Image Brightness & BRDF Workshop Issues

David L B Jupp & Alan Strahler

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1. ATMOSPHERIC & SCENE BRIGHTNESS VARIATIONS

Optical, shortwave and thermal image data from airborne and satellite platforms have varying degrees of angle dependent brightness variation which change with the sun position, atmospheric conditions, land surface type and sensor characteristics. If left uncorrected, these broad level variations can make it difficult to use the data with standard image processing and interpretation methods.

For example, a Daedalus airborne scanner has a scan angle of ±38° and if flown with the sun at an azimuth away from 'in front' or 'behind' (i.e. away from the Principal Plane) this will result in significant image brightness variations created by the atmospheric component phase functions and any surface angle dependent reflectance effects. The reflectance function describing the surface effects is the Bi-Directional Reflectance Distribution Function, or BRDF. These atmospheric and surface effects are present in all satellite data as well as aerial photography and video data to a greater or lesser degree depending on the variation in the phase angle between the sun, target and sensor among the pixels in the resulting image. Topography enters into the equation in a way that depends on scale (or pixel size) leading to quite complex variations in an image being scanned.

The atmosphere contributes to the total effect partly due to the varying path length at different parts of the scan and partly to the atmospheric scattering phase variation described by the composite phase function of the atmospheric constituents. This describes the way radiation is scattered out of a volume relative to the direction it enters. In optical remote sensing, air molecules and aerosols account for much of the scattering and the effects are greatest at shorter wavelengths. Hence, if the aerosol atmospheric turbidity is high, the atmospheric brightening in (say) the blue-green will be visible and significant in most remotely sensed data. In the thermal bands, the angular variation is almost all due to the changing path length and the major atmospheric effect is due to water vapour on the path.

The land surface contributes to the broad level brightness variations common to all remotely sensed images. The base 'colour' and brightness is a function of the spectral properties of the material types making up the scene (e.g. leaf reflectances and transmittances or soil grain mineralogy) plus structural effects which give rise to the angular variations. The angular effects can be ascribed to three main factors - the volume effect, the occlusion (or hotspot) effect and the specular or glint effect:

- **Volume Effect**: Because of the changes in path lengths and extinction in complex surfaces as the relative sun and look angles change, there is a volume BRDF which has some similarity to the atmospheric phase function induced variations. It will depend on surface structure and in vegetation it depends on factors like leaf density variations and angle distributions as well as total leaf area.
- **Occlusion Effect**: The occlusion effect is a more specific effect induced by the fact that the shadows cast by the sun represent parts of the surface that are not 'seen' by the sun. The areas that are not 'seen' by the sensor which are also not 'seen' by the sun are the common areas between shadow cast by the sun if it were in the two positions. The varying overlap induces a brightness variation as when the sun and sensor are aligned, no shadows are 'seen' and the scene seems bright and when the look angle is opposite to the sun many shadows are 'seen' leading to lower brightness.
- **Specular (or Glint) Effect**: The specular or glint effect is most pronounced on water surfaces. It refers to the surface 'mirror' (or Fresnel) reflectance in which the radiation is usually unaltered by the surface material from which it is reflected. On land surfaces it is a composite of reflections diffused from facets of varying angular positions and specularity. In Australia, Eucalypt leaves are especially specularly reflective due to their waxy coating. On water, glint is probably the major component of the BRDF and the hotspot effect does not occur.

The sum of these effects in remotely sensed data is an image brightness variation that is a sum of the atmospheric brightness and the scene brightness. The atmospheric and surface effects also interact to provide a composite effect that varies with sun, target & sensor geometry. The effects are more obvious in aerial photography and video images where the central perspective means that at high sun angles the hotspot and specular points are within the angular radius of the frame. For airborne scanners and satellite borne scanners it is possible to avoid the brightest hotspot and glint points by careful consideration of the scan geometry but since the variations are significant for all angles the effects cannot be ignored in any image.

The scene and atmospheric brightness variations are all minimised for a scanner if the sensor data are scanned at right angles to the 'principal plane'. The principal plane is the plane formed by the vectors joining the earths centre to the sensor and to the sun. For an airborne scanner, this means flying level, with the sun in front or behind the flight line. If the hotspot or specular points need to be avoided at high sun times, the scanning sensor is sometimes tilted forward or back to ensure it. These 'avoiding' strategies are not easily used with photography or video images.

2. APPLICATIONS DEMANDING ATTENTION

Applications using images which have wide scan angles or are captured when the sun and observer positions are such that these angular variations are significant must take them into account or correct the images for them in some way. Examples are:

- Single scenes where classification and other image processing is predicated on consistent values from similar target land or water types;
- Mosaics of images which are intended to produce a consistent composite image on which spectral (location independent) image processing can be done; and
- Multiple images, such as time series where the data must be compared for change in the surface that must be detectable over changes due to image brightness differences within and/or between images.

In a sense, the objective is to ensure a spatial and temporal 'stationarity' in which a given target with given unchanging reflectance will be the same at all locations and in all images over the time series. Obviously, the degree to which this needs to be accomplished depends on the application, and the value of spending time and effort on image correction depends on the value put on the final product by the client.

From the economic perspective, there will always be

1. project planning and management costs;
2. image and ancillary data acquisition costs;
3. data base processing costs;
4. value adding costs;
5. data integration costs; and
6. product presentation costs.

