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On the Potential of CHRIS/PROBA for Estimating Vegetation Canopy Properties from Space

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The Compact High Resolution Imaging Spectrometer (CHRIS), to be launched on board the PROBA (Project for On-Board Autonomy) satellite in 2001/2002, will provide remotely-sensed data for terrestrial and atmospheric applications. The mission is intended to demonstrate the potential of a compact, low-cost, imaging spectrometer when combined with a small, agile satellite platform. CHRIS will provide data in 18 – 62 user-selectable spectral channels in the range 400 nm to 1050 nm (1.25 nm – 11 nm intervals) at a nominal spatial resolution of either 25 m or 50 m. Since PROBA can be pointed off-nadir in both the along-track and across-track directions, it will be possible to use CHRIS to sample the Bidirectional Reflectance Distribution Function (BRDF) of the land surface. This combination of an agile satellite and a highly configurable sensor offers the unique potential to acquire high spatial resolution, spectral BRDF data sets and, from these, to study the biophysical and biochemical properties of vegetation canopies. It will also provide an important means of validating similar data sets from other, coarser spatial resolution sensors, such as VEGETATION, POLDER2, MODIS and MISR. This paper presents key features of the instrument, and explores the potential of CHRIS for estimating canopy biophysical parameters from space by means of a LUT-based BRDF model inversion scheme.

Keywords: BRDF; Albedo; Biophysical parameters; Model inversion; Hyperspectral; Smallsat

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1. INTRODUCTION

A primary aim of terrestrial remote sensing is to derive accurate estimates of selected *state* (*e.g.*, leaf biochemistry, Leaf Area Index (LAI) and the fraction of Absorbed Photosynthetically-Active Radiation (*f*APAR)) and *rate* (*e.g.*, Net Primary Productivity (NPP)) variables pertaining to vegetation canopies. This information is required by applications ranging from precision agriculture to modelling the global carbon cycle (Gao 1994, Defries *et al.*, 1995). Attempts to derive such variables from optical remote sensing data have traditionally been founded on the use of vegetation indices (VIs) (Baret and Guyot 1991; Myneni *et al.*, 1995). Although VIs can be designed to be less sensitive to certain influences such as soil variations (Huete 1988), terrain slope and aspect (Holben *et al.*, 1986), and atmospheric effects (Kaufman and Tanré 1992; Myneni and Asrar, 1994), they cannot adequately reflect the complex variations in reflectance due to leaf/soil biochemistry, vegetation amount and canopy structure. Furthermore, since the relationships they embody are empirical, they must be 'tuned' for different sensors, spatial resolutions, viewing/illumination conditions, vegetation types *etc*. (Myneni *et al.*, 1995; Verstraete *et al.*, 1996).

A more powerful and generic approach is to invert physically-based models of canopy reflectance against measured reflectance data (Pinty and Verstraete 1991; Kuusk 1991; Knyazikhin *et al.*, 1998), using both angular and spectral sampling. This is particularly true for determining vegetation structural parameters (Asner *et al.*, 1998), solving for coupled atmosphere-surface parameterizations (Martonchik, 1997), or for calculation of integrated properties such as albedo (Wanner *et al.*, 1997). Inversion gives the possibility for direct retrieval of biophysical variables like LAI, clumping, leaf angle distribution and leaf/soil biochemistry, as well as radiometric properties such as *f*APAR or albedo. There are several limiting factors however. The first is the requirement for sufficient measurements of the surface BRDF, with the associated requirement for good calibration and atmospheric correction. Such properties can be reliably estimated from the remote sensing data themselves if multi-angle or polarization measurements are available, using either a separate atmospheric correction procedure or a coupled atmosphere-surface reflectance model (Diner and Martonchik 1985, Rahman *et al.*, 1993; Liang and Strahler, 1994; Leroy *et al.*, 1997). A second difficulty is the existence of spatial heterogeneity, particularly given that most current and future sensors with multiangle capabilities operate at so-called 'moderate' spatial resolutions, typically > 1 km (Leroy *et al.*, 1997; Diner *et al.*, 1998; Justice *et al.*, 1998). Sub-pixel mixing of cover types at this spatial scale makes inversion of physically-based canopy reflectance models difficult or unreliable. Thirdly, there is a need for inversion algorithms which are both fast and robust enough to avoid becoming stuck in local minima.

