## Recent developments in estimating land surface biogeophysical variables from optical remote sensing

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# Recent developments in estimating land surface biogeophysical variables from optical remote sensing

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**Abstract:** Earth system models and many other applications require biogeophysical variables, and remote sensing is the only means by which to estimate them at the appropriate spatial and temporal scales. Developing advanced inversion methods to solve ill-posed multidimensional nonlinear inversion problems is critical and very challenging. This article reviews state-of-the-art algorithms for estimating land surface biogeophysical variables in optical remote sensing (from the visible to the thermal infrared spectrum) to stimulate the development of new algorithms and to utilize existing ones.

**Key words:** atmospheric correction, data assimilation, genetic algorithm, look-up table, neural network, reflectance modelling, remote sensing, vegetation index.

## I Introduction

Timely, high-quality, long-term global information from remote sensing benefits society in numerous ways. Geographers and scientists from other Earth science disciplines are developing various process-oriented models to characterize Earth system components. These models represent a consolidation of the scientific understanding of the range of physical processes driving the Earth system, that predict and relate knowledge useful in the policy and management decision-making processes of federal agencies and international organizations. To advance global and regional models at various scales and to improve their predictive capabilities, a variety of biogeophysical variables must be estimated from remote sensing observations that are used to calibrate, validate and drive these models.

This article provides a comprehensive review of the methodologies that were recently developed for estimating land surface biogeophysical variables from optical remote sensing – from the visible to the thermal infrared spectrum. The emphasis is on papers published in the last few years because the earlier literature has already been reviewed (Liang, 2004).

All inversion algorithms in the land remote sensing community are traditionally grouped into two categories: statistical and physical.

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Statistical algorithms usually consist of regression (linear or nonlinear) equations based on the correlation between land surface variables and remote sensing observations. Physically-based algorithms follow the physical laws and establish cause-and-effect relationships. They make inferences about model parameters based on general knowledge, such as radiation transfer models, and a set of remote sensing measurements. In general, these inversion problems are multidimensional and ill-posed (the number of unknowns is far greater than the number of observations), and they are often strongly affected by noise and measurement uncertainty. Because both types of algorithms tend to rely increasingly on surface radiation models, we provide a brief overview of model development at the beginning of this paper.

Land surfaces are characterized by both continuous variables (eg, albedo) and categorical variables (eg, land cover). Because of the scope of this article, we only discuss methods for estimating continuous variables. Thus, a large group of algorithms for estimating category variables, such as land cover/use and change detection mapping, are excluded from this article. Fortunately, Richards (2005) recently reviewed some of these algorithms. Because inversion is a common theme in many disciplines, the inversion methods reviewed in this article are helpful for remote sensing specialists, geographers and scientists in other disciplines.

## II Surface reflectance modelling

To formulate inverse problems and interpret inversion estimates, the following questions often needed to be addressed:

(1) How accurately is the land surface modelled?
(2) Does the model include all the physical effects that contribute significantly to the data?
(3) What is known about the model before the data are observed?
(4) What does it mean for a model to be reasonable?

Even after many years of efforts by the land remote sensing community, we still are not able to answer these questions completely. Most models are based on the detailed physical processes occurring on a point or plot scale, but remote sensing pixels cover a much larger area. More studies are needed to bridge this gap.

All land surface radiation models can be classified into three groups: radiative transfer (RT), geometric-optical (GO), and computer simulations. RT models work better for dense vegetation canopies, while GO models are more accurate for sparse vegetation canopies. The distinction between RT and GO models is becoming fuzzy because hybrid models that integrate RT and GO models have been developed. Computer simulation models require extensive computer resources and processing time and are appropriate for surface radiation simulations.

Developing new radiative transfer models has slowed significantly in recent years. An exhaustive review of the literature produced only a few publications describing new radiative transfer models, albeit in a wide variety of fields. For example, Pitman *et al*. (2005) applied the numerical RT algorithm to calculate quartz emissivity. Kokhanovsky *et al*. (2005) developed an approximate snow reflectance model based on the asymptotic solution to the RT equation. Li and Zhou (2004) simulated the snow-surface bidirectional reflectance factor (BRF) and hemispherical directional reflectance factor (HDRF) of snow-covered sea ice through a multilayered azimuth- and zenith-dependent plane-parallel RT model.

