data centers including the: Goddard Space Flight Center in Greenbelt, MD (*i.e.,* level-2, level-2G, ocean color, sea surface temperature); U.S. Geological Survey EROS Data Center in Sioux Falls, SD (*i.e.,* land products); and National Snow and Ice Data Center (NSIDC) in Boulder, CO (*i.e.,* snow and sea ice). MODIS Level-1 and atmosphere products are distributed through the level-1 and Atmosphere Archive and Distribution System (LAADS) website.

2. MODIS LAND PRODUCTS

MODIS land products are developed by the MODIS land discipline group (MODLAND). The standard land products include both remote sensing surface variables (*i.e.,* radiance, surface reflectance) and a wide-range of derived variables such as VI's (Vegetation Indexes), LAI (Leaf Area Index), fPAR (fraction of Photosynthetically Active Radiation), BRDF (Bidirectional Reflectance Distribution Function), LST (Land Surface Temperature), NPP (Net Primary Production), fire and burn scar, land cover and land cover change, and snow and sea ice cover (Justice et al., 1998; Running *et al.,* 1994). Detailed descriptions about MODIS land products are provided by Justice *et al.* (1998) and ATBDs developed by the MODIS science team. A review of selected MODIS land products, algorithms and validation issues was conducted in this section.

2.1 Surface Reflectance

The core of the MODIS surface reflectance algorithm is atmospheric correction. Atmospheric gases, aerosols and clouds have direct impacts on solar radiation though absorption and scattering. The atmospheric effects may modify pixel brightness and change wavelength dependence on radiance (Herman and Browning, 1975; Kaufman, 1989). The objective of atmospheric correction is to remove atmospheric effects, and thus extract the surface reflectance values as if they were measured at ground level. The successful retrieval of surface reflectance is important for improving remote sensing data quality and subsequent data analysis and applications (Gordon *et al.,* 1988; Liang *et al.,* 2002; Tanre *et al.,* 1992).

One of the principal challenges for an operational atmospheric correction algorithm is high variations of aerosols and water vapor in space and time. Aerosol optical characteristics are often very difficult to model because of high variations of aerosol loadings, particle sizes, and distributions. Due to the lack of available data on aerosol characteristics, previous operational atmospheric correction algorithms have often assumed standard atmosphere with zero or constant aerosol loading to simplify the problem. The main advantage of the MODIS atmospheric correction algorithm is that it derives atmospheric characteristics from the MODIS data itself. The MODIS-derived aerosol optical thickness and water vapor content are coupled with MODIS spectral information and other ancillary data (*i.e.,* digital elevation model) in a radiative transfer model to derive surface reflectance values. The direct implementation of the radiative transfer model at a per-pixel level is impossible for daily global MODIS data, considering the high computational cost; thus a look up table (LUT) approach is used to simplify the radiative transfer computation. A number of atmospheric effect quantities such as path radiance, atmosphere reflectance for isotropic light, and diffuse transmittance are pre-calculated for different aerosol loadings and sun-view geometries using the 6S (Second Simulation of a Satellite Signal in the Solar Spectrum) (Vermote *et al*., 1997) code. The surface reflectance values are then estimated using a second degree equation. The detailed mathematical equations and algorithms are described by Vermote and Vermeulen (1999).

It should be noted that the MODIS atmospheric correction algorithm also considers adjacent effects, Bidirectional Reflectance Distribution Function (BRDF) and atmosphere coupling effects. The adjacent effects occur when the reflectance of a target pixel is mixed with those from surrounding pixels (Tanre *et al*, 1981). The adjacent effects should not be ignored for heterogeneous ground surfaces, especially for fine resolution pixels (*i.e*., 250 m). The MODIS atmospheric correction algorithm employs an inverting approach to correct the adjacent effects under linear combination assumptions (Tanre et al, 1981). The coupling of BRDF into atmospheric correction is implemented using *a-priori* estimates of the surface BRDF. The MODIS algorithm uses the BRDF from the previous 16-day period (Strahler *et al*., 1996); which increases accuracy compared to a commonly used Lambertian assumption.

MODIS surface reflectance values are derived for MODIS bands 1–7 using the above described atmospheric correction algorithms. The major advantage is to use MODIS-derived atmospheric optical properties to achieve automated and operational correction at the global level (Kaufman and Tanre, 1996). The quality of MODIS surface reflectance is highly dependent on a number of MODIS-derived input data products (*i.e*., atmospheric properties) and radiative transfer models that incorporate various theoretical assumptions. Validation of the MODIS surface reflectance products has been conducted by intensive field campaigns and continuous validation at various validation sites. Liang *et al*. (2002) suggested that the direct comparison of MODIS surface reflectance values and ground "point" measurements are unrealistic due to scale mismatch. They proposed deriving surface reflectance values using higher resolution remote sensing data (*e.g*., Landsat) along with field calibration data, then upscaling (*i.e*., degrading) the high resolution surface reflectance values to the MODIS spatial resolution. In their validation work, MODIS surface reflectance values appeared to have reasonable accuracy (±5%) when compared to the degraded Landsat derived surface reflectance values. It should be noted that this validation effort was mostly for vegetated areas on relatively clear days. Additional continuous validation is needed for different land cover conditions and aerosol loadings. It is important to incorporate additional validation results to further improve the quality of MODIS surface reflectance data product, because the product serves as an important input to many higher level MODIS algorithms that produce MODIS land products such as VI's, land cover classification, change detection, fire products, and others.

2.2 Vegetation Indexes (VIs)

Vegetation indexes have been widely shown to provide valuable measurements of vegetation activity and conditions (Tucker *et al.,* 1979; Tucker *et al.,* 1985). The Normalized Difference Vegetation Index (NDVI) is probably the most commonly used vegetation index, because it is highly correlated with many other biophysical parameters related to vegetation canopy properties, processes and functions (Curran, 1980; Tucker *et al.,* 1981; Asrar *et al.,* 1984; Goward *et al.,* 1985). NDVI is mathematically a simple ratio of two linear combinations of spectral reflectance values of near infrared (NIR) and red bands:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \qquad \text{Eq. (1)}$$

Where ρ_{NIR} and ρ_{red} denote surface reflectance values at the NIR and red wavelength intervals, respectively. NDVI data is one of the standard MODIS VI products (Justice *et al.,* 1998; Huete *et al.,* 2003). It is also referred as "continuity" data which extends the AVHRR's long-term NDVI records.