The total cost must reflect the value of the product to the end user. If the emphasis is on low costs the effort justified by correcting for, or using, effects like image brightness variations may be small. On the other hand, if the accuracy of the product is crucial and the value of the information is high then extra effort in correcting for image brightness may be fully justified. In the face of this, there are a range of approaches and methods that can be used to model or correct the type of brightness variations described above. Which among them is 'best' will depend on the application and value of the data.

3. TYPOLOGY OF APPROACHES

The general approach to image brightness is to 'correct' it in some way. Correction means changing a pixel spectrum so that it is what would have been measured if the sun and sensor geometry were a fixed standard pair rather than a varying pair of angles over the image extent. As discussed later, this action may be valid as an average over a spatial area but can be a difficult concept at the scale of a single tree crown or soil clump.

We will outline three main approaches to scene brightness modelling and 'correction'. They are the empirical methods, the measurement modelling methods and the semi-empirical methods.

3.1 Empirical Methods

Empirical methods involve fitting the variation in general brightness ascribed to the atmosphere and BRDF effects by a parametric function (using least squares or some other criterion) and then normalising by some combination of additive and multiplicative image transformation. The simplest methods involve fitting polynomials to average variations over scanlines or frames and subtracting or dividing out the general level to 'flatten' the data. These methods are well known and have been used with single frame photographs or scanner runs prior to other image processing operations.

For mosaics, brightness normalisation has a strict analogy with geometric mosiacking where images are geometrically matched to the ground by ground control points (ie GCPs) and to other images by tie points. At tie points, in geometric mosaicking, the constraint is that the same feature must be located at the same point in the geometric frame model. In the same way, in brightness normalisation, there may be targets in some frames of known reflectance. These are sometimes called 'invariant targets'. When their reflectance is only assumed from previous work they are sometimes called 'pseudo-invariant' targets. These are analogous to GCPs. In the overlap between frames, the analogy to tie points are patches or features that are assumed to have the same corrected spectra. For a given functional form of brightness model, the estimation reduces to a linear 'bundle adjustment'.

The greatest problems with the simple empirical approach are image variance and heterogeneity. It is often extremely difficult to determine which components of the variation are atmospheric or BRDF brightening and which are differences in surface type. The high image spatial variance that is most obvious in high resolution images also makes fitting functions very difficult. Another problem is to decide which effects are additive and which are multiplicative. As long as the variation is not too great, the additive approximation is not too bad but when raw uncalibrated data are used, the interaction between additive and multiplicative effects can be a problem.

For example, calibration and atmospheric correction are linear effects but the atmospheric terms are angle dependent and vary with incident (μ_i) and view (μ_v) directions. That is, even if the surface were lambertian (with a flat BRDF) the digital data recorded by a scanner in waveband j (dn_j) will be related to the reflectance (ρ_j) by:

$$L_j = \alpha_j \; dn_j + \beta_j$$

$$L_j = \frac{1}{\pi} E_T^*(\mu_i)\, T(\mu_v) \rho_j + L_p(\mu_i, \mu_v)$$

hence

$$dn_j = \gamma_j(\mu_i, \mu_v)\, \rho_j + \delta_j(\mu_i, \mu_v)$$

where

L_j is the radiance recorded in waveband j;

μ_j is the sun or 'incident' radiation direction;

E_T^* is the total irradiance at the target; and

L_p is the radiation scattered into the sensor from the atmosphere.

The brightness variation described here (which has no surface BRDF effect in that ρ_j is not dependent on sun or view angles) obviously has both additive and multiplicative terms which are complex functions of the incident and view angles. When the surface target itself has a strong BRDF effect the variability will compound.

In the face of this, the empirical methods are generally constrained to be of low order functional forms that still have the structure of the variation being fitted. In this way, it is hoped that variance and image heterogeneity are 'orthogonal' to the function being fitted. In addition, the fitting is best done in the physical framework of the brightness variation - that is in terms of the phase angles between sun and sensor view angle and between sensor view angle and the specular vector. There have been many functions of this type developed such as Walthall, Hapke, Roujean and others. These will be addressed below in the section of semi-empirical methods.

For the purely empirical approach and for small frames such as occur with aerial photography and video data (or even single scanner runs) the main problem is scene heterogeneity. There will be scene variations that occur at spatial scales near to or greater than the image and it is very difficult to separate these effects from atmospheric and broad BRDF effects. To illustrate this you can consider an image to be roughly approximated by:

$$I = I_H + I_L + I_A$$

where I_H is the high spatial frequency component, I_L is the low frequency component and I_A is the angular brightness variation. In many images, over the extent of a single frame, the low frequency and angular components are not in any way orthogonal. Hence it is near impossible to estimate the angular function from the single frame data. Moving to models based on view geometry and semi-empirical functions can help (Pickup *et al.*, 1995) but essentially some way to bring in the wider spatial context is needed.

Among empirical methods are also 'referencing' methods. In the case of image digitising, a reference approach is to scan an image and scan a reference (white lambertian) standard sheet with the same illumination. The image is then 'normalised' by subtracting or dividing the reference from the image to remove lighting based view angle effects. In reconnaissance image data this is not possible unless a large reference target were to exist and scene BRDF effects would still remain. Hick and Ong (Ong *et al.*, 1995) have used a referencing method to extract brightness variations from video frames by referencing against the background of a Landsat TM image. It may be possible to fit empirical functions to the residual between the individual frame and the reference image. In this way, the problem of heterogeneity and correlated spatial frequencies described above could be reduced significantly.