In the field of vegetation canopy studies, recent efforts are mainly focused on determining the three-dimension (3D) structure of the canopy field using one-dimensional (1D) models (Pinty, Gobron *et al*., 2004; Rautiainen and Stenberg, 2005; Smolander and Stenberg, 2003; Widlowski *et al*., 2005) or stochastic radiative transfer models (Kotchenova *et al.*, 2003; Shabanov *et al.*, 2005). Liangrocapart and Petrou (2002) developed a two-layer model of the bidirectional reflectance of homogeneous vegetation canopies, taking into account the anisotropic scattering of both the vegetation canopy and the background, such as bare soil or leaf litter. Community efforts to compare some vegetation radiative transfer models are ongoing (Pinty, Widlowski *et al.*, 2004; Widlowski *et al.*, 2007). Nilson *et al.* (2003) demonstrated the possible applications of a multipurpose forest reflectance model.

The classic GO models essentially characterize the interaction of direct solar radiation with land surfaces. Including diffuse radiation field into the GO model leads to a hybrid RT/GO models (Peddle *et al.*, 2004). The GO models have been recently used for classifying forest types and estimating biophysical parameters (Peddle *et al.*, 2004), and detecting forest structural change (Peddle *et al.*, 2003) from TM imagery, modelling soil reflectance (Cierniewski *et al.*, 2004), determining the gap fraction of forest canopy (Liu *et al.*, 2004), and estimating woody plant coverage of the grasslands (Chopping *et al.*, 2006) and background reflectance (Canisius and Chen, 2007) from multiangular observations. The same principle has also been used for topographic correction of remote sensing imagery in forested terrain (Soenen *et al.*, 2005).

There is not much progress in developing computer simulation models (eg, radiosity, Monte Carlo ray tracing), but several studies use this approach. For example, Casa and Jones (2005) estimated potato crop biophysical parameters using a look-up table created from a ray tracer. Borner *et al.* (2001) developed an end-to-end multispectral and hyperspectral simulation tool based on the ray tracing principle. Ray-tracing methods are used to simulate both optical and microwave signatures (Disney *et al.*, 2006) and to estimate forest structural parameters (Kobayashi *et al.*, 2007).

## III Statistical algorithms

Statistical algorithms are very useful in various remote sensing applications. All statistical algorithms are developed using either experimental data collected in the field or model simulations. Algorithms based on experimental data perform best for the conditions under which data are collected. Other conditions require interpolation and extrapolation. Ideally, experimental data is collected for a wide range of conditions, but financial and human resources and time constraints always limit data collection. As a result, the statistical algorithm ability to estimate and predict are usually associated with large uncertainties. Alternatively, physical-based models are used to simulate those 'experimental' data and empirical statistical algorithms are then established. This approach works, of course, only if physical models represent reality sufficiently well.

### *1 Algorithms based on indices*

Numerous indices-based biophysical algorithms have been proposed. A brief description of some of these algorithms follows. Gitelson *et al.* (2003) compared a series of indices and found the following three perform very well ($(R_{800}-R_{700})/(R_{800}+R_{700})$, $R_{860}/(R_{708} * R_{550})$ and $R_{750\text{–}800}/R_{695\text{–}740} - 1$). The last index is linearly related to chlorophyll concentrations. In a recent study estimating LAI and crown volume (VOL), Schlerf *et al.* (2005) demonstrated that linear regression models quantify LAI and VOL accurately for hyperspectral image data. Harris *et al.* (2005) used the floating-position water band index to estimate leaf water moisture. To assess the water content of vegetation, they also compared leaf water moisture to the normalized difference water index (NDWI) and the moisture stress index (MSI). The normalized difference snow index (NDSI) is an indicator of the snow cover (Salomonson and Appel, 2004). Chen, Zhang *et al.* (2005) developed a biological soil crust index (BSCI) that exaggerates the difference between biological soil crusts and bare sand, dry plant material or green plant backgrounds. Chikhaoui *et al*. (2005) recently proposed a 'land degradation' index to characterize land degradation in a small Mediterranean watershed using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data and ground-based spectroradiometric measurements.