In addition to NDVI product, MODIS VI products also include a newly developed Enhanced Vegetation Index (EVI) (Huete *et al.*, 2002):

$$EVI = G \times \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L} \qquad \text{Eq. (2)}$$

Where G is the Gain factor, C_1 and C_2 are aerosol resistance coefficients, and L is the canopy background adjustment. The numeric values for these coefficients are 2.5, 6, 7.5 and 1 for G, C_1, C_2, and L, respectively (Huete *et al.,* 1994; Liu and Huete, 1995). Compared to NDVI, EVI provides improved sensitivity of vegetation signals in high biomass or dense forest regions (Huete *et al.,* 2003). EVI is also better correlated with tree canopy structure characteristics such as LAI (Gao *et al.,* 2000). The finest spatial resolution of the MODIS VI product is 250 m. It should be noted that there is no 250 m blue band for MODIS instrument, thus the 500 m blue band surface reflectance values are used as replacements to generate 250 m EVI products. Also, water, clouds/shadows, and pixels with heavy aerosol loadings are masked out for the VI products, since VI values are not robust for these cover types.

MODIS standard VI products are provided at 250 m, 500 m, 1.0 km and 0.05° (5,600 m) resolutions through 16-day data composites. The MODIS VI data composite algorithm was developed based upon the experiences gained from the AVHRR-NDVI composite algorithm. The motivation is to generate cloud free and consistent NDVI product at the global scale. The AVHRR-NDVI composite algorithm selects the maximum NDVI value for a pixel within each 14-day time interval. This is commonly referred as maximum value compositing (MVC) algorithm. One main drawback is that the MVC algorithm favors pixels with large view angles. These large view angle pixels often have higher NDVI values than the nadir view pixels, but they may not be cloud-free (Goward *et al.,* 1991). The MODIS science team developed two new approaches to solve this problem: CV-MVC (constrained-view angle – maximum value composite) and BRDF-C (bidirectional reflectance distribution function composite). The CV-MVC compares the two highest NDVI/EVI values and selects the one with smaller view angle for compositing, which typically improves the spatial consistency for VI time-series data. The BRDF-C algorithm is considered to be more complicated. It requires a minimum of five valid VI values for each pixel to mathematically interpolate nadir-view reflectance values and VIs (Walthall *et al.,* 1985). This largely limits its applicability in regions with frequent cloud cover, thus it can be considered a region-dependent algorithm. Currently, CV-MVC is used as the primary compositing algorithm for MODIS VI products with MVC as a backup algorithm. BRDF-C algorithm is turned off due to its regional dependency.

The results of MODIS VI's validation have been reported by a number of researchers (Huete *et al.,* 2002; Gao *et al.,* 2003; Brown *et al.,* 2006). Gao *et al*. (2003) compared MODIS vegetation indices with those from high spatial resolution images through the scaling up approach. It was found that both MODIS single-day VI and 16-day composited VI matched well with those values derived from higher spatial resolution datasets. Huete *et al.* (2002) conducted validation work in four field campaigns across the U.S. and at sites in North and South America. They compared MODIS NDVI and EVI with regard to temporal (seasonal) vegetation profiles, dynamic range and saturation, and their relationships with biophysical variables such as LAI, biomass, canopy cover, and fAPAR. The MODIS NDVI and EVI temporal profiles matched well in vegetation growing season in selected biomes. One noticeable difference of MODIS NDVI and EVI is the dynamic range. MODIS NDVI appears to be saturated (*e.g.,* > 0.9) in high biomass regions, while EVI shows more sensitivities in those regions without suffering data saturation. EVI also has advantages in differentiating forest types such as broadleaf and needleleaf forests, while MODIS NDVI shows very similar signals for these forest types. These differences can have direct impact on vegetation index-based land cover mapping applications. The comparison of MODIS-NDVI and AVHRR-NDVI also shows interesting results (Huete *et al.,* 2002). These two time-series products have very similar signals for arid and semi-arid regions in dry seasons; however, MODIS-NDVI products have much higher values in wet seasons. Brown *et al.* (2006) further suggested that the differences between these two NDVI products are land cover-dependent and they can not simply be interchanged for analyzes. These studies suggested the challenge of data "continuity" between AVHRR and MODIS-NDVI data records. The contributing factors include differences in sensor band characteristics, and atmospheric correction and compositing algorithms used. Further research is needed to link AVHRR-NDVI and MODIS-NDVI in a more consistent manner for monitoring global vegetation conditions and changes.

2.3 Land Cover and Change Detection Products

Timely and accurate global land cover information is important for a wide range of studies including global climate change, carbon and hydrologic balance, terrestrial ecosystem, and human impacts on the natural earth system (Townshend and Justice, 2002). Operational global land cover mapping; however, is extremely challenging due to limitations in training data, high computational cost, and intrinsic spectral confusion between land cover classes. Historically, global land cover maps have been complied by a number of research institutions and organizations (Friedl *et al.*, 2002). The first remote sensing-based global map was produced by DeFries and Townshend (1994) using time-series AVHRR-NDVI monthly composite data at a 1.0° spatial resolution. AVHRR-based global maps at finer spatial resolutions (*e.g.,* 1–8km) have been subsequently developed using a variety of classification algorithms (Loveland *et al.,* 2000). The main concern for the AVHRR-derived land cover data products is related to AVHRR sensor characteristics, which were not configured for land cover mapping. The MODIS science team has high expectations for the MODIS-derived land cover map products, mainly due to the improved sensor characteristics (spatial, spectral, and radiometric resolutions) and advances in computer algorithms such as atmospheric correction, image classification, and improved quality and quantity of training data sites. Land cover mapping and land cover change was identified as the most import task for the MODIS land science team (Asrar and Dokken, 1993; Running *et al.,* 1994).

The MODIS land cover classification follows the IGBP (International Geosphere-Biosphere Programme) classification scheme. A total of 17 land cover classes are defined including 11 natural vegetation classes, three non-vegetation classes, and three human-altered classes (Friedl *et al.,* 2002). The training data points are designed to ensure the global representation through the System for Terrestrial Ecosystem Parameterization (STEP) (Muchoney *et al.,* 1999). This global site database includes more than 1,373 sites globally. Training data points are developed mainly through visual interpretation of high resolution remote sensing imagery. Additional ancillary data was also used to augment training data points. It should be noted that the global site database is dynamic and needs to be updated continually to meet the requirements of operational global land cover mapping. The inputs for the MODIS land cover classification include the 16-day composite of MODIS surface reflectance values (bands 1–7) and the EVI. Two image classification algorithms were considered for the land cover classification by the MODIS science team. A supervised decision-tree algorithm (Quinlan, 1993) was selected over a neural network (Carpenter *et al.,* 1992) algorithm, based on global operational considerations. An advanced boosting algorithm (Freund, 1995) was integrated with the decision-tree algorithm. This provided more robust estimates of per pixel probabilities of class membership. Currently, standard MODIS land cover products are provided at 500 m and 0.05° spatial resolutions on annual intervals.