It is worth mentioning here that as soon as the empirical methods extend from simple functional forms to ones involving image and sun geometry, the processing methods start to become more costly. The cost is in extra work registering images and/or in extra costs associated with collecting attitude and position (eg INS and GPS) information for the platform. If it is worth this extra cost then it may be worth some extra modelling as discussed below.

3.2 Measurement Model Approach

3.2.1 Atmospheric Correction & Reflectance Normalisation

It would clearly be an advantage to model the atmospheric and BRDF effects by physical models and estimate the corrected image in terms of a normalised reflectance factor. The added value would be the link this gives to physical models of the relationship between earth parameters of interest and the measured reflectance. Obviously, a reflectance is closer to a material property and therefore resolves the problem of monitoring.

If reference targets in the image have measured reflectances (ie the invariant or pseudo-invariant targets) it is possible to get close to reflectances from the empirical approach. However, it will never be clear how much residual atmosphere and BDRF effect remains. Obviously, most natural targets chosen as ‘invariant’ will have some BRDF which may not be known and that effect will be folded into the final image data.

Assuming the data are accurately calibrated to radiances, there are different ways to describe the process of correction. One is as follows:

An equation relating the recorded radiance sensed at altitude h above the target to the target reflectance factor is:

$$L_t(\mu_v,\mu_s,h,\lambda) = \frac{1}{\pi} E_T^*(\lambda)\, t(\mu_v,h,\lambda)\,(\rho_t + \rho_{env}) + L_p(\mu_v,\mu_s,h,\lambda)$$
$$\left[+ L_g(\mu_v,\mu_s,h,\lambda)\right]$$

where:

$L_t(\mu_v,\mu_s,h,\lambda)$ is the radiance observed by the instrument from altitude h, with look (or view) direction μ_v and sun direction μ_s at wavelength λ;

E_T^* is the effective irradiance at the target, or

$$E_T^*(\lambda) = \frac{E_T(\lambda)}{1 - s\,\rho^*}$$

where:

$E_T(\lambda)$ is the irradiance at the target for a 'black' earth;

s is the sky hemispherical albedo; and

ρ* is the background earth albedo.

$t(\mu_v, h, \lambda)$ is the beam transmittance through the layer between the surface and altitude h in direction μ_v;

ρ_t is the target directional reflectance factor;

ρ_{env} is the environmental reflectance due to the background albedo ρ^* or:

$$\rho_{env} = \rho^* \left[\frac{T(\mu_v, h, \lambda)}{t(\mu_v, h, \lambda)} - 1 \right]$$

$T(\mu_v, h, \lambda)$ is the diffuse transmittance for a layer of thickness h and for initial beam direction μ_v.

$L_p(\mu_v, \mu_s, h, \lambda)$ is the path radiance of light which did not interact with the surface; and

$L_g(\mu_v, \mu_s, h, \lambda)$ is the glint term that is most significantly present over water covered targets and is sometimes present over land targets.

If the atmosphere is characterised then it is possible to retrieve the directional reflectance factor (ρ_t) for each pixel. This term needs careful definition as there are many different types of 'reflectance' used.

The directional reflectance factor (ρ_t) as used here is defined as:

$$\rho_t(\mu_s, \mu_v, f_d, \lambda) = \frac{\pi\, L(\mu_v, \lambda)}{E_T^*(\mu_s, f_d, \lambda)}$$

in which the irradiance (E_T^*) is the sum of diffuse and direct terms and the fraction of diffuse (fd) is included as a parameter. The assumption that the irradiance can be characterised in this context by the sun position and the fraction of diffuse radiation is one that needs evaluation. The value of using this form of reflectance is that it corresponds to what is measured in the field using an irradiance radiometer or a reference standard.

The physical approach depends on two steps. The first is to determine this reflectance factor for a surface by atmospheric correction. In atmospheric correction, the atmospheric terms are modelled and measured from image and ancillary data. The reflectance factor in an image may be obtained iteratively if the atmospheric turbidity makes the adjacency and other atmosphere/surface interactions significant. The second step is to normalise the reflectance factor in some way to account for its BRDF variation.

In order to go from the reflectance factor to such a corrected value, however, we effectively need to assume that:

$$\rho_t(\mu_s,\mu_v,f_d,\lambda)=\rho_t^0(\lambda)\,\iota(\mu_s,\mu_v,f_d,\lambda)$$

where $\iota(\mu_s,\mu_v,f_d,\lambda)$ is the angular variation function that is assumed to characterise the land surface type and be normalised to 1.0 at a reference pair of sun and view angles and standard atmosphere. Then 'corrected' data are reachable as:

$$\rho_t^0(\lambda)=\frac{\rho_t(\mu_s,\mu_v,f_d,\lambda)}{\iota(\mu_s,\mu_v,f_d,\lambda)}$$

The value of getting to this point is that both $\rho_t^0(\lambda)$ and $\iota(\mu_s,\mu_v,f_d,\lambda)$ can be interfaced with radiative transfer models to obtain parameters for the earth's surface by inversion. The inversion may be simple (such as end member methods) or sophisticated (such as complete nonlinear modelling).

This physical approach is obviously highly sophisticated but demands a level of data quality and time in value adding that sometimes cannot economically be committed. However, if the end products are of high information value and valued by the client it is clearly an approach that could be pursued.

3.2.2 Analytic BRDF Models

Assuming the atmospheric correction can be done (and the surface interaction needs to be flagged here as the coupling means the atmospheric correction and surface BRDF estimation are not independent) the surface BRDF can sometimes be defined by an analytic model.