### *2 Machine learning techniques*

Although the conventional multivariate regression analyses are widely used in land remote sensing, different machine learning methods and other advanced statistical analysis techniques are also used, such as *artificial neural network (ANN) methods* for estimating various biophysical variables (Fang and Liang, 2003; 2005); *genetic algorithms* for estimating LAI (Fang *et al*., 2003), *regression tree methods* for estimating fractional vegetation coverage (Hansen *et al*., 2002); *Bayesian networks* for estimating LAI (Kalacska *et al*., 2005), and *support vector machines* for estimating LAI from multiangular observations (Durbha *et al*., 2007). Most machine learning techniques (eg, ANN) are 'black-box' methods. The term 'black box' reflects an important drawback of these techniques, the lack of understanding of how the technique works. The full potential of machine learning techniques is unlikely to be realized without development of explanation capability.

## IV Physically-based inversion algorithms

### *1 Atmospheric correction*

Because the observed radiance recorded by a spaceborne or airborne sensor contains both atmospheric and surface information, atmospheric effects must be removed to estimate land surface biogeophysical variables. Atmospheric correction consists of two major steps: atmospheric parameter estimation and surface reflectance retrieval. Atmospheric correction is easier if all atmospheric parameters are known. The most challenging aspect of atmospheric correction is to estimate atmospheric properties (particularly water vapour content and aerosol optical depths) from the imagery.

The differential absorption technique is widely used to estimate the total water vapour content of the atmosphere directly from multispectral or hyperspectral imaging systems. The general idea is to utilize one spectral band in the water absorption region (eg, 0.94 μm) and one or more bands outside of the absorption region. In a recent study, Liang and Fang (2004) applied an ANN to estimate water vapour from hyperspectral data. Miesch *et al*. (2005) developed a water vapour correction algorithm for hyperspectral data using Monte Carlo simulations. Two thermal bands are used to estimate the precipitable water content by means of the split-window algorithm or simple ratio (Jimenez-Munoz and Sobrino, 2005; Li *et al*., 2003), although some evidence suggests that these formulae may not be stable under different conditions.

A relatively long history exists for estimating aerosol loadings from remotely sensed imagery. Besides various statistical methods, the physically-based methods recently developed include those using *spectral signatures*, such as the blue-band based method (eg, Hsu *et al*., 2004) and the hyperspectral method (Liang and Fang, 2004); *angular signatures* (Grey *et al*., 2006); and *temporal signatures* (Liang, Zhong *et al*., 2006; Tang *et al*., 2005; Zhong et al., 2007).

### *2 Optimization algorithms*

The optimization algorithms estimate the parameters (ψ) of the surface radiation model by minimizing the cost function defined as follows:

$$F^2 = \sum_{i=1}^{n} \varpi_i [R_i - f_i(\psi)]^2$$

where , $R_i$,i = 1,2,…n denote the remotely sensed signals (radiance, reflectance or brightness temperature), $\omega_i$ are the weighting coefficients, and $f_i(\psi)$ are the predicted values of the surface radiation model. After being provided with the initial values, a searching algorithm determines the parameter set $\Psi$ iteratively.

This approach is widely used by the land remote sensing community. For example, Gascon *et al*. (2004) estimated LAI, crown coverage, and leaf chlorophyll concentration from SPOT and IKONOS imagery, using a 3D canopy radiative transfer model. To reduce computational requirements, some parametric functions are determined using LUTs created by the 3D reflectance model. Meroni *et al*. (2004) applied this algorithm to invert LAI from hyperspectral data. Schaepman *et al*. (2005) inverted biophysical and biochemical variables from multiangular and hyperspectral remote sensing data using a coupled leaf-canopy-atmosphere radiative-transfer model. The multi-angle imaging spectroradiometer (MISR) science team also used this method to produce land surface products (Diner *et al*., 2005).