The validation of MODIS land cover data products is ongoing. Initial results from Friedl *et al.* (2002) suggested improved classification performance compared to AVHRR-derived products. This can be attributed to increased MODIS sensor characteristics and advances in atmospheric correction and improved classification algorithms. The accuracy of MODIS land cover products, however, does appear to have high regional differences. The quality of MODIS land cover products at high latitudes is particularly questionable due to the deterioration of MODIS inputs at those latitudes (*e.g.,* low solar zenith angles). Considerable confusion is present between agriculture and natural vegetation. In a recent study, Giri *et al.* (2005) compared the MODIS global land cover data and the Global Land Cover 2000 (GLC-2000) data. These two global land cover datasets are derived using very different input data and classification algorithms. Although a general agreement was found at the class aggregated level, there were substantial differences for individual classes. Moreover, the agreements were highly variable across different biomes. This calls for further studies in the development of land cover classification schemes and classification algorithms.

The MODIS land cover change algorithm does not use a post-classification comparison approach. The main reason is that the classification errors associated with two individual image classifications can be accumulated during the post-classification comparisons; which may seriously impact change detection performances (Stow, 1980; Singh, 1989). Instead, the MODIS land cover change algorithm relies on the analysis of multi-temporal image stacks or time-trajectories to assess land cover dynamics caused by processes such as deforestation, agricultural expansion and urbanization. Change vector analysis (Lambin and Strahler, 1994) is the primary change detection technique used in the MODIS land cover change algorithm (Strahler *et al.,* 1999). The input data to the change vector analysis includes a variety of MODIS-derived spectral/spatial variables such as vegetation indexes, surface temperature, and spatial structure indexes. To detect the annual land cover change between consecutive years, these variables are compiled for each individual year by monthly (32-day) composites. The land cover statuses from the two consecutive years can be treated as two ‘points’ located in a multi-temporal feature space. A change vector thus can be generated by linking these two ‘points’ in the multi-temporal feature space. The direction and magnitude of the change vector is assessed to identify potential land cover changes (Lambin and Strahler, 1994). The main advantages of using change vector analysis are to overcome the error accumulation problem and subtle land cover changes can be identified. Currently, the MODIS land cover change product is provided at 1.0 km spatial resolution. In addition to the annual land cover change product, Zhan *et al.* (2002) developed the Vegetative Cover Conversion (VCC) product as a global alarm of land cover change caused by anthropogenic activities and extreme natural events. The spatial resolution of the land cover change alarm product is 250 m. The MODIS Level 1B data was used as input for decision trees to detection wildfire, flood, and deforestation activities. Furthermore, the MODIS research team at the University of Maryland (UMD) are actively developing enhanced land cover and land cover change products. These include the global 250 m land cover change indicator product, the global 500 m Vegetation Continuous Fields (VCF) product, and the global 1.0 km land cover classification at-launch product. The validation of MODIS land cover change products is an ongoing process. A review of recent literature suggests that very few studies have been performed for the validation of MODIS land cover change products at local, regional and global levels.

2.4 Fire Products

MODIS fire products consist of both fire detection and burn scar products. The theoretical background of the fire detection algorithm is provided by Ward *et al.* (1992) and Kaufman *et al.* (1992). The MODIS fire detection algorithm also benefits from rich experiences gained from AVHRR and Visible and Infrared Scanner (VIRS) (Giglio *et al.,* 1999). The main objective was to automatically detect locations where active burning is occurring. The primary inputs for the fire detection algorithms are MODIS spectral signals at 4 μm and 11 μm. The MODIS channel at 4 μm is considered to be the most sensitive channel for both fire flaming and fire smoldering, while the channel around 11 μm (TIR) detects strong emission from fires (Dozier, 1981; Justice *et al.,* 2006). The MODIS fire detection algorithm consists of multiple processing steps to identify fire pixels. The initial step removes obvious non-fire pixels through a preliminary classification, potential fire pixels are then identified through thresholding of brightness temperatures (T_4 and T_{11}) derived from MODIS channels at 4 μm and 11 μm. The threshold values of T_4 are specified as 310 K and 305 K for daytime and nighttime pixels, respectively. In addition, the difference between T_4 and T_{11} needs to be larger than 10 K for a pixel to be labeled as potential fire pixel. MODIS spectral values at bands 1 (0.648 μm), 2(0.858 μm), and 7 (2.13 μm) are also incorporated in the decision rules to reduce false alarms (*e.g.,* sun glint) and confusion caused by clouds (Nath *et al.,* 1993).

Within the potential fire pixels, the MODIS fire algorithm further considers two approaches to identify unambiguous fire pixels. The first approach relies on high threshold values of brightness temperatures to identify actual fire pixels. The second approach examines contextual information of neighboring pixels (3 × 3 to 21 × 21) to identify active fire pixels. At least eight valid neighboring pixels are required for the background contextual analysis using 4 μm and 11 μm brightness temperature values. The brightness temperature values for the focal pixels are compared with the background contextual statistics to make decisions. The final fire products are labeled using the following categories: missing data, cloud, water, non-fire, fire, or unknown (Giglio *et al.,* 2003). The fire radiative power (FRP) is also computed for each fire pixel using the empirical relationship developed by Kaufman *et al.* (1998). A range of standard MODIS fire products are provided at various processing levels (level-2, level-2G, and level-3) with different spatial (1.0 km and 0.5°) and temporal resolutions (daily, 8-day and monthly composite).

The MODIS burn scar algorithm was developed by Roy *et al.* (2002; 2005). The burn scar products identify the spatial extent of the recent burn area, in contrast to the identification of active fire in the MODIS fire algorithm. The identification of burn scars at the global scale is an extremely challenging task since the spectral signals of burn areas are very similar to those of other land cover types such as flooding area and shadows from clouds and surface relief. The current MODIS burn scar algorithm can be considered a change detection approach through a statistical and temporal modeling of bi-directional reflectance variables. For each pixel, the bi-directional reflectance values within a pre-defined temporal window (*i.e.,* 16-day) are used in a statistical model to predict a subsequent reflectance value. This predicted value is then compared to the actual observed surface reflectance value to identify the chance of change. Threshold values are specified to identify pixels with large decreases of surface reflectance values. The primary inputs to the MODIS burn scar algorithm are MODIS band-2 (841–876 nm) and band-5 (1230–1250 nm); which are the most sensitive to burning and post-fire reflectance change. Additionally, simple band relationships between MODIS bands 2, 5, and 7 are used in the MODIS burn scar algorithm to reduce false alarms such as cloud, shadow, or soil moisture changes (Justice *et al.,* 2006).