Among the many models for the volume effect are the Suits and Sail models as well as many more sophisticated ones such as the hotspot based model described (as an example) in Qin and Jupp (1993). The literature is vast (Myneni and Ross, 1990 provides a very good review although it is becoming dated!).

The hotspot effect is a geometric or occlusion effect and from among the many papers that exist describing it the following text has been editied and extracted from Jupp and Walker (1996).

"A simple model for the remote sensing of a canopy is the Geometric Optical (GO) model. The simple GO (or hotspot) model for scenes which describe open forest or woodland areas is based on the one described in Jupp *et al.* (1986), Strahler and Jupp (1991a&b) and Li and Strahler (1992). In this model, there are four kinds of ground cover 'visible' from a given direction. These are referred to as scene components and consist of sunlit canopy (symbol *sc*), shaded canopy (*shc*), sunlit background (*sb*), and shaded background (*shb*). Each component is assumed to have a characteristic radiance and the radiance of a pixel is modelled as the area weighted combination (or linear mixture) of the characteristic component radiances. That is, the observed radiance of a single pixel (r_S) is modelled as:

$$r_S=k_{sc}R_{sc}+k_{shc}R_{shc}+k_{sb}R_{sb}+k_{shb}R_{shb}$$

where the subscripts *sc*, *shc*, *sb*, and *shb* indicate the radiances of the four components as named above, R_j represents the (mean) radiance of component ‘j’ and k indicates the sensed proportion of each component within the pixel from the given view direction.

The mean radiance over the scene (R_S), assuming the view and sun directions are constant, can be written as:

$$R_s = K_{sc}R_{sc} + K_{shc}R_{shc} + K_{sb}R_{sb} + K_{shb}R_{shb}$$

where, capital K_j represents the mean or expected value of the varying proportions k_j over the scene for j as the components *sc*, *shc*, *sb* or *shb*. The mean value (R_s), as a function of sun and observer position, defines the BRDF of the scene.

In order for the scene BRDF model to be computed, a description of the size and shapes of the objects, their density and how they are distributed over the background is needed and the geometrical relationships between the objects and the expected values of the four components must be established. Jupp *et al.* (1986), Strahler and Jupp (1991a&b) and Li and Strahler (1992) describe such a model for spheroidal crown (not necessarily opaque) volumes which is valid for any view or illumination angles using the ‘Boolean’ model of Serra (1982). In the Boolean model, the object ‘centres’ are assumed to be randomly distributed in a ‘Poisson’ distribution. By defining the geometry and the distributions, expressions for K_j may be derived. Strahler and Jupp (1991a&b) use a simple model for spheroids which is adequate for moderate sun and view zenith angles and Li and Strahler (1992) provide some more general alternative models for resolving the K_j. These basic scene BRDF models are quite simple and are easily implemented in various forms such as mathematical packages or spreadsheets.

In the woodlands and open forest areas typical of the area of Australia where the model studies have been made, the pixel to pixel behaviour of the image is conveniently (if not as accurately) described by a simpler form of the model in which the shaded background, sunlit (but still relatively dark) tree and shaded tree components are combined into one so that:

$$r_s = R_X + k_{sb}(R_{sb} - R_X)$$

where X is a composite component combining sunlit and shaded tree and shaded background and R_X. is computed as:

$$R_X = \frac{K_{sc}R_{sc} + K_{shc}R_{shc} + K_{shb}R_{shb}}{1 - K_{sb}}$$

The simpler model has the advantage for this discussion that it shows clearly how, in many woodlands, the image pixel to pixel variation is driven primarily by the variation in the proportion of sunlit background which is visible in the pixels and the contrast between this sunlit background and the other components. It also provides a simple estimate for k_{sb} from images where R_{sb} and R_X are known for an appropriate image channel, or channel combination, as:

$$k_{sb} = \frac{r_s - R_X}{R_{sb} - R_X}$$

For such a model, the mean radiance (ie BRDF) over all pixels in a patch with the same basic underlying type of cover and structure is therefore:

$$E(r_s) = R_s = R_X + (R_{sb} - R_X)K_{sb}$$

where K_{sb} is the mean value of k_{sb}, or the expected proportion of visible sunlit background for the particular sun and view positions. This simple model has been found to be adequate to describe the data obtained by a Daedalus scanner over woodlands.

Linear end-member analysis is similar to the estimation of components described above. It has been the subject of useful research and application in Australia (Pech *et al.* 1986, Pickup and Foran 1987) and at regional scales where all pixels are mixtures of land covers of interest (Cross *et al.*, 1991). End-member analysis assumes each pixel to be a composition, or mixing, of a few base components or ‘end-members’. The pixel signature is assumed to be a linear sum of reflectances from each of n end-members weighted in proportion to its cover (k_j) in the pixel:

$$r_s = \sum_{j=1}^{n} k_j R_j$$

$$k_j \geq 0 \ for \ j = 1,n$$

$$\sum_{j=1}^{n} k_j = 1$$

End-member analysis seeks to invert this mixing by deriving the proportions (k_j) of each component in the pixel signature. This can feasibly be derived from the remotely sensed data provided that if there are *n* components (trees, shrubs, grass etc) then there are at least (*n*-1) channels of data that separate the end-members spectrally. The key assumptions built into the end-member method are that:

a) The end-members (pure examples of total cover by trees, shrubs, grass and background) are spectrally consistent between sites and

b) Reflectance values for end members (Rj) are available from remotely sensed data or can be accurately derived by other means (such as field spectral measurements).