The high computational demands of the optimization approach have led to use of simpler surface reflectance models, rather than forcing optimization algorithm efficiencies. One of the general trends in optical remote sensing is to use simpler empirical or semi-empirical models. The optimization algorithms are used to estimate the parameters in these simple models. The parameters are then related to surface properties. For example, Widlowski *et al*. (2004) fitted a simple BRDF model to multiangular observations and then linked the surface structural properties to one of the parameters. Chen, Menges *et al*. (2005) used this approach to map the global clumping index from multiangular observations.

### *3 Look-up table algorithms*

Optimization algorithms are computationally expensive and very slow when inverting large amounts of remotely-sensed data. The look-up table (LUT) approach is used extensively to speed up the inversion process. It pre-computes the model reflectance for a large range of combinations of parameter values. In this manner, the most computationally expensive aspect can be completed before the inversion is attempted, and the problem is reduced to searching a LUT for the modelled reflectance set that most resembles the measured set.

This method is used for a variety of remote sensing inversion issues, such as atmospheric correction (Liang, Zhong *et al*., 2006), estimating LAI (Koetza *et al*., 2005) and incident solar radiation (Liang, Zheng *et al*., 2006). In an ordinary LUT approach, the dimensions of the table must be large enough to achieve high accuracy, which leads to much slower on-line searching. Moreover, many parameters must be fixed in the LUT method. To reduce the dimensions of the LUTs for rapid table searching, Gastellu-Etchegorry *et al*. (2003) developed empirical functions to fit the LUT values so that a table searching procedure becomes a simple calculation of the local functions. Alternatively, Liang *et al*. (2005) developed a simple linear regression instead of table searching for each angular bin in the solar illumination and sensor viewing geometry.

### *4 Data assimilation method*

Various published methods for estimating land surface variables have been described in previous sections. The values of these variables, estimated from different sources, may not be physically consistent. Most techniques cannot process observations acquired at different times and spatial resolutions. Most importantly, the techniques described thus far only estimate variables that strongly affect radiance received by the sensors. However, the estimation of some variables not directly related to radiance is desirable in many cases.

Given the ill-posed nature of remote sensing inversion (the number of unknowns is far greater than the number of observations) and the vast expansion of the amount of observation data, a challenge emerges: how best can observations derived from many different sources be combined and integrated? How will observations specific to location, time, and setting be connected to understanding that comes from a diverse body of nonspecific theory? Data fusion techniques that simply register and combine data sets from multiple sources may not be adequate to solve these pressing problems. The data assimilation method allows use of all available information within a time window to estimate various unknowns of land surface models (Liang and Qin, 2007). The information that can be incorporated includes observational data, existing pertinent *a priori* information, and, importantly, a dynamic model that describes the system of interest and encapsulates theoretical understanding. Data assimilation has been widely used in meteorology and oceanography, but more effort is needed to explore its potential for characterizing land surface environments in the land remote sensing community.

The meteorology and oceanography communities are at the forefront in developing and using data assimilation methods. In recent years, meteorologists and oceanographers have tended to view data assimilation as a model state estimation problem. The land community is aggressively trying to catch up and is now applying data assimilation methods. Examples of data assimilation in hydrology and water cycle research include the global land data assimilation system (Rodell *et al*., 2004) and the North American Land data assimilation system (Mitchell *et al*., 2004). Wang and Barrett (2003) developed a modelling framework that synthesizes various types of field measurements at different spatial and temporal scales to estimate monthly means and standard deviations of gross photosynthesis, total ecosystem production, net primary production and net ecosystem production for eight regions of the Australian continent between 1990 and 1998. Williams *et al*. (2005) developed a data assimilation approach that combines stock and flux observations with a dynamic model to improve estimates of, and provide insights into, ecosystem carbon exchanges. Rayner *et al*. (2005) developed a terrestrial carbon cycle data assimilation system for determining the space-time distribution of terrestrial carbon fluxes for the period 1979–1999. Hazarika *et al*. (2005) integrated the MODIS LAI product with an ecosystem model for accurate estimation of NPP. Validations of results in Australia and the USA show that NPP estimated using the data assimilation method is more accurate than estimates derived from the data 'forcing' method. Their research demonstrates the utility of combining satellite observations with an ecosystem process model to achieve improved accuracy in estimates and monitoring global NPP. Fang *et al*. (forthcoming) assimilated MODIS LAI product into a crop growth model for estimation of crop yield by determining some critical parameters of the crop model.