Several practical solutions to the third problem have been suggested in recent years, namely (i) linearize the models or (ii) use non-linear inversion schemes which place the computational emphasis on pre-calculation of reflectance data rather than repeated forward modelling 'on the fly'. The linearization approach is exemplified by models which are being used operationally in connection with data from NASA's MODIS sensor (Wanner *et al.*, 1997; Justice *et al.*, 1998). Such models are suitable for normalization of angular effects (Roujean *et al.*, 1992) and to estimate properties involving angular integrals, such as the surface albedo (Wanner *et al.*, 1997). They provide a fast description of the 'shape' of the BRDF from a sparse angular sample of directional reflectance measurements. Moreover, their linearity permits implicit modelling of spatial heterogeneity in the surface reflectance field. The model abstraction performed during linearization, however, makes the relationship between the derived model parameters and the actual canopy properties unreliable or at least indirect. What is required, then, is a method by which more realistic scattering models might be inverted.

Two practical examples of the second approach mentioned above are: (i) Artificial Neural Networks (ANNs) (Kimes *et al.*, 1998) and (ii) look-up tables (LUTs) (Knyazikhin *et al.*, 1998). Both methods transfer the burden of intensive computation out of the operational inversion process. ANNs provide a practical method of inverting complex models through the repeated training of an inter-connected network of processing nodes, each with its own non-linear response function, using a large variety of input data. The ANN 'learns' how to respond under a wide range of input conditions which are presented to it. ANN methods are ideally suited to developing their own basis functions adaptively. They can, therefore, compensate for potential errors in the assumptions made regarding canopy scattering behaviour. A number of studies have shown that ANNs, once trained, can provide very rapid estimation of biophysical parameters from measurements of canopy scattering (Kimes *et al.*, 1998; Pragnere *et al.* 1999).

The LUT approach requires construction of a table of pre-calculated spectral directional reflectance data as a function of the key canopy biophysical properties (Weiss *et al.*, 2000). Operational inversion is reduced to searching through the resulting LUT for the reflectance values which most closely fit the observations (a minima of the error function quantifying the difference between measured and modelled values) and the retrieval of the corresponding parameter values. If the model used to populate the LUT is altered, the LUT is simply regenerated. Ancillary knowledge of biome type and/or land cover can also be used to further restrict the search space. A significant advantage of both the ANN and LUT approaches to model inversion is that arbitrarily complex scattering models can be used, as the forward modelling is performed only once, prior to inversion.

If the issues of atmospheric scattering and surface heterogeneity, discussed above, can be dealt with appropriately, it may be possible to use these rapid inversion techniques to derive biophysical parameters from satellite sensor measurements of directional reflectance. This paper presents a preliminary investigation into the potential of the forthcoming CHRIS/PROBA mission for this purpose, focusing on the use of LUT-based, non-linear BRDF model inversion methods. The approach is applied to simulated reflectance data with spectral and directional sampling characteristic of the CHRIS/PROBA satellite sensor.

2. CHRIS ON BOARD PROBA

The PROBA small satellite mission (ESTEC 1999), due for launch in 2001/2002 is a technology proving experiment designed to demonstrate the use of on-board autonomy in respect of a small, generic platform suitable for scientific or application missions. A number of Earth observation instruments have been included in the payload to test platform pointing and data management capabilities. These offer interesting opportunities to acquire novel data sets for scientific investigations. The instrument payload includes the Compact High Resolution Imaging Spectrometer (CHRIS) (Sira Electro-Optics Ltd. 1999), a radiation measurement sensor (SREM), a debris measurement sensor (DEBIE), a wide angle Earth pointing camera, a star tracker and gyroscopes. The combination of CHRIS and PROBA, in particular, provides a pointable, spectrally-configurable sensor operating in the visible and near infrared (Tab. I).

2.1. CHRIS/PROBA Angular Sampling Regime

Multi-angular sampling of a point on the Earth surface will be achieved by tilting the PROBA platform and, hence, pointing the CHRIS instrument. This feature is programmable, with across-track tilting of up to $\pm 30^{\circ}$ and along-track pointing of up to $\pm 60^{\circ}$ (equivalent at-ground angles) envisaged for the mission. An approximate orbital/camera model was created by modifying the Xsatview software (Barnsley *et al.*, 1994) to provide a general indication of the potential angular sampling regime of CHRIS/PROBA under