The validation of MODIS fire data product has been conducted by several researchers using ASTER- (Advanced Spaceborne Thermal Emission and Reflection Radiometer) derived fire products as references (Morisette *et al.,* 2005; Csiszar *et al.,* 2006). The studies concluded that approximately 50% of the large fire clusters (45–60 ASTER pixels) were correctly identified. Ellicott *et al.* (2009) validated the MODIS-derived fire products (2001–2007) and found a slight underestimation of fire extent. They further analyzed the spatial distribution and found that Africa and South America contribute about 70% of global fires annually, suggesting high rates of biomass burning in those regions. For the validation of burn scar products, Chang and Song (2009) compared the standard MODIS burn scar products to burned areas derived in the SPOT-based L3JRC product from years 2000–2007. The spatial and temporal patterns from these two products were consistent, especially during the fire season. The research also suggested that MODIS burn scar products performed better than L3JRC products when compared to selected ground-based measurements in Canada, China, Russia, and the U.S. One noticeable problem in the MODIS burn scar product is the underestimation of burn area in boreal forests.

2.5 Snow and Sea Ice Cover

The spatial extents and dynamics of global snow cover are important for studies in hydrologic and bio-geochemical cycling, surface albedo, global energy balances, and climate change (Robinson et al., 1993). Although large-scale hemispheric snow maps have been routinely developed by the National Environmental Satellite Data and Information Service (NESDIS) and the Interactive Multi-Sensor Snow and Ice Mapping System (IMS), the spatial resolutions are generally coarse (*e.g.,* IMS product at 25 km). The main objective of the MODIS snow cover algorithm, or Snowmap, was to develop an automated computer algorithm that can be used to identify snow cover at higher spatial resolution (*e.g.,* 500 m) globally (Hall *et al.,* 2001; 2002).

Snow cover has distinct spectral signals that can be clearly differentiated from most other natural cover types. The primary confusion is with clouds, but previous research suggests that snow and cloud cover have different spectral responses at visible and short-wave infrared channels. Specifically, snow cover has a strong reflectance in the visible range, but a low reflectance in the short-wave infrared spectral region. On the other hand, clouds typically have strong reflectance values in both spectral regions (Kyle *et al.,* 1978; Dozier 1989). A ratio-based Normalized Difference Snow Index (NDSI) has been developed for snow mapping with Landsat data (Dozier 1989). The NDSI is also one of the primary algorithms used for MODIS Snowmap products.

$$NDSI = \frac{band4 - band6}{band4 + band6} \quad \text{Eq. (3)}$$

The MODIS Snowmap algorithm uses sensor reflectance values in bands 4 and 6 to compute the NDSI (Eq. 3). A pixel is labeled as snow if the NDSI is larger than the threshold value of 0.4. Additional decision rules in the Snowmap include the thresholding of MODIS band-2 (> 0.11) and band-4 (> 0.10). Generally, the NDSI value decreases as the purity of snow pixels are reduced. To identify partial snow pixel (*e.g.,* > 50%) in forested region, Snowmap incorporates MODIS-NDVI to map the snow pixel. For instance, pixels might be labeled as snow in cases of NDVI =~0.1 and NDSI < 0.4 (Hall *et al.,* 2002). Currently, standard MODIS snow products are provided at daily and temporal compositing of 8-day and monthly intervals. The temporal composting algorithm simply selects a maximum value within a specified temporal interval. A similar decision rules technique used in Snowmap has also been employed for the MODIS sea ice product through the sea ice mapping algorithm (Icemap).

Validation of the Snowmap product has been difficult due to the limited reference data and scale mismatch between various remote sensing-derived snow map products. Klein and Barnett (2003) conducted a snow map validation work for the Upper Rio Grande River Basin of CO and NM using snow cover map products developed by the National Operational Hydrologic Remote Sensing Center (NOHRSC). A high overall agreement of 86% was reported. The two snow cover maps were also compared with *in situ* snow measurements. The MODIS snow map performed best with a 94% agreement. Noticeable MODIS snow maps errors included locations where snow depths are less than 4 cm. Ault *et al.* (2006) compared MODIS snow products with data from a number of observation stations that included amateur observations across the Laurentian Great Lakes Region. The MODIS snow cover map matched very well with observational datasets. Major errors identified in the MODIS snow maps occurred in the forested areas. Hall and Riggs (2007) reported that the accuracy of selected MODIS snow product images (500 m) was approximately 93%. The confusion between snow and cloud was a major problem. Although the Snowmap algorithm successfully differentiates a majority of snow and cloud pixels at a 500 m spatial resolution, there were large uncertainties at the partial or sub-pixel level. Additional uncertainties were attributed to thin snow cover. The snow cover composite data is believed to be less accurate due to error accumulation from the daily snow product (Hall and Riggs, 2007).

2.6 LAI and fPAR

Leaf area index (LAI) denotes the one-side green leaf area per unit ground area. LAI is a plant-canopy attribute that is often used in process-based ecosystem, hydrology, and global climate models (Sellers et al., 1997). The term fPAR denotes the fraction of photosynthetically active radiation absorbed by plant canopies. A large amount of research has been conducted to study the relationships among plant canopy reflectance, spectral vegetation indexes, LAI and fPAR (Asrar *et al.,* 1984; Asrar *et al.,* 1989). One common approach to estimate LAI and fPAR is to develop empirical models based on remote sensing surface reflectance or vegetation indices such as NDVI (Asrar *et al.,* 1989).

The MODIS LAI/fPAR algorithm relies on a three-dimensional radiative transfer model and a look up table (LUT) approach to estimate LAI/fPAR. A global biome map is developed to allocate land cover types into six broad biomes including grasses and cereal crops, shrubs, broadleaf crops, savannas, broadleaf forests and needle leaf forests (Myneni *et al.,* 2002). This simplifies a number of assumptions and input parameters for the radiative transfer model. The three-dimensional radiative transfer model generates several spectral and angular signatures which can be compared to the MODIS directional surface reflectance values through a look up table. The MODIS LAI/fPAR algorithm then derives location-specific results by incorporating the law of energy conservation (Knyazikhin *et al.,* 1998). Further details about the MODIS LAI/fPAR algorithm and its theoretical background can be found in Knyazikhin *et al.* (1999). Standard MODIS LAI/fPAR products include 1 km spatial resolution data for both the daily and 8-day maximum value composite dataset.