## V Algorithms for estimating specific biogeophysical variables

Section IV provides an overview of several inversion algorithms. This section shows how these algorithms are used for estimating a group of biogeophysical variables from various remote sensing data.

### *1 Mapping LAI and FPAR*

LAI characterizes vegetation canopy function and energy absorption capacity. For these reasons, LAI is used as a variable in most land surface process models. A common procedure to estimate LAI is to establish an empirical relationship between vegetation indices (VI) and LAI by statistically fitting observed LAI values to the corresponding VI.

Besides the VI-based statistical model, all other inversion methods mentioned in Section IV are used to map LAI. Several instrument science teams provide global LAI maps. MODIS, MISR, Advanced Very High Resolution Radiometer (AVHRR), MERIS, Polarization and Directionality of the Earth's Reflectances (POLDER) and VEGETATION are among the notable satellite instruments that provide the LAI product with various spatial and temporal resolutions (Bacour *et al*., 2006; Deng *et al*., 2006; Fang and Liang, 2005; Kalacska *et al*., 2005; Koetz *et al*., 2007; Plummer and Fierens, 2006).

Foliage clumping, a parameter related to LAI, is an important forest structural canopy attribute. It affects both the gap fraction for LAI, radiation interception and distribution within the canopy, which in turn affect photosynthesis. Chen, Menges *et al*. (2005) mapped the global clumping index from multiangular POLDER data.

The fraction of the absorbed PAR by green vegetation (FPAR) is recognized as one of the fundamental terrestrial variables in the context of global change science. Many production efficiency models for calculating gross primary productivity (GPP) and net primary productivity (NPP) are based on the following formulation: $GPP/NPP \propto FPAR \cdot PAR$. Multiple satellite sensors and a variety of methods are used to generate FPAR products (Bacour *et al*., 2006; Gobron, Pinty *et al*., 2006; Plummer and Fierens, 2006).

### *2 Mapping fractional vegetation coverage*

Fractional green vegetation coverage is a critical variable that is used for parameterization in biogeochemical modelling and various other applications. Generating an accurate global product is a challenge. Various methods are used to estimate this parameter from numerous sensors, such as AVHRR (Zeng *et al*., 2003), MODIS (Hansen *et al*., 2002), MERIS (Bacour *et al*., 2006), MISR (Chopping *et al*., 2006; forthcoming), and other sensors (Danson *et al*., 2007; Garcia-Haro *et al*., 2006; Koetz *et al*., 2007; Morsdorf *et al*., 2006; North, 2002).

### *3 Mapping broadband albedo*

Land surface broadband albedo is a critical variable affecting the Earth's climate and is still among the main radiative uncertainties of current climate modelling (Dickinson, forthcoming; Wang *et al*., 2006). The surface of the Earth absorbs roughly twice as much solar radiation as the atmosphere, and land surface albedos largely modulate the surface absorptance. It is well recognized that surface albedo is among the main radiative uncertainties of current climate modelling.