TABLE I CHRIS instrument characteristics

PROBA orbital characteristics	
Orbit	Virtually circular, Sun-synchronous
Altitude	829 km
Inclination	98.7°
Orbital period	101.3 minutes
Equatorial crossing time	10:30 am
Platform revisit period	14 days
CHRIS spatial characteristics	
Swath width	18.6 km
Typical image area	19 km × 19 km
Spatial resolution	25 m – 50 m
CHRIS spectral characteristics	
Spectral range	410 nm – 1050 nm
Spectral resolution	1.25 nm – 11 nm
Spectral band displacement	User-selectable
Number of selectable spectral bands	
Full swath width	18 bands @ 25 m spatial resolution 50 – 62 bands @ 50 m spatial resolution
Half swath width	37 bands @ 25 m spatial resolution
PROBA pointing capability	
Across-track	± 30°
Along-track	± 60°
CHRIS data characteristics	
Data per 19 km × 19 km scene	131 Mbits
Quantization	12 bits (CDS noise reduction)
SNR	200 (at target albedo of 0.2, baseline conditions)
Data I/F	2 × 20 Mbits/s
Effective data rate	18 Mbits/s (link overhead)
CHRIS power, weight and dimensions	
Power Consumption	< 10 W primary power
Weight	< 15 kg
Dimensions	790 mm × 260 mm × 200 mm

these conditions. The orbit is assumed to be circular, and the model does not allow for orbital precession, drift or slewing, but typically provides information on expected sampling behaviour to within a few degrees. Although the view zenith angles are essentially programmable, we assume a typical configuration with at-ground zenith angles of 0°, ± 15°, ± 30° and ± 60° for the purpose of this paper.

Figure 1 shows the angular sampling regime for a latitude of 13°N. The nine view angles form a trace across the plot, which rotates in azimuth relative to the solar principal plane (the plane containing the solar direction vector) over the year. It is close to the solar principal plane in January, but nearly perpendicular to it at other times of the year. Figure 2 shows similar information for 52°N, with all potential samples over a 14-day period

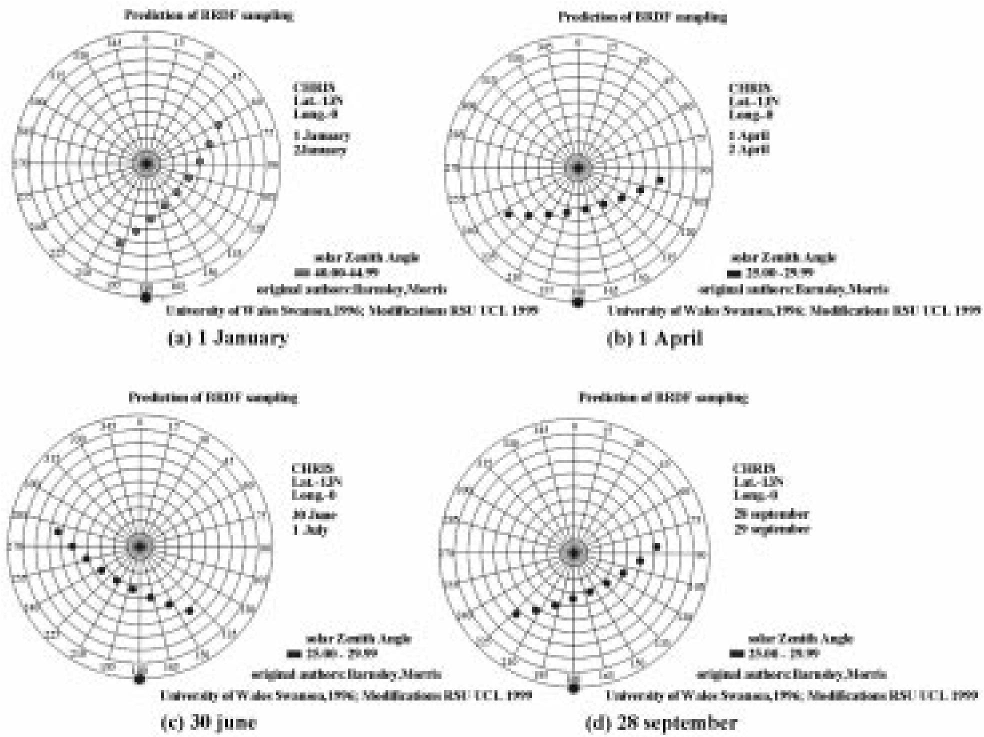
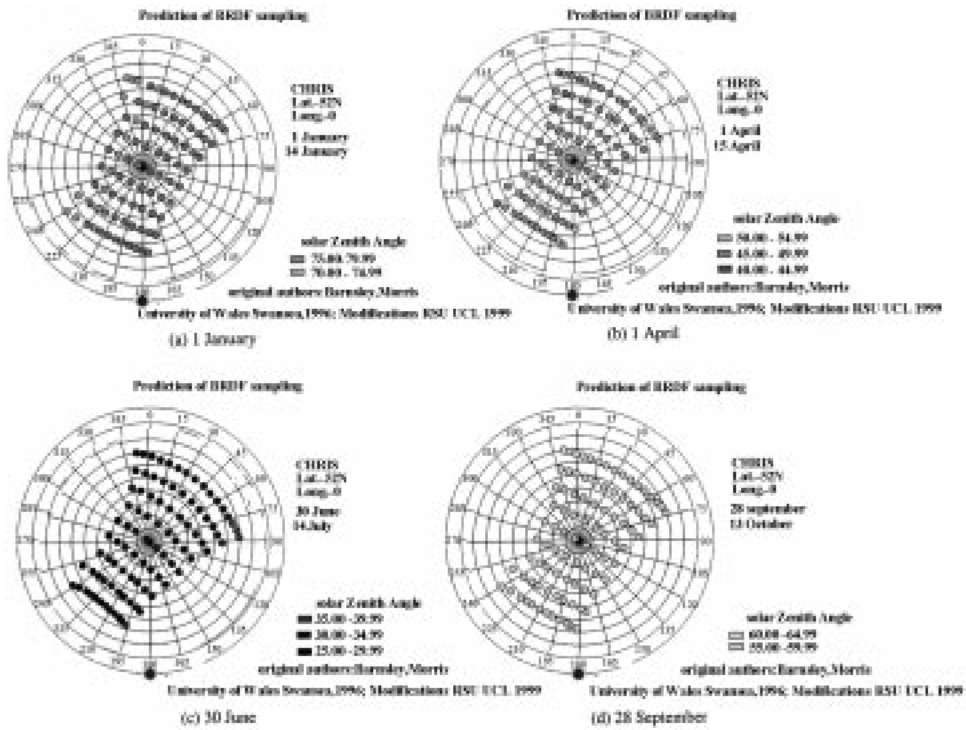