There has been considerable work aimed at deriving end-members from the data (a form of principal components analysis, see Boardman, 1990) and employing high spectral resolution data to effect separation of more than a few components (Adams *et al.*, 1989). However, with a lack of available high resolution spectral data, this linear approach suffers from several significant limitations to its applicability in Australia:

1. Available broad band signatures of the tree and shrub crowns over much of Australia whilst different, are not markedly spectrally distinct.
2. Even if spectrally distinct crowns did exist for the available bands, their distinction is confounded by the effects of shadowing within crowns and cast shadow on the background (with bigger plants shading smaller plants). This makes the signature of the end-members difficult to estimate as the signature depends on the proportions of crowns and shadows present and variations in sun and look angles.
3. Relatively low covers of trees and shrubs, together with shadowing, introduce such high spectral variance into the data relative to the spectral contrasts between end-members that the numerical methods used in the end member analysis become highly unstable.

Shadow effects obviously depend primarily on the sun angle. Although the crown cover is the same, lower sun angles clearly decrease image brightness. Differences due to shadowing can be taken into account in end-member analysis, provided the end-member values are recalculated for each temporal image and one or more components labelled ‘shade’ are added to the list. However, its successful application still depends on an assumption of linear scaling along cover gradients due to sun positional and sensor view angle changes. These assumptions in practice are erroneous in structured vegetation (e.g. vegetation with discontinuous cover of trees or shrubs), and this limits the application of such methods to general synoptic estimates of change in cover.

It is therefore better to model vegetation cover directly as an assemblage of various sizes and shapes of 3-dimensional objects (trees, shrubs, grass tussocks, herbs, etc.) scattered on a background that may be uniform or heterogeneous (Li and Strahler 1985, Jupp *et al.* 1986). The GO model may then be used to model the bidirectional reflectance of the canopies. In this approach, the effects due to shadowing on the overall reflectance (or infrared temperature) from a scene become important and useful features and the correlated interactions between shaded and sunlit components are built into the analysis - although it now becomes nonlinear. The directional radiance of the vegetation is then a mixture of four components (sunlit and shaded tree crowns, and sunlit and shaded backgrounds) that is seen from a given viewing angle. The areal proportions of these four components, for given illumination and viewing directions (which can be off-nadir), will be a function of the sizes, shapes, orientations and placements of the objects (i.e. individual plants) within the scenes.

A GO model is most appropriate to woodlands or vegetation in which the vegetative cover is discontinuous, that is, where tree and shadowed background interactions account for a large proportion of the variance in the image. The further advantage of these models is that they are also potentially invertible to provide structural as well as cover information. The invertibility of GO models was demonstrated by Strahler *et al.* (1988), Franklin and Strahler (1988) and Wu and Strahler (1993) in which tree size and density were estimated from reflectance data. When size, shape and orientation are fixed or characterised by distributions of known parameters, and the object centres are randomly distributed, then the proportions of the four components can be estimated using the Boolean model of Serra (1982). This GO model is termed the Boolean version (Strahler and Jupp, 1991a&b; Li and Strahler, 1992). It accounts for the changes in proportions that occur with random overlapping objects as the density of objects increases and can easily model scale effects and changing sun and view directions. The GO aspect of the model implies that multiple scattering of radiation in the vegetation layer is neglected. While the evidence of our eyes supports this, there are wavelengths (in particular the near infrared) where multiple scattering is very significant. This has been recently addressed by Li *et al.* (1995)."

3.3 Semi-empirical Methods

Semi-empirical models have also been developed which are empirical but are based on physical models and often contain parameters that relate to surface parameters. They offer the means of using the mosaic approach and 'empirical' model fitting but also enable surface parameters to be extracted. The methods are called 'semi-empirical' because they generally assume atmospheric correction can be done and also often have forms that involve earth surface parameters. The main class of these models is that of the 'kernel' models.

The following text describing the kernel approach was extracted from the MODIS-Land ATBD (Strahler *et al.*, 1995; or at the following web site: http://spso.gsfc.nasa.gov/atbd/modistables.html).

3.3.1 Theoretical Description

Kernel-driven models for the bidirectional reflectance distribution function of vegetated land surfaces attempt to describe the BRDF as a linear superposition of a set of kernels that describe basic BRDF shapes, with the coefficients or weights chosen to adapt the sum of the kernels to the given case. Typically, semiempirical kernels are based either on one of several possible approximations to a radiative transfer scenario of light scattering in a horizontally homogeneous plant canopy (*e.g.*, a crop canopy), or on one of several approximations feasible in a geometric-optical model of light scattering from a surface covered with vertical projections that cast shadows (*e.g.*, a forest canopy). Deriving a kernel of this nature requires simplifying and manipulating a model for the BRDF until it reaches the form

$$R = c_1 k + c_2$$

in which k is a function only of view and illumination geometry, c_1 and c_2 are constants containing physical parameters, and R is the modeled value of the true BRDF, ρ.

Semiempirical kernels can be of two types. First, they may contain only geometric terms, but no physical parameters. The complete model then is linear, and may be scaled to arbitrary scales even for mixed scenes;

neglecting adjacency effects, the weights of the kernels will be linear functions of the areal proportions of the subpixel weights. The so-called Ross-kernels, which are approximations to the radiative transfer theory in plant canopies of Ross (1981) described below, belong to this class, as does the so-called Roujean geometric-optical kernel (Roujean *et al.*, 1992). In the second case, kernels contain one or very few physical parameters and thus instead of having one kernel, provide a family of kernels depending on these parameters. The geometric-optical Li-kernels (Wanner *et al.*, 1995) belong to this type. In order to reduce them to the form given in (5), the kernel-internal parameters are fixed to a selection of a few values each. The following discussion presents each of the kernels used in the BRDF/Albedo algorithm. For more complete information on the theory and derivation of the kernels, see Wanner *et al.* (1995).