A typical albedo mapping algorithm, such as that used for generating the MODIS albedo product, includes three components (Schaaf *et al*., 2002): (1) an atmospheric correction that converts top-of-atmosphere (TOA) radiance to surface directional reflectance, (2) BRDF modelling that converts directional reflectance to spectral albedos, and (3) a narrowband to broadband conversion that converts spectral albedos to broadband albedos. Atmospheric correction algorithms are discussed in Section IV.1, and surface BRDF modelling is also briefly covered in Section II. Various statistical formulae exist that convert narrowband albedo to broadband albedo (Liang, 2004). Using a physical approach, albedo product depends on the performance of all the procedures that characterize the known processes, such as performance of the atmospheric correction and the accuracy of the angular model used to describe the directional distribution of the reflectance. It is unknown whether errors associated with each procedure cancel or enhance each other.

Instead of retrieving most of the variables explicitly from remote sensing data, an alternative method to physically-based retrieval is to combine all procedures together in one step through regression analysis aiming only to make a best-estimate broadband albedo. The direct retrieval method primarily consists of two steps (Liang, 2003; Liang *et al*., 2005). The first step is to produce a large database of TOA directional reflectance and surface albedo for a variety of surface and atmospheric conditions using radiative transfer model simulations. The second step is to link the simulated TOA reflectance with surface broadband albedo using nonparametric regression algorithms (eg, neural networks and projection pursuit regression) or linear regression analysis. This method will be used for producing the albedo product from VIIRS in the future. Land surface albedo can also be mapped from multiangular sensors, such as MISR (Diner *et al.*, 2005), and geostationary satellite data (Govaerts and Lattanzio, 2007; Govaerts, Lattanzio *et al.*, 2004). Samain *et al.* (2006) created a consistent albedo product by integrating multiple satellite data from MODIS, VEGETATION and MERIS. Jacob and Olioso (2005) estimated the albedo diurnal cycle from airborne POLDER data.

### 4 *Mapping incident solar radiation*

Incident solar radiation, either PAR in the visible spectrum (400–700 nm) or insolation in the total shortwave (300–4000 nm), is a key variable required by almost all land surface models. Many ecosystem models calculate biomass accumulation linearly proportional to incident PAR. Information on the spatial and temporal distribution of PAR, by control of the evapotranspiration process, is required for modelling the hydrological cycle and for estimating global oceanic and terrestrial NPP.

The only practical means of obtaining incident PAR at spatial and temporal resolutions appropriate for most modelling applications is through remote sensing. Methods to calculate incident solar radiation fall into roughly two types. The first approach is to use the retrieved cloud and atmosphere parameters from other sources, with the measured TOA radiance/flux acting as a constraint. The Clouds and Earth's Radiant Energy System (CERES) algorithm (Wielicki *et al.*, 1998) employs the cloud and aerosol information from MODIS, and TOA broadband fluxes as a constraint, to produce both insolation and PAR at the spatial resolution of 25 km with the instantaneous sensor footprint. The ISCCP has produced a new 18-year (1983–2000) global radiative flux data product called ISCCP FD, constructed for a repeating three-hour period on a 280 km equal-area global grid (Zhang, Rossow *et al.*, 2004). ISCCP FD is calculated using a radiative transfer model from the Goddard Institute for Space Studies General Circulation Model (GCM) using the atmosphere and surface properties obtained primarily from TIROS Operational Vertical Sounding data.

The second approach to calculating incident solar radiation is to establish the relationship between the TOA radiance and surface incident insolation or PAR based on extensive radiative transfer simulations. This method was first applied to analyze Earth Radiation Budget Experiment (ERBE) data. Liang, Zheng *et al.* (2006) generated the PAR and insolation products at 1 km from MODIS data directly using a similar approach. Liu *et al.*, (2007) revised this approach to map incident PAR and insolation over China. This algorithm has also been extended to GOES data (Zheng *et al.*, forthcoming) and is being revised for other satellite data (eg, AVHRR, SeaWiFS) as well.

### 5 *Mapping downward thermal radiation*

Downward longwave radiation is a crucial component in energy balance calculations. Total downward radiation must include longwave thermal radiation in addition to the insolation discussed in the previous section. Downward thermal radiation is normally taken from the atmospheric forcing data that are usually calculated from the GCM models resulting in large errors at fine spatial resolution. The accurate product has to be estimated from satellite observations directly.