FIGURE 1 Polar plots of viewing angles relative to the solar principal plane and associated solar zenith angles for 1-day sampling at a latitude of 13°N and four different times of year.



(a) 1 January (b) 1 April (c) 30 June (d) 28 September

FIGURE 2 Polar plots of viewing angles relative to the solar principal plane and associated solar zenith angles for 14-day sampling at a latitude of 52°N and four different times of year.

TABLE II Range of solar zenith angles (degrees) over a 14-day sampling period at four latitudes and four times of year

	Latitude			
Day of year	52° *N*	43° *N*	13° *N*	32° *S*
1st January	70 – 80	65 – 70	35 – 50	5 – 30
1st April	40 – 55	35 – 45	15 – 30	50 – 65
30th June	25 – 40	20 – 35	15 – 30	50 – 65
28th September	55 – 65	45 – 60	20 – 40	25 – 40

shown. The various traces over this period combine to provide more complete sampling over the viewing hemisphere. The sampled view angle traces do not rotate as much as at lower latitudes and there are more traces owing to orbital convergence towards the poles. PROBA's potential across-track sampling of up to $\pm 30°$ means that, over a 14-day sampling period, CHRIS can potentially provide traces of up to 30° in view zenith angle in the solar principal plane for sites close to the equator, even though individual traces lie in the cross-principal plane. The solar zenith angle changes only slightly for sites close to the equator (Fig. 1), but varies considerably at higher latitudes (Fig. 2). Table III provides representative data for the variation in solar zenith angle at different latitudes and times of year for samples gathered over a 14-day period. The variation in solar zenith angle for a single day trace is typically of the order of 5°.

The CHRIS/ PROBA sampling regime seems to have good potential for sampling in or close to the solar principal plane, particularly at middle latitudes, especially if samples are gathered over a 14-day period. The quality of sampling towards the equator can be expected to vary over the year as the general trace direction rotates but, even in the worst case, sampling of up to 30° in the solar principal plane can potentially be achieved. This discussion assumes two factors which are unlikely to hold in reality for CHRIS/PROBA: (i) no angular samples are lost due to cloud cover; and (ii) all potential samples can be downloaded from the satellite to a ground receiving station. In this context, it should be noted that while high latitude sites may, in theory, be observed more frequently than low latitude ones, due to orbital convergence towards the poles, this may be off-set by an increased incidence of cloud cover. Regardless of whether one is imaging high or low latitude sites, the period of time over which data are acquired can, in principle, be lengthened so that an adequate sample of the BRDF can be built up. There is, however, inevitably a tradeoff between the number of angular samples that can be acquired within a given period of time and the potential for significant changes to occur in the biophysical properties of