3.3.2 Kernels

The Ross kernels are derived from a formula presented by Ross (1981) for the directional reflectance above a horizontally homogeneous plant canopy calculated from radiative transfer theory in a single scattering approximation. The Ross-thick kernel was derived and described by Roujean *et al.* (1992). It is based on an approximation for large LAI values:

$$k_{thick} = \frac{(\pi/2-\xi)\cos\xi + \sin\xi}{\cos\theta_i + \cos\theta_v} - \frac{\pi}{4}$$

$$c_1 = \frac{4s}{3\pi}\left(1 - e^{-LAI\,B}\right)$$

$$c_2 = \frac{s}{3} + e^{-LAI\,B}\left(\rho_s - \frac{s}{3}\right)$$

In the kernel, θ_i and θ_v are zenith angles for illumination and view, respectively; ϕ is the relative azimuth of illumination and view directions; and ξ is the phase angle of scattering, $\cos\xi = \cos\theta_i \cos\theta_v + \sin\theta_i \sin\theta_v \cos\phi$. In the constants, s is leaf reflectance (= leaf transmittance; ρ_s is the (assumed isotropic) surface reflectance of the soil or understory; LAI is the leaf area index; and B is the average of secants of possible view and illumination zenith angles. For this formulation, a spherical leaf angle distribution is assumed.

The Ross-thin kernel simplifies Ross's equation based on an approximation for small LAI values:

$$k_{thin} = \frac{(\pi/2-\xi)\cos\xi + \sin\xi}{\cos\theta_i \cos\theta_v} - \frac{\pi}{2}$$

$$c_1 = \frac{2sLAI}{3\pi}$$

$$c_2 = \frac{sLAI}{3} + \rho_s$$

Although this kernel applies primarily to the case of a thin canopy of scatterers over a uniform background, it can also be appropriate for a very dense, uniform canopy of high leaf area, since in that case the leaf layers below the uppermost can act like a uniform background (Strahler *et al.*, 1995).

The derivation of the Roujean geometric-optical kernel is presented in the appendix to the paper of Roujean *et al.* (1992). The kernel may be regarded as accounting for the scattering of a random arrangement of three-dimensional rectangular solids (“bricks”) with isotropic scattering surfaces. Shadows are taken as perfectly black. Mutual shadowing, in which the shadow of one object falls on another object, is not taken into account. The bricks are long with respect to their height h and width b. The kernel is:

$$k_{brick} = \frac{1}{2\pi}\left[(\pi-\phi)\cos\phi + \sin\phi\right]\tan\theta_i \tan\theta_v \\ -\frac{1}{\pi}\left(\tan\theta_i + \tan\theta_v + \sqrt{\tan^2\theta_i + \tan^2\theta_v - 2\tan\theta_i \tan\theta_v \cos\phi}\right)$$

$$c_1 = \rho_s \frac{h}{b}$$

$$c_2 = \rho_s$$

The Li kernels are derived from the modeling approach of Li and Strahler (1986, 1992). In this approach, the surface is taken as covered by randomly-placed projections (*e.g.*, tree crowns) that are taken to be spheroidal in shape and centered randomly within a layer above the surface. The BRDF is modeled as a function of the relative areas of sunlit and shaded, crown and background that are visible from the viewing position in the hemisphere. For the Li-sparse kernel, it is assumed that shaded crown and shaded background are black, and that sunlit crown and background are equally bright. Under these circumstances, and with some further approximations in the way that view and illumination shadows overlap, the Li-sparse kernel is:

$$k_{sparse} = O(\theta_i, \theta_v, \phi) - \sec\theta_i' - \sec\theta_v' + \frac{1}{2}(1+\cos\xi')\sec\theta_v'$$

where

$$O = \frac{1}{\pi}(t - \sin t \cos t)(\sec\theta_i' + \sec\theta_v')$$

$$\cos t = \frac{h}{b}\frac{\sqrt{D^2 + (\tan\theta_i' \tan\theta_v' \sin\phi)^2}}{\sec\theta_i' + \sec\theta_v'}$$

$$D = \sqrt{\tan^2\theta_i' + \tan^2\theta_v' - 2\tan\theta_i'\tan\theta_v'\cos\phi}$$

$$\cos\xi' = \cos\theta_i'\cos\theta_v' + \sin\theta_i'\sin\theta_v'\cos\phi$$

$$\theta' = \tan^{-1}\left(\frac{b}{r}\tan\theta\right)$$

In these expressions, b is the vertical radius of the spheroid; r is the horizontal radius of the spheroid; and h is the height of the center of the spheroid. For this model,

$$c_1 = C\lambda\pi r^2$$

$$c_2 = C$$

Here, C is the brightness of sunlit surface, and λ is the count density of spheroids (number of spheroids per unit area).