There have been several comprehensive reviews of methods for estimating surface thermal radiation from satellite data (eg, Diak *et al.*, 2004). The downward longwave radiation algorithms include three types. The first type consists of empirical functions using satellite-derived meteorological parameters, for example, the near-surface temperatures and water vapour burden. The second type calculates the radiation quantities with radiative transfer models using satellite-derived soundings. An important feature of this approach is the validity of the physics. The third type uses satellite-observed radiances directly to avoid the propagation of retrieval errors of meteorological parameters into the final radiation estimate (Lee and Ellingson, 2002). It embeds the physical merits of radiative transfer within the parameterization of nonlinear functions of observed radiance.

*6 Mapping emissivity and skin temperature*

Upwelling thermal radiation mainly depends on the land surface temperature (LST, T) and emissivity (ε):

$$F_u = (1-\varepsilon)F_d + \varepsilon\sigma T^4$$

where $F_d$ is downward thermal radiation and σ is a constant. For dense vegetation and water surfaces, broadband emissivity is almost one (0.96–1). For non-vegetated surfaces, ε is much less than one. Unfortunately, most GCMs and land surface models assume a constant emissivity, which can lead to large errors in net radiation and other quantities (Jin and Liang, 2006).

Estimating both emissivity and land surface temperature simultaneously from thermal infrared remotely-sensed data is very challenging. Radiance received by the sensor contains information about the atmosphere (eg, temperature and water vapour profiles) and surface properties (emissivity and LST). Therefore, the first step for retrieving surface emissivity and LST is to perform an atmospheric correction. The second step is to separate emissivity and temperature from the retrieved surface leaving radiance.

For two-thermal-band sensors, such as AVHRR and GOES, a known emissivity is assumed (or inferred from land cover maps or vegetation indices) to estimate LST using a split-window algorithm. Fortunately, the new generation of sensors, such as ASTER and MODIS, has multiple thermal bands that allow estimation of spectral emissivities and LST simultaneously. The MODIS land team developed two approaches for retrieving LST and emissivity (MOD11). The MODIS atmospheric temperature profile product (MOD07) (Seemann *et al*., 2006) also includes LST. In our recent validation study, Wang *et al*. (2007) found that the MOD07 and MOD11 products have comparable accuracy.

LST can also be estimated from other sensors, such as TM (Sobrino, Jimenez-Munoz *et al*., 2004), SEVIRI (Sobrino and Romaguera, 2004), AVHRR (Jin, 2004; Pinheiro *et al*., 2006), ATSR (Jimenez-Munoz and Sobrino, 2007; Sobrino, Soria *et al*., 2004), AATSR (Coll *et al*., 2006), GOES (Sun *et al*., 2004), GMS (Oku and Ishikawa, 2004) and VIIRS (Yu *et al*., 2005).

Because the land surface is not homogeneous at the resolution of about 1 km, the subpixel temperature and emissivity must be considered. Most land surface process models (eg, Bonan *et al*., 2002; Dai *et al*., 2003) that calculate surface energy balance, use several component temperatures, such as soil skin temperature, sunlit canopy temperature, and shadow temperature. No practical algorithms are developed to effectively estimate these component temperatures from remote sensing data at this time (Jia *et al*., 2003), but some modelling studies on mixed emissivities are reported (Chen *et al*., 2004; Su *et al*., 2003; Zhang, Li *et al*., 2004).

Another issue is the directional properties of LST and emissivity. Effects caused by shading and differential heating are understood well at fine spatial scales (Guillevic *et al*., 2003; Lagouarde *et al*., 2004; Soux *et al*., 2004; Yu *et al*., 2004), but are usually overlooked or ignored at coarser scales. Good models exist for understanding shading and differential heating effects in structured scenes, such as orchards and urban environments. There is a considerable body of evidence supporting the notion of angular variation in the emissive properties of many natural materials and surfaces.