TABLE III Mean retrieved values (and associated actual values) of LAI, chlorophyll concentration, leaf angle distribution and the first of Price's soil parameters using different LUT grid sizes based on 1-day sampling at a latitude of 52° *N*

	Retrieved values			
Actual values	*Grid* $4 \times 3 \times 3 \times 3$	*Grid* $5 \times 4 \times 4 \times 4$	*Grid* $7 \times 6 \times 4 \times 4$	*Grid* $11 \times 10 \times 8 \times 8$
LAI:				
0.5	0.24	0.44	0.40	0.36
0.8	0.46	0.44	0.65	0.65
1.5	1.46	1.41	1.33	1.30
2.1	1.54	1.30	1.63	1.84
3.2	3.32	3.40	3.20	2.99
5.3	6.05	6.17	5.16	5.04
Chlorophyll				
39	37.60	31.71	31.09	34.49
54	59.10	48.68	46.63	46.98
69	70.10	57.72	59.66	57.65
81	74.35	71.18	69.04	68.77
87	82.76	78.52	75.97	75.33
Leaf angle distribution				
0.6	0.28		0.97	0.77
4.8	3.90		5.95	4.69
7.9	6.66		7.91	7.65
Soil parameter				
LAI: 0.6				
0.13	0.16		0.15	0.14
0.22	0.23		0.22	0.23
0.31	0.31		0.31	0.31
LAI: 5.3				
0.13	0.19		0.21	0.20
0.22	0.19		0.21	0.20
0.31	0.19		0.21	0.20

the observed surface (*e.g.*, due to phytophenological or episodic effects). Achieving a suitable compromise between these two factors is likely to be highly complex, with the most appropriate solution varying from site-to-site and as a function of time of year.

2.2. Potentials of CHRIS/PROBA

CHRIS data will provide the potential to overcome many of the difficulties associated with physically-based model inversion from satellite data. First, around seven views of a fixed point on the Earth surface can be obtained in a single orbital over-pass. This offers the potential to solve the models for the effects of both the atmosphere and the surface directional reflectance.

Secondly, the high spatial resolution of the instrument will make the application of physically-based models simpler, since there will be fewer problems with sub-pixel mixtures of land cover type than for 'moderate' resolution sensors. Thirdly, CHRIS/PROBA provides both hyperspectral and directional sampling, which can be expected to have greater information content than either domain alone (Barnsley *et al.*, 1997). In the following section, we explore these issues in a modelling study, by attempting to invert biophysical parameters from simulated CHRIS data using a variant on the LUT approach.

3. MAPPING BIOPHYSICAL PARAMETERS

3.1. Experimental Design

A feasibility study has been conducted of the use of CHRIS/PROBA data with a simple LUT inversion scheme (O'Dwyer 1999). The main elements of this study and its major conclusions are examined here. The study investigated the extent to which the angular and spectral sampling provided by CHRIS/PROBA was sufficient to derive estimates of selected surface biophysical parameters. In addition, the applicability of a variation on the LUT approach was explored. The study assumed the availability of data recorded in 18 spectral bands within the visible/near-infrared, in a number of different configurations. The Xsatview camera/orbit model, described above, was employed. No limitations were placed on data download rates and cloud-free conditions were assumed. The study also assumed that there were no errors resulting from uncertainties in the atmospheric correction of the data, although the study did consider the impact of random additive noise on the retrieved properties.

Vegetation canopy reflectance was simulated using the model developed by Kuusk (1991), using a wide range of values for the model (biophysical) parameters. The model assumes a plane-parallel homogeneous vegetation canopy whose lower boundary represents the soil surface. The model parameters relevant in this context are (i) leaf chlorophyll concentration, (ii) leaf structure, (iii) leaf area index, (iv) leaf clumping, (v) relative leaf size, and (vi) soil brightness. Leaf size estimation requires good angular sampling in the retro-reflection direction (*i.e.*, the 'hot spot'). This was not well sampled by the angular configuration considered and so is not analyzed in detail in this paper.

3.2. Inversion Strategy

A key concern in designing a LUT approach for model inversion is to keep the size of the LUT as small as possible. Knyazikhin *et al.* (1998), for example, achieve this by limiting the range of possible values for the canopy structural and spectral variables as a function of the biome being considered. In addition, they formulate the problem for canopy transmittance, absorptance and reflectance, allowing the application of principles of energy conservation. The information they store in the LUT is reconfigured in wavelength-independent terms, reducing the LUT storage requirements and allowing the calculation of the required terms for any given spectral functions. Properly used, this type of inversion scheme can provide information not only on the most likely values of the retrieved biophysical properties, but also on their expected variation. However, since the main consideration here is testing the utility of CHRIS/PROBA's anticipated angular and spectral sampling regime for deriving estimates of selected surface biophysical properties, we will not consider these points any further in this paper.