Privette *et al.* (2002) conducted initial validation work for the MODIS LAI products using field-sampled data in southern Africa and found the accuracy of the MODIS LAI product is within an acceptable level. The MODIS LAI products successfully depicted the structural and phenological variability in semiarid woodlands and savannas. Wang *et al.* (2004) conducted LAI validation work in a needle-leaf forest site near Ruokolahti, Finland. The field LAI measures were first linked to high resolution Landsat images and then aggregated to match the MODIS spatial resolution. The MODIS LAI products showed higher variation than expected. The values were also overestimated compared to the field-based LAI measures. The authors suggested that the understory vegetation might cause the uncertainties. Iiames (2006) assessed MODIS LAI products for the evergreen needle leaf biome in the southeastern United States. The major challenges were attributed the uncertainties in the creation of the high-resolution LAI reference map, land cover classification, and the influences from vegetative understory. Yang *et al.* (2006) further addressed sources of MODIS LAI uncertainties, including the inputs of land cover maps, surface reflectance, and look-up tables used in the MODIS LAI algorithm. Kanniah *et al.* (2009) assessed the accuracy of LAI and fPAR for a northern Australian savanna site and found that the MODIS products captured the seasonal variation in LAI and fPAR well, especially the most recent Collection-5 data. However, Xiao *et al.* (2009) raised concerns related to the spatial/temporal discontinuity of MODIS LAI products for many numerous locations. They proposed a new algorithm for estimating LAI from time-series MODIS reflectance data to increase temporal continuity and improve accuracy.

2.7 Net Primary Productivity (NPP)

In addition to developing standard products linked to plant canopy structure and bio-optical properties, the MODIS science team also emphasizes developing algorithms and standard products for plant productivity and processes. Net primary production (NPP) is one of the standard MODIS products that provides a key measure of vegetation productivity. NPP denotes the rate of net carbon gain by vegetation over a specified time period and can also be represented as the different between gross primary production (GPP) and plant respiration. NPP is commonly measure at monthly, annual or longer temporal intervals. The estimation of NPP requires the integration of ecological principles, remote sensing data and other ancillary surface datasets. Potter *et al.* (1993) found that NPP can be estimated as a product of absorbed photosynthetically active radiation (APAR) and an efficiency of radiation use. The theoretical basis of the relationship between APAR and NPP is provided by Monteith (1972; 1977).

Theoretically, NPP values can be estimated based on an empirical relationship between APAR and NPP; which has been demonstrated in numerous studies (Asrar *et al.,* 1984; Goward *et al.,* 1985). However, the relationship between the two variables is also dependent upon vegetation type and numerous other control factors such as concentration of photosynthetic enzymes, canopy structure, and soil water availability (Russell *et al.,* 1989; Running *et al.,* 1999). This represents a considerable challenge to the development of an operational MODIS NPP algorithm using the APAR-based approach. The current MODIS NPP algorithm relies on an alternative approach that computes the difference between GPP and plant respiration. The basis for this approach is that APAR is actually more closely related to GPP than to NPP (Hunt, 1994; Running *et al.,* 1999). A detailed algorithm flowchart can be found in Running *et al.* (1999). The primary algorithm can be broken down into two sub-routines. The first estimates the daily GPP using standard MODIS fPAR products and ancillary surface meteorological measures as inputs. Different radiation conversion efficiency parameters are also provided as inputs using a look-up table (stratified by biome types). The second sub-routine estimates daily plant respiration. MODIS LAI is used as one of the inputs to estimate leaf mass, which is further used as an input for plant respiration estimation. The results from the two sub-routines (estimated GPP and plant respiration) are used to derive daily NPP. The daily NPP product is provided at a spatial resolution of 1.0 km. In addition to the daily NPP, MODIS algorithm also provides annual NPP. The annual NPP is estimated by integrating daily NPP and subtracting a number of respiration parameters for live woody tissue, leaves and fine roots (Running *et al.,* 1999).

Turner *et al.* (2006) evaluated MODIS NPP and GPP products across multiple biomes. The GPP at eddy covariance flux towers and plot-level measurements of NPP were scaled up to 25 km^2 and compared to the MODIS products. The authors reported high variations of results over different biome types and land uses. The MODIS products overestimated NPP and GPP at low productivity sites while underestimated those values at high productivity sites. One of the main error sources was attributed to the input (e.g., fPAR estimates) to the MODIS NPP algorithm (Turner *et al.,* 2006).

3. MODIS ATMOSPHERIC AND OCEAN PRODUCTS

3.1 Aerosols

Aerosols, especially human-made aerosols may lead to large reductions in the amount of solar irradiance reaching the Earth's surface, and increase in solar heating of the atmosphere (Ramanathan *et al.,* 2001). Aerosol loadings and distributions are often poorly characterized because they are highly variable in space and time. Remote sensing-based characterization is generally performed by estimating aerosol optical depth or thickness. To account for the very different surface reflective properties associated with ocean and land surface, the MODIS products incorporate two independent algorithms to retrieve aerosol optical depth (Kaufman *et al.* 1997, Tanre *et al.* 1997).

The aerosol algorithm over ocean integrates a radiative transfer model and LUT to produce aerosol optical depth estimates. The radiative transfer model has been run under a range of pre-defined aerosol conditions that describe particle modes (fine and coarse particles), total loadings, sensor/sun geometry angles, wind speed and other parameters computed from ancillary data (Ahmad and Fraser, 1981). The theoretical background is provided by Wang and Gordon (1994) who use fine/coarse particle modes to model multiple scattering process of radiance. The radiative transfer model produces a LUT table which can link spectral reflectance values and aerosol spectral properties or optical depth estimates. The observed MODIS surface reflectance values are simply compared to the values in the LUT to find the best fit using a least-square algorithm.

Aerosols over land surface are more concentrated compared to those over the ocean surface because the majority of aerosol sources are located on land (Kaufman *et al.,* 1997). The estimation of aerosol optical depth over land surface is considered to be more challenging due to the highly variable reflective properties associated with different cover types. The radiance components from land surface cannot be easily separated from those of aerosols (note that ocean surface is generally darker and water-leaving radiance can often be assumed to be zero). This is one of the major reasons that aerosol optical depth has not been routinely estimated at the global level before the use of MODIS data (Kaufman *et al.,* 1997).