*7 Mapping all-sky all-wave net radiation*

For all land surface and hydrological models that are based on surface energy balance, net radiation is a required quantity, but users have to calculate it from multiple satellite products. It is easy to compute surface net radiation (shortwave, longwave and total) by combining products using the previously described algorithms. Surface shortwave net radiation can be calculated from insolation ($F_d^s$) and upwelling radiation ($F_u^s$) or the total shortwave broadband albedo ($\alpha$):

$$\Delta F^s = F_d^s - F_u^s = F_d^s(1-\alpha)$$

Longwave thermal net radiation can be calculated based on the methods in Sections V.5 and V.6. Both methods are suitable only for clear-sky conditions. Cloudy-sky thermal net radiation can be determined from shortwave net radiation. A number of scientists have tested estimation methods, and the most successful ones are simple linear regressions (Offerle *et al*., 2003) using either insolation or shortwave net radiation. Although coefficients vary slightly from one site to another, the overall fits are excellent (Alados *et al*., 2003). Thus, these components calculate all-sky, all-wave net radiation well.

## VI Discussion

This review is incomplete if we fail to discuss calibration, geometric processing, and validation. Quantitative remote sensing requires accurate radiometric calibration. Pre-launch instrument characterization, onboard (inflight) calibration, vicarious calibration, and inter-instrument cross-calibration (Chander *et al*., 2004; Pan *et al*., 2004; Thome *et al*., 2003) are all critical components of a calibration system. Recent publications on this subject include vicarious calibrations for many different satellite sensors (eg, Barsi *et al*., 2003; Biggar *et al*., 2003; Govaerts, Clerici *et al*., 2004; Martiny *et al*., 2005; Murakami *et al*., 2005; Ohde *et al*., 2004; Thome *et al*., 2004).

Validation of the model, inversion algorithm, and product is also critical in quantitative remote sensing. Although the model may be developed at the local scale and validated using limited measurements, its application to regional or global scales from local studies is essentially an extrapolation problem. Extensive validation ensures the success of extrapolation. The inversion algorithms, based on 'training' data under certain conditions, may not work well for other conditions. Characterizing the uncertainties of land surface high-level products is important not only for their applications but also to evaluate different algorithms. A special issue of the *IEEE Transactions on Geosciences and Remote Sensing* was devoted to validation of remote sensing land products (Morisette *et al*., 2006). A novel method is needed to generate high-level products by taking advantage of the strengths of different algorithms without introducing their weaknesses.

Geometrical registration of multiple data sources is another critical issue because many algorithms must deal with remote sensing data with different spectral, spatial, and angular characteristics. No details are provided here, because there are several review articles on this subject (Toutin, 2004; Zitova and Flusser, 2003).

## VII Concluding remarks

The immense amount of data available from satellite observations offers promise yet also presents great challenges. Considerable time and effort is invested into developing physical models to understand surface radiation regimes. State-of-the-art remote sensing modelling and inversion are well advanced. Some of these models have been incorporated into useful algorithms for estimating land surface variables from satellite observations.

Developing realistic and computationally simplified surface radiation models suitable for inversion of land surface variables from satellite data is urgently required. Experimental data that represent the actual values of the land surface biogeophysical variables are usually limited and noisy, thus, adequate error characterization, although difficult, is imperative. Choosing a forward modelling procedure is crucial to adequately describe observations. It is also important to know how many model parameters are required and which parameters are the most significant.

Another issue is model error. We are uncertain not only about values of the numerous model parameters, but also about the model parameterizations and the model errors.

Inversion of land surface parameters is generally a nonlinear, ill-posed problem, and solving a multidimensional, ill-posed inversion problem is very challenging. Use of regularization methods by incorporating *a priori* knowledge and integrating multiple-source data from different instruments with different spatial, spectral, temporal, and angular signatures deserves further research. One emerging area is the data assimilation method that synthesizes diverse, temporally inconsistent, and spatially incomplete remotely-sensed data products into a coherent representation of an evolving dynamic system. Data assimilation methods incorporate a prior knowledge into the inversion process objectively, and account for errors in both data products and the physical models. Although studies on error incorporation in land optical remote sensing are in at early stage, they appear very promising.

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