Instead, we start from the observation that a function stored on LUT grid points will, of necessity, produce quantized results. A simple, naïve LUT approach can be considered which quantizes the required reflectance function for all observation angles into N samples per biophysical property. If N is large, the resultant parameter set will be quasi-continuous, but as the inversion time is a function of p^N for p properties, the processing time would soon become too great. Operationally, it may be possible to restrict the property search-space by considering the likely behaviour of a given biome, as noted above, but we prefer not to impose this constraint here. Rather, we attempt to reduce N to a minimum such that it produces acceptable results (in computational terms) while seeking to mimic the behaviour of a large-N system by means of linear interpolation between LUT grid points. This approach can be justified on the basis that we expect CHRIS/PROBA to provide a reasonable angular and spectral sampling scheme and, therefore, the large-scale variations within the error function are likely to be relatively well-behaved. Departures from this assumption will, of course, translate into error in the solution which can be attributed to the inversion algorithm, on top of those due to the CHRIS/PROBA sampling scheme.

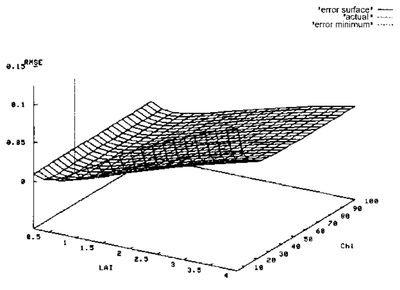
In this instance, the LUT is generated by running the Kuusk (1991) model in the forward mode for a range of parameter values and angular sampling regimes. The resultant reflectance values populate a grid (the LUT), the dimensions of which are described by the various biophysical properties.

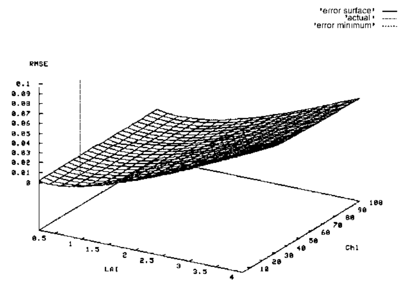
The approach outlined above has obvious similarities to the linearization approach to model inversion: effectively, we are designing a piecewise linear inversion strategy based on the LUT. We assume that a coarse minimization of the error function on the defined LUT grid points will localize the solution sufficiently for a linearized solution around the grid points to be valid. Following Knyazikhin *et al.* (1998), we could permit all grid-point solutions within an acceptable tolerance value to be possible solutions to the inversion. These localization points would then form a set of candidates for application of the linearized inversion. The linearized inversion leads to a second-order description of the error function as a function of the p variables. Here, a range of possible solutions can be considered for each property by thresholding this function. In this context, we chose to accept only the absolute minimum grid point and the absolute minimum of the linearized error function. In an operational algorithm, however, it might prove more useful to consider a range of solutions.

3.3. Errors due to CHRIS/PROBA Sampling

In this study, the LUT is populated using spectral directional reflectance data simulated using the model of Kuusk (1991). We first consider the effect of angular and spectral sampling on the retrieval of two major biophysical properties, namely Leaf Area Index (LAI) and leaf chlorophyll concentration. CHRIS angular sampling over a 1-day period was simulated for 4 different times of year and a site located at 52°N. Spectral sampling was assumed to be at regular intervals over 18 wavebands in the range 450 nm – 1045 nm. An alternative spectral sampling scheme is investigated below. In each case, reflectance data were simulated with and without noise (at a magnitude of up to 0.1 in reflectance). A high density two-dimensional grid was defined to span the full range of parameter values allowed for in the Kuusk (1991) model. Simulated reflectance values were then compared to each point in the grid and the root mean square error (RMSE) used to create the error surfaces in Figure 3.

The results show that the error function is well-behaved and, in each case, the minimum region within which a linearized solution can be found is clearly defined. The error surfaces are distinctively different for cases of low LAI (Figs. 3a and b) and high LAI (Figs. 3c and d), respectively. Although some deviation of the retrieved value from the real value is to be expected, owing to the quantized nature of the LUT, most of the uncertainty can be attributed to variations in the angular sampling schemes used (Fig. 3a – d). The addition of noise further increases the uncertainty associated with the





(a) Low LAI/chlorophyll content; January angular sampling.