The Li-dense kernel differs from the Li-sparse kernel in that it accommodates mutual shadowing. It assumes a random distribution of crown heights to maximize the geometric-optical effect in a dense ensemble of canopies.

$$k_{dense} = \frac{(1+\cos\xi')\sec\theta_v'}{\sec\theta_i' + \sec\theta_v' - O(\theta_i', \theta_v', \phi)} - 2$$

$$c_1 = \frac{C}{2}$$

$$c_2 = C$$

These kernels are not yet linear in that they still contain two parameters, namely the ratios b/r and h/b, describing crown shape and relative height. The kernels therefore actually represent two families of kernels, governed by the values of these two internal parameters. For the present, we provide two choices for each parameter, thus providing four kernels within each family. For the b/r ratio, the values 2.5 (prolate shape) and 0.75 (oblate shape) are used; for the h/b ratio, we use values of 2.5 (tall) and 1.5 (short).

3.3.3 Kernel-Driven Models

A complete kernel-driven semiempirical model is formulated as a linear combination of kernels. Most suitably it has the form

$$R = f_{iso} + f_{geo}k_{geo} + f_{vol}k_{vol}$$

which is derived from adding appropriate choices of geometric-optical surface-scattering and radiative-transfer volume-scattering kernels, each multiplied by a proportion α or $(1-\alpha)$ that weights the contribution of each model. These proportions may be regarded as the areal proportions of land cover types exhibiting each type of scattering (neglecting multiple scattering between the two components), or as mixing proportions for land cover types that display both a volume-scattering and a geometric-optical contribution to the BRDF. The quantities k_{geo} and k_{vol} are the respective kernels; the factors f_{geo} and f_{vol} are their respective weights; and the term f_{iso} is the isotropic contribution. Using the kernels presented above, there will be two choices for k_{vol} and three for k_{geo}, providing six possible models (disregarding here the four sets of internal parameters used for the Li kernels). The formulae for f_{iso}, f_{geo},and f_{vol} are shown in Table 4.

In the inversion and fitting of a semiempirical model to data, estimates of the weights f are retrieved from bidirectional reflectances and specification of viewing and illumination positions. Although this objective satisfies many of the goals of the BRDF/Albedo product, the existence of formulae for the weights f in terms of physical parameters could provide for direct inference of physical parameters from the weight values fitted (see Section 3.3.5). This possibility will be explored in the postlaunch phase as a research topic.

3.3.4 The Modified Walthall Model

Empirical models can be understood as being of the kernel-driven model type as well, where the kernels are empirical functions. An example is the modified Walthall model, derived by Walthall *et al.* (1985) and improved by Nilson and Kuusk (1989). It has the form

$$R = p_0\left(\theta_i^2 + \theta_v^2\right) + p_1\theta_i^2\theta_v^2 + p_2\theta_i\theta_v\cos\phi + p_3$$

Note that this is the same form as the semiempirical models discussed above—it is comprised of a weighted superposition of functions of angles, and the weights $p_{0\ldots3}$ are the parameters of the model. As a consequence, models like the modified Walthall model can be processed along with linear semiempirical models by the same linear inversion scheme.

3.3.5 Advantages of Linear Models

Linear models have a number of advantages in the context of global data processing. Linearity in BRDF models is comprehensively discussed by Lewis (in preparation) and demonstrated with the modified Walthall model. A first advantage is that any linear model can be inverted analytically through matrix inversion for the system of equations obtained by setting the derivative of the error function to zero (see Section 3.2.1). This provides direct estimates of the parameters f_{iso}, f_{geo}, and f_{vol} while avoiding numerical inversion problems.

Second, both the directional-hemispherical and bihemispherical integrals of the BRDF (black-sky and white-sky albedos) may be precalculated for each kernel individually. The albedo of a model then is simply the sum of the kernel albedos, weighted by *f* values. By using a look-up table, numerical integration of the models can thus be avoided.

Third, linear BRDF models scale linearly in space if adjacency effects are assumed to be small. This allows for mixed pixel cases, as indicated by the areal proportion parameter α in the model factors listed above. This feature also allows scaling BRDF and albedo from one spatial resolution up to a coarser one, *e.g.*, to a particular resolution needed for a climate model. Finally, since some of the parameters driving the models are dependent on wavelength while others are not (*e.g.*, structural parameters), it may be possible to extract all or some of them from multiband analysis, making assumptions about the others.

Table 4. Semiempirical weight formulas

Model	Weight Formulae
Ross-thin + Roujean	$f_{iso} = \alpha\rho_S + (1-\alpha)\left(\frac{s\,LAI}{3} + \rho_S\right)$ $f_{geo} = \alpha\rho_S \frac{h}{b}$ $f_{vol} = (1-\alpha)\frac{2s\,LAI}{3\pi}$
Ross-thick + Roujean	$f_{iso} = \alpha\rho_s + (1-\alpha)\left[\frac{s}{3} + e^{-LAI\,B}\left(\rho_s - \frac{s}{3}\right)\right]$ $f_{geo} = \alpha\rho_S \frac{h}{b}$ $f_{vol} = (1-\alpha)\frac{4s}{3\pi}\left(1-e^{-LAI\,B}\right)$
Ross-thin + Li-sparse	$f_{iso} = \alpha C + (1-\alpha)\left(\frac{s\,LAI}{3} + \rho_S\right)$ $f_{geo} = \alpha C\lambda\pi r^2$ $f_{vol} = (1-\alpha)\frac{2s\,LAI}{3\pi}$
Ross-thick + Li-sparse	$f_{iso} = \alpha C + (1-\alpha)\left[\frac{s}{3} + e^{-LAI B}\left(\rho_S - \frac{s}{3}\right)\right]$ $f_{geo} = \alpha C\lambda\pi r^2$ $f_{vol} = (1-\alpha)\frac{4s}{3\pi}\left(1-e^{-LAI\,B}\right)$