The MODIS aerosol algorithm over land relies on the accurate identification of dark surface pixels. Vegetation index-based dark pixel detection was found to be unreliable for global applications because vegetation indices themselves are affected by the presence of aerosols (Holben *et al.,* 1986). For the MODIS aerosol algorithm over land, two MODIS spectral bands at 2.1 µm and 3.8 µm are used to detect dark pixels (Kaufman *et al.,* 1997). The spectral band at 2.1 µm is preferred; especially when the reflectance value for this band is lower than 0.05. The wavelengths of these two spectral bands are considerably longer than those of typical aerosol particles, thus the surface reflectance retrieved for these spectral bands can be considered as free of aerosol impacts. Under aerosol-free conditions, there are stable relationships between surface reflectance in the visible bands (0.47 µm and 0.66 µm) and SWIR bands (2.1 and 3.8 µm), thus the surface reflectance values in visible bands can be estimated from surface reflectance values derived for the SWIR channels (Kaufman *et al.,* 1997). The difference between the estimated and the MODIS-derived surface reflectance values in visible bands can be attributed to the presence of aerosols. This is the fundamental assumption for the MODIS aerosol algorithm for land surfaces.

Validations of aerosol optical depth estimates have been conducted by a number of researchers. Remer *et al.* (2004) compared 8,000 MODIS-derived optical depth values and AERONET (Aerosol Robotic Network) measurements. MODIS estimates were reported to be within the acceptable uncertainty levels over ocean and land surfaces. Chu *et al.* (2002) compared MODIS-derived aerosol optical depths and measurements from 30 AERONET sites. They found that the levels of consistency are higher for continental inland regions than for coastal regions. The partial water surface may have contaminated the aerosol optical depth estimation in the coastal regions. The authors also suggested that the lack of AERONET sites in East Asia, India and Australia makes global validation of MODIS aerosol optical depths particularly challenging. Aloysius *et al.* (2009) compared MODIS-derived aerosol optical depths and NCEP (National Centers for Environmental Prediction) reanalysis data over the South East Arabian Sea. They reported high correlations ($R^2 = 0.96$) between the two datasets. At the local level, Li *et al.* (2005) suggested that the standard MODIS 10 km aerosol optical depth estimates are insufficient to characterize the local aerosol variation over urban areas. They modified the MODIS aerosol algorithm and derived aerosol optical depth at 1.0 km spatial resolution over Hong Kong. High accuracies are reported compared to field measures. This suggested high potential of MODIS data for the estimation of aerosol optical depth at higher spatial resolution over local areas.

3.2 Clouds

Clouds play major roles in the Earth's radiation budget and climate change research (Ramanathan, 1987). The MODIS atmosphere science team has developed a variety of algorithms to generate MODIS cloud products including a cloud mask and optical properties. The review provided here focuses on the MODIS cloud detection, or cloud mask algorithm. The MODIS cloud mask algorithm employs an automated and threshold-based approach to identify clouds. The algorithm is developed upon previous cloud detection research and experiences from the International Satellite Cloud Climatology Project (ISCCP) (Rossow and Garder, 1993) and the AVHRR processing scheme Over Cloud Land and Ocean (APOLLO) (Gesell, 1989) cloud detection algorithm (Ackerman *et al.,* 2006). These algorithms primarily use multiple radiance thresholds testing to label pixels as cloudy or clear. The ISCCP algorithm also integrates spatial and temporal information in its decision rules.

The primary inputs to the MODIS cloud detection algorithm include 19 MODIS visible and infrared radiance values. Additional ancillary datasets include sun and sensor geometry angles, ecosystem classifications, land and water distributions, elevation above mean sea level, daily snow and ice maps from NSIDC (National Snow and Ice Data Center) and the daily sea ice concentration product from NOAA (National Oceanic and Atmospheric Administration). The ancillary data provide a basis to segment the Earth's surface into a range of surface conditions over time including: daytime land; daytime water; nighttime land; nighttime water; daytime desert; and daytime and nighttime snow or ice surfaces (Ackerman *et al.,* 2006). The MODIS cloud detection algorithm employs different threshold testing for different surface conditions over time. For a specific surface condition at a given time, each 1.0 k pixel is put through a variety of radiance and temperature-based threshold tests; which can be classified into the following five groups: simple IR threshold tests; brightness temperature differences; solar reflectance tests; NIR thin cirrus; and IR thin cirrus testing. One advance of the MODIS cloud detection algorithm was to include a confidence level for each threshold test, rather than provide simple categorical labels such as cloudy or clear. The confidence level is computed based on the distance from the threshold value and a continuous value is derived for each test (high confidence of clear pixel = 1, high confidence of cloudy pixel = 0). For each threshold testing group, a minimum confidence value is determined. The final confidence level is then integrated from the results of five groups. As a result, the MODIS algorithm provides multiple levels of 'confidence' for the cloud mask product (*i.e.,* cloudy, probably clear, confidently clear, and uncertain). This allows users to develop their own decision rules to process or use the standard MODIS cloud mask product.

Berendes *et al.* (2004) compared MODIS-derived daytime cloud products and observations from ground-based instrumentation located in North Alaska. They reported agreement within ±20% between the two datasets. In their study, the MODIS cloud mask appeared to be more accurate in the detection of thin cirrus clouds than the surface-based instruments. However, other researchers suggested that a major challenge in MODIS cloud masking is still cirrus cloud cover. Dessler and Yang (2003) analyzed MODIS cloud mask products for two 3-day periods from December 2000 and June 2001. They reported that approximately one-third of the pixels flagged as cloud free by the MODIS cloud mask contains detectable thin cirrus clouds. Further research is needed to improve the detection of thin cirrus clouds in the MODIS cloud algorithm.

3.3 Ocean

Numerous standard MODIS ocean data products are provided by the MODIS science team, including normalized water-leaving radiance, pigment concentration, chlorophyll fluorescence, chlorophyll-a pigment concentration, photosynthetically available radiation, suspended solids concentration, organic matter concentration, ocean water attenuation coefficient, ocean primary productivity, sea surface temperature, phycoerythrin concentration, and ocean aerosol properties.

Many MODIS ocean algorithms were developed upon experiences from the Coastal Zone Color Scanner (CZCS) (Gordon and Voss, 1999). A common perception is that water color (spectral measures) can be used to derive important biophysical parameters related to phytoplankton pigment concentration, primary productivity and sea surface temperature. One main challenge of ocean color characterization is that the retrieval of the relevant signal from the total radiance is difficult, because the water-leaving radiance is quite small (<10%) compared to the total radiance received at the sensor. In other words, at-sensor radiance is dominated by atmospheric effects over the ocean surface. It is therefore necessary to conduct atmospheric correction for the MODIS ocean color products. A detailed atmospheric correction algorithm is provided by Gordon and Voss (1999). The output of the algorithm is called normalized water-leaving radiance, which approximates water-leaving radiance (sun at zenith) free of atmospheric impacts for most oceanic conditions. The normalized water-leaving radiance is further used as input to generate almost all other MODIS ocean products. For instance, the current MODIS pigment concentration and bio-optical properties are largely dependent on empirical or semi-empirical relationships derived between spectral and biophysical measures obtained from the same field observations. The normalized water-leaving radiance over a large ocean area thus can be compared to those spectral measures obtained at field observations to generate estimations of pigment concentration or other biophysical properties.