(b) Low LAI/chlorophyll content; June angular sampling.

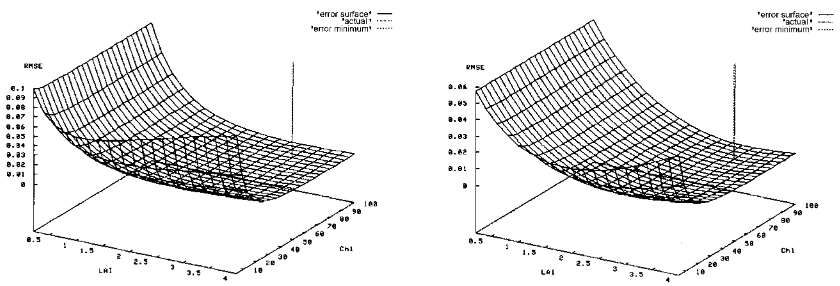


FIGURE 3 Three-dimensional error surfaces created using a high density LUT and associated identified and actual minima shown as vertical lines for 1-day sampling at a latitude of 52°N. Figures (a) to (d) show variations in the 'shape' of the surfaces produced by differences in angular sampling and LAI.

identified minima and leads to larger deviations between the retrieved and actual property values (O'Dwyer 1999).

3.4. Effect of LUT Grid Size

The inversion scheme developed above was used with four different LUT grid sizes, to retrieve four bio-physical parameters, namely (i) LAI, (ii) chlorophyll concentration, (iii) leaf angle distribution and (iv) the first of the Price (1990) soil parameters. The densities at which the biophysical properties were sampled varied between LUTs. In the coarser grids, a reduced density of points was achieved for LAI and chlorophyll by using multiplicative increments in the model parameter values. This is because, although the effect of soil brightness is essentially linear for single scattered radiation, terms such as LAI and chlorophyll vary almost exponentially. CHRIS angular sampling over a 1-day period was used to simulate reflectance data at 52°N for a single date, using a variety of parameter configurations. Ten replicates of each data set were created, with random noise added at a magnitude of up to 0.1 in reflectance to simulate a comparatively noisy signal. The four different grids were used to retrieve parameter values from the simulated data sets. Table IV shows the mean values of all four parameters retrieved using each grid, and the corresponding 'actual' values (*i.e.*, the values used to parameterize the model).

The results (Tab. IV) show the inversion method to be robust to random additive noise up to about 0.1 in reflectance. More importantly, they indicate that the differences in retrieved and 'actual' values attributable to different grid densities are minimal. More specifically, increasing the density of the grid does not appear to improve significantly the accuracy of retrieved parameter values. This suggests that the coarsest grid can be used with minimal loss of precision, while resulting in a significant reduction in processing time. An identifiable drawback of using a coarse grid, however, is that the retrieval of the LAI seems to break down at high values. It seems likely that this is a consequence of canopy reflectance being insensitive to increasing LAI beyond some threshold (saturation) value, rather than a flaw in the inversion strategy *per se*.

TABLE IV Mean retrieved values (and associated actual values) of LAI, chlorophyll concentration, leaf angle distribution and the first of Price's soil parameters using targeted wavebands and a single coarse LUT grid, based on 1-day sampling at a latitude of 52°N

Property/parameter	*Actual values*	*Mean retrieved values*
LAI	0.5	0.37
	0.8	0.92
	1.5	2.29
	2.1	3.40
	3.2	7.53
	5.3	10.42
Chlorophyll concentration	39	30.2
	54	49.8
	69	76.1
	81	85.7
	87	89.3
Leaf angle distribution (eccentricity)	0.6	1.16
	4.8	5.99
	7.9	9.37
First soil parameter		
LAI: 0.6	0.13	0.20
	0.24	0.32
	0.36	0.49
LAI: 5.3	0.13	0.37
	0.24	0.40
	0.36	0.44

The sensitivity of the model parameters to spectral and directional sampling also holds performance implications for the inversion: if any given parameter is insensitive to such changes, it will not be retrievable from hyperspectral, multiple-view-angle imagery such as that provided by CHRIS/PROBA. Practically, if a parameter cannot be retrieved, or if it has a low sensitivity to sampling changes, it should be excluded from the inversion, and kept at a plausible fixed value. The sensitivity of parameters may also vary depending on canopy type; for obvious reasons, the soil parameters are more likely to be sensitive to the spectral and directional sampling in canopies with a low LAI. An ideal implementation would comprise an adaptive grid, where the model parameters are included or excluded depending on assessments of their sensitivity to the sampling scheme.

