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The role of earth observation in land-surface – climate feedback studies

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A review of the scientific requirements for information on the biophysical and biochemical properties of the land surface is presented, with particular reference to land surface parameterization schemes (LSPs) in Global and Regional Climate Models (GCMs and RCMs). The ability of Earth observation satellite-sensors to provide this information is examined. Emphasis is placed on the potential of the new generation of hyperspectral imagers, as well as pointable satellite-sensors able to sample the surface Bidirectional Reflectance Distribution Function (BRDF). In this context, a novel smallsat mission, CHRIS/PROBA, is introduced. This combines a highly configurable imaging spectrometer and an agile (pointable) satellite platform.

1 CONTEXT

Feedbacks between the land surface and the atmosphere are important determinants of the Earth's climate at a range of spatial and temporal scales. Since the pioneering work of Charney et al. (1975), who demonstrated the potential role of vegetation removal in maintaining drought in sub-Saharan Africa, numerous studies have shown a sensitivity of climate to both natural and anthropogenically-induced changes in land surface properties (Bounoua et al. 1999; Friedlingstein et al. 2001; Govindasamy et al. 2001; Otto-Bleisner & Upchurch 1997). Similarly, many of these properties — e.g. vegetation type and cover, soil moisture and snow cover — evolve continuously in response to atmospheric/climatic forcing, while the initial forcing may be amplified or dampened as a consequence of their interaction (Delworth & Manabe 1993; Koster et al. 2000; Taylor & Lebel 1998). Cox et al. (2000), for example, suggest that die-back of the Amazonian rainforests over the next 50–100 years, resulting from 