3.4 Other

It must be noted that the MODIS science team has developed a large number of algorithms over the periods of MODIS instrument design, pre-launch, and post-launch phases. Some of the algorithms are continually updated, which leads to several MODIS data reprocessing procedures. This chapter only reviews a selected number of MODIS algorithms and products, thus it is by no means a complete description of MODIS algorithms and products. There is a range of MODIS standard products that were not discussed in this chapter, particularly for the atmosphere and ocean disciplines. The ATBDs developed by the MODIS science team is probably the best resource for those readers interested in more detailed MODIS algorithms, theoretical background, and data products.

4. MODIS APPLICATIONS

Since the launch of MODIS-Terra, hundreds of scientific papers have been published on the application of MODIS data at global, regional and local levels. The remote sensing literature has covered research on the following topics: global climate models (Oleson *et al.,* 2003; Tian *et all,* 2004); land cover and change detection (Lunetta *et al.,* 2006; Zhang *et al.,* 2008; Gill *et al.,* 2009); forest disturbance and vegetation dynamics (Evrendilek and Gulbeyaz 2008; Hansen *et al.,* 2008; Hilker *et al.,* 2009; Maeda *et al.,* 2009); vegetation and crop phenology monitoring (Zhang *et al.,* 2003; Sakamoto *et al.,* 2005), terrestrial ecosystem carbon exchange (Garbulsky *et al.,* 2008; Xiao *et al.,* 2009); eco-hydrological analysis (Hwang *et al.,* 2008); crop mapping and crop yield estimation (Doraiswamy *et al.,* 2004; Sakamoto *et al.,* 2009); human health issues (Hu

2009); air quality assessment (Gupta and Christopher, 2008); water quality monitoring and assessment (Hu *et al*, 2004); species and habitat distribution (Vina *et al.,* 2008).

At the global level, various MODIS data products have been used as primary inputs into climate models, and as reference data to validate the climate models (Oleson *et al.,* 2003; Tian *et al.,* 2004). For example, Tian *et al.* (2004) compared the land surface albedo from the Community Land Model (CLM) (Bonan *et al.,* 2002) to MODIS albedo products (Gao *et al.,* 2005) under two land surface scenarios. The first land scenario used older standard parameters in the CLM for a "control run". The second scenario uses a range of newly derived MODIS land parameters such as vegetation continuous fields (VCF), LAI, land cover, and plant functional type as the model inputs. Improved CLM results are reported when the MODIS-derived products are used as land surface parameters. Lawrence and Chase (2007) developed new CLM land surface parameters based on MODIS land products and found that the new model had substantial improvements in surface albedo estimation; which further improved the simulation of precipitation and near-surface air temperature. Although the MODIS data algorithms and products show promise for climate modeling, Dickson (2009) also suggested that one of the major challenges for the current remote sensing data are the spatial and temporal discontinuities. For example, general land cover on the earth's surface should be quite stable over time, except for some small random changes caused by human or natural disturbance. Spatial and temporal discontinuity, however, often occur in remote sensing-derived land surface parameters as a result of system limitations or systematic errors. Future research should address these problems, mainly through algorithm improvements.

The use of MODIS data for applications in forest disturbance, vegetation dynamics, urban development, agricultural expansion, and crop mapping and management generally rely on image classification and change detection techniques. Instead of using the standard MODIS global data, researchers often need to develop their own classification and change detection algorithms for local and region applications. There are three motivations for researchers to develop their own products using MODIS spectral information. First, the information desired at local and regional levels is generally more detailed than those of the MODIS global datasets. Second, the spatial resolution of standard MODIS global data might be too coarse for local applications. Third, the accuracy of the MODIS global datasets varies across regions. It is often possible to improve accuracy using an increased number of training data points, ancillary data, and algorithms that fit better with local conditions.

The desire to obtain more detailed land use and cover type information can be illustrated through a number of research projects that focused on the crop mapping using MODIS data. The standard MODIS land cover product does not include specific crop types in its mapping scheme. Recent studies suggest that MODIS data has sufficient spatial and temporal resolution to identify major crop types such as corn, soybean, and wheat in intensive agricultural regions in the United States (Wardlow *et al.,* 2007; Wardlow and Egbert, 2008; Shao *et al.,* 2010). These studies often rely on the use of MODIS time-series NDVI or a phenology-based analysis for the land cover and crop identification. Xiao *et al.* (2005) found that the MODIS-NDVI profiles were also useful in characterizing rice distributions, mainly due to the unique NDVI profiles associated with rice transplanting, growing and fallow periods. The results from these studies suggest that the unique combination of spatial, spectral, and temporal resolutions associated with MODIS data is a major advantage for more detailed land use and cover type classification at regional and local scales.

The 500 m or 1.0 km spatial resolution land cover products may be too coarse for many regional to local scale applications. This is particularly evident for areas with complex or heterogeneous land cover patterns at finer spatial scales (Lobell and Asner, 2004; Knight *et al.,* 2006). Many researchers have employed spectral mixture analysis (SMA) to unmix MODIS pixels, and thus derive proportional land cover at the sub-pixel level. Chang *et al.* (2007) estimated proportional corn and soybean cover within MODIS 500 m data. Knight *et al.* (2006) examined the potential of sub-pixel land cover estimation using multi-temporal MODIS-NDVI 250 m data. The sub-pixel land cover mapping problem is also addressed by the MODIS science team. It is actually designed as a part of the MODIS enhanced land cover and land cover change products. Hansen *et al.* (2002) employed a regression tree algorithm to derive sub-pixel tree cover products at 500 m spatial resolution. His sub-pixel classification approach relied on training pixels that contain tree cover proportions derived from high-resolution satellite images. The regression tree was trained to model the relationship between the MODIS signals and tree proportions at the sub-pixel level. The assessment of the sub-pixel tree cover estimation accuracy was extremely challenging due to the lack of reference datasets, especially at regional or global scales. The trend towards sub-pixel analysis is not limited to land cover classification; researchers are also actively working on sub-pixel cloud detection and sub-pixel snow cover mapping (Salomonson *et al.,* 2004). The relationship between sensor spatial resolution and ground surface features continue to be a challenging topic for the remote sensing research community.