The effects of variations in the directional (angular) sampling – as a function of the day-of-year and latitude – on parameter retrieval using a coarse LUT were also examined (O'Dwyer 1999). Results show that, as expected, combining samples over a two-week period allows consistently better parameter retrieval than that possible with 1-day sampling. This is a result of the larger number and broader range of viewing and illumination angles sampled, particularly in the solar principal plane (Fig. 2). For the same reason, the angular sampling regimes characteristic of higher latitudes sites result in more accurate retrievals of the model parameters than for sites closer to the equator. The distribution of solar zenith angles seems to become increasingly important as the overall number of samples drop.

3.5. Effect of Spectral Sampling

The effect of spectral sampling on biophysical parameter retrieval using a coarse LUT grid was investigated through use of an alternative spectral sampling scheme, in which 18 wavebands were selected at 'critical' points along the spectrum. These included six bands around the peak in the visible wavelength reflectance (500 nm – 570 nm; controlled by leaf chlorophyll concentration), six bands placed along the 'red edge' (680 nm – 770 nm), and two in the near-infrared (at 990 nm and 1020 nm, respectively). Angular sampling was assumed to be over a 1-day period for a single day and a site located at 52°N. Random noise (at a magnitude of 0.1 reflectance) was added to ten replicate data sets. Table VI shows the mean values retrieved for each of the four parameters using the inversion strategy described above.

The results show that targeting the wavebands can be beneficial to those parameters most sensitive to spectral changes. LAI, especially, is more accurately retrieved using the alternative spectral sampling scheme, although the procedure breaks down at high LAI values, as before. Similarly, retrieval of chlorophyll concentration is improved, although the differences are minor. It is thought that by combining directional samples over a 14-day period and using targeted wavebands the improvements in the accuracy with which the biophysical parameters are retrieved would be more significant.

More generally, we note that the combination of a sensor with a large number of user-selectable, narrow spectral channels and a very agile satellite platform, such as that provided by the CHRIS/ PROBA mission, opens up the debate on both the absolute and the relative information content of the two domains (*i.e.*, spectral and angular) in terms of estimating the biophysical properties of the land surface. This debate is currently only in its formative stage. Barnsley *et al.* (1997), for example, consider the issue from an empirical stand-point, by examining the statistical information content of multiple-view-angle images. However, their relatively simple analysis has yet to be formalized or extended to a consideration of the optimum combination of spectral channels and viewing/illumination geometries for biophysical property retrieval through BRDF model inversion.

4. DISCUSSION AND CONCLUSIONS

The results above indicate that a relatively coarse LUT can be used for inversion if interpolation between LUT grid points is used. The resulting LUT typically requires only 3 – 5 samples per parameter to achieve an acceptable accuracy and so is very fast to invert. The inversion method also proved robust to random additive noise up to about 0.1 in reflectance. The parameter retrieval is sensitive to variations in the angular sampling scheme as anticipated. Combining samples over a two week window permits the inversion of model parameter values to a high degree of accuracy (errors of only a few percent for most parameters); although as the precise nature of the angular sampling varies as a function of time of year and latitude, the absolute accuracy values will vary accordingly. The angular sampling, and therefore the parameter retrieval accuracy, provided by CHRIS/PROBA over most of Europe is generally good (ignoring, for the moment, the effects of cloud cover and data download limitations), generally improving towards the poles. There is evidence to suggest that the accuracy of parameter retrieval can be improved by careful selection of appropriate spectral wavebands, targeting known features of soil, and vegetation spectra.

The results suggest that the interpolated LUT method developed in this study has excellent potential for biophysical parameter retrieval based on the angular and spectral sampling characteristics of the CHRIS/PROBA mission. Since the interpolated LUT procedure essentially comprises a piece-wise linear surface, there are inevitable discontinuities at the boundaries between the LUT grid points. This creates inconsistencies in the application of the inversion algorithm, so investigations into the potential of using different functions imposing continuity may be beneficial. As the LUT approach is not limited to simple canopy reflectance models it should, in future, be possible to populate the LUT using numerical solutions to the radiative transport problem. Finally, the successful application of the interpolated LUT scheme used in this paper in conjunction with data from CHRIS/PROBA is reliant upon (i) satisfactory atmospheric correction of those data, (ii) accurate co-registration of the images acquired at different sensor view angles, and (iii) the ability to download sufficient data, given the current limitations on data rates and on-board mass memory.

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