Ross-thin + Li-dense	$f_{iso} = \alpha C + (1-\alpha)\left(\frac{s\,LAI}{3} + \rho_s\right)$ $f_{geo} = \alpha \frac{C}{2}$ $f_{vol} = (1-\alpha)\frac{2s\,LAI}{3\pi}$
Ross-thick + Li-sparse	$f_{iso} = \alpha C + (1-\alpha)\left[\frac{s}{3} + e^{-LAI B}\left(\rho_s - \frac{s}{3}\right)\right]$ $f_{geo} = \alpha \frac{C}{2}$ $f_{vol} = (1-\alpha)\frac{4s}{3\pi}\left(1 - e^{-LAI\,B}\right)$

4. THE ISSUE OF SCALE

The BRDF models mentioned above and used to develop the kernels are general ‘average’ scene models that apply to spatially averaged data over homogeneous target areas. They do not model the image variance (which is also angle dependent) nor do they apply to a single object in a scene. The BRDF of a single tree is different from that of a stand of trees and the BRDF of a stand of trees is different from that of an open soil area.

Scaling affects the basis for image stratification. The tree and gap structure at one scale provides different functions for a stand and bare area delineation. At a broad scale, the composite of tree and gap merges into stands and at another stands and clearings merge in a ‘woodland’ category. At each level, th BRDF of the separated components will be different from each other and the composite land cover.

This leads to the consideration of some issues most important in an approach to correcting high resolution images for BRDF effects. The atmospheric effect is very smooth having been ‘filtered’ by an MTF with a size of about 200 metres in most cases. However, the BRDF is highly variable. Consider a photograph with a wide field of view and the solar hotspot near to its centre. A tree near the nadir view and a similar one near the edge will have different brightnesses but the difference will not be as great as the overall brightening due to volume and hotspot effects. In particular, there will be much more shadow at the edges reached away from the hotspot direction and path lengths for volume scattering will be longer through the canopy than at the geometric centre of the frame. The ‘colour’ of shadow near the edges will also be slightly darker than at the nadir but not very different. In this case, applying an overall BRDF correction function will tend to change the colour of shadows and tree crowns at the edge in a way that may be quite wrong - even though the overall area average may be ‘balanced’. Obviously, what works at one scale may not help at another.

Even if an H-resolution (high resolution) approach is taken in which the BRDF of the objects is modelled (trees for example), the fact will still be that the image contains different geometric proportions of scene objects and components in a way that depends on the phase angles between the sun, the target object(s) and the view. Perhaps the only perfect way to resolve the issue is by 3D stereo modelling. This is unlikely to be cost-effective with video or digitised aerial photograph data.

5. SCOPE FOR AN EOC WORKING GROUP

An Working Group is defined as described in the following (edited) excerpt from the EOC Science Plan:

“An EOC Working Group is the essential initial step in developing generic Tasks from the applications oriented Threads and is the entry point for all approved Tasks. The results of the Working Groups form the basis for priority setting. Working Groups identify and help rank issues and (following prioritisation) lead to the selected focus activities of the EOC. These are Science Projects and/or Implementation Teams. Science Projects resolve the scientific issues and publish results. Implementation Teams may take the results from the Science Project and implement then (for example) as software or develop a technology transfer strategy. The outcomes of the science teams will be formal scientific publications but those of the implementation teams may not be. For example, Implementation Teams may involve commercial software houses working with scientists to provide products that are documented, quality controlled and work correctly.

The Working Groups offer an opportunity for scientists in different Divisions, the EOC and from other groups to develop collaboration and locate major centres of expertise and interest. The projects selected will seek the best teams and be subject to approval in competition with other Working Group outcomes. The priority setting and approval process for the Science Projects and Implementation Teams that arise from this activity will be explicit and include specific identification of deliverables and milestones. While the EOC has a central location in Canberra where a critical mass of scientists will tackle generic science issues and algorithm development, locations of EOC project and implementation activities can also be decided by infrastructure and core staff locations and be potentially at any location with adequate research support among CSIRO sites. The key characteristics of EOC projects are collocation of scientists, efficient use of resources, inter-Divisional collaboration, support for the goals of the EOC and a generic Earth Observation Science focus that provides support across different applications and/or involves a range of tools.

Science Projects and Implementation Teams will be formed according to specific guide-lines and will be monitored for progress within the EOC structure and evaluated against criteria defined at the outset of the activity. The outcomes of an EOC Task will emphasise quality of product and excellence of production. A primary role of and criterion for EOC activities includes making the findings accessible and useful to areas of CSIRO and industry not currently exploiting Earth Observation to its fullest extent.”

A Scene Brightness Working Group needs to consider these as guidelines and develop Science Project(s) and/or Implementation Team(s) to resolve issues identified. In particular, the WG will need to establish effective data sets to provide objective tests of the methods and allocate cases where only empirical models and field measurements are appropriate and those where measurement models are appropriate to the teams. Standard data sets that are needed to evaluate the alternative models must be carefully considered as well the end uses and the means to evaluate methods against the value of the product.

The best methods could be implemented in software by an implementation team. During development and testing a standard language such as IDL could be used for easy exchange. Other than such general statements as these, an initial meeting is needed to plan actions and delineate the scopes of the Working Group and expected times until when Project objectives are in place.

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