MODIS-based change detection has been employed by many researchers to study deforestation, urbanization, and agricultural expansion (Lunetta *et al.,* 2006; Zhang *et al.,* 2008; Gill *et al.,* 2009). Most of the change detection algorithms are developed for the 250 m MODIS data, because many human-introduced land cover changes occur at fine spatial scales. Lunetta *et al.* (2006) developed an automated land cover change alarm product in the Albemarle-Pamlico Estuary System (APES) region of the U.S. The approach relied on detecting pixels that have experienced significant changes in the annual-integrated NDVI values. A large drop of annual-integrated NDVI may suggest possible land cover changes such as urban development or vegetation clear cutting. Jin and Sader (2005) also used the MODIS 250 m vegetation indexes to detection forest harvest disturbance in north Maine. It was found that although the MODIS single day and 16-day composite NDVI data showed no significant difference in overall detection accuracies, the single day NDVI actually performed better when disturbed patch sizes are smaller.

Zhang *et al.* (2003) examined vegetation phenology using a time-series of the MODIS vegetation index (VI). They used a series of piecewise logistic functions to detect transition dates of vegetation activity on an intra-annual basis. Sakamot *et al.* (2005) analyzed time-series data of the enhanced vegetation index (EVI). Subsequent to data smoothing the points of maximum, minimal and inflection were then identified to examine phenological stages of paddy rice, which were then used to evaluate crop productivity and management. Soudani *et al.* (2008) examined vegetation phenological dates for deciduous forest stands using 250 m daily MODIS-NDVI data. Key phenological dates (*e.g.,* onset of green-up) matched well with in-situ observations. The level of temporal uncertainty for the MODIS-NDVI data is approximately 8-days. This MODIS-derived vegetation phenologycan be particularly useful for research in vegetation-climate interactions and modeling (Pettorelli *et al.,* 2005).

One potential sources of uncertainty in time-series studies is the error of mis-registration. Although the MODIS science team has substantially increased the registration accuracy over several reprocessing procedures, the 75–100 m mis-registraion error is still a substantial challenge for performing time-series analysis at the 250 m spatial resolution (Tan *et al.,* 2006). The impacts of mis-registration in time-series composite data can be even larger due to a potential 'multiplier effect' and the selection of pixels under different sun-sensor geometry angles. Therefore, it is important for users to understand these potential error sources. Additional research is needed to further our understanding of the cumulative impacts associated with MODIS data quality, sensor-sun geometry information, and mis-registration errors.

5. SUMMARY

The MODIS instrumental characteristics represent a new generation of sensor system for global observation. Global coverage of MODIS data are obtained every 1-2 days. The spectral, spatial, and radiometric resolutions are also substantially improved compared to previous global sensor systems such as the AVHRR. In addition to the spectral products commonly provided for all remote sensing platforms, the MODIS science team devoted tremendous efforts in developing a wide range of MODIS-derived scientific datasets that are readily available for scientific communities. MODIS data represent not only a 'continuity' remote sensing data record to extend previous sensor systems, but also a substantial improvement by integrating the most advanced remote sensing theory, algorithm development, data processing, validation and distribution.

A majority of current MODIS algorithms are operational at the global level. The data quality has been improving over several data reprocessing cycles. Validation of MODIS standard products is an ongoing effort by both the MODIS science team and independent researchers. Most validation work has suggested a high level of data quality for the MODIS products. This can be attributed to the improvement of spectral, spatial, temporal, and radiometric resolution, as well as advances in the algorithm development from the MODIS science team. The success of MODIS is also evident from the exponential growth of applications that use MODIS data products at global, regional, and local levels. Future development of MODIS data and algorithms may integrate more feedback from continuous data quality validation and applications. These include many potential topics such as sub-pixel analysis, scaling problems, biophysical applications, in-situ data integration (cloud, ice, water, and land data), and optical and climate modeling.

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Table 1. MODIS technical specifications including primary use, band numbers, band widths, spectral radiance, spatial resolutions, and signal-to-noise ratio.

Primary Use	Band	Bandwidth (μm)	Spectral Radiance (W/m2-μm-sr)	Signal-to-noise ratio (SNR)	Spatial Resolution at Nadir
Land/Cloud	1	0.620 - 0.670	21.8	128	
Boundaries	2	0.841 - 0.876	24.7	201	250 m
	3	0.459 - 0.479	35.3	243	
	4	0.545 - 0.565	29.0	228	
	5	1.230 - 1.250	5.4	74	
Land/Cloud	6	1.628 - 1.652	7.3	275	
Properties	7	2.105 - 2.155	1.0	110	500 m
	8	0.405 - 0.420	44.9	880	
	9	0.438 - 0.448	41.9	838	
	10	0.483 - 0.493	32.1	802	
	11	0.526 - 0.536	27.9	754	
	12	0.546 - 0.556	21.0	750	
	13	0.662 - 0.672	9.5	910	
Ocean Color/	14	0.673 - 0.683	8.7	1087	
Phytoplankton/	15	0.743 - 0.753	10.2	586	
Biogeochemistry	16	0.862 - 0.877	6.2	516	1000 m
	17	0.890 - 0.920	10.0	167	
Atmospheric Water	18	0.931 - 0.941	3.6	57	
Vapor	19	0.915 - 0.965	15.0	250	1000 m
Primary Use	Band	Bandwidth (μm)	Spectral Radiance	Required NEΔT(K)[1]	Spatial Resolution at Nadir
	20	3.660 - 3.840	0.45	0.05	
	21	3.929 - 3.989	2.38	2	
Surface/Cloud	22	3.929 - 3.989	0.67	0.07	
Temperature	23	4.020 - 4.080	0.79	0.07	1000 m
Atmospheric	24	4.433 - 4.598	0.17	0.25	
Temperature	25	4.482 - 4.549	0.59	0.25	1000 m
Cirrus Clouds	26	1.360 - 1.390	6.00	150[2]	1000 m
	27	6.535 - 6.895	1.16	0.25	
	28	7.175 - 7.475	2.18	0.25	
Water Vapor	29	8.400 - 8.700	9.58	0.05	1000 m
Ozone	30	9.580- 9.880	3.69	0.25	1000 m
Surface/Cloud	31	10.780 - 11.280	9.55	0.05	
Temperature	32	11.770 - 12.270	8.94	0.05	1000 m
	33	13.185 - 13.485	4.52	0.25	
	34	13.485 - 13.785	3.76	0.25	
	35	13.785 - 14.085	3.11	0.25	
Cloud Top Altitude	36	14.085 - 14.385	2.08	0.35	1000 m

[1]NEΔT(K) = Noise-equivalent temperature difference

[2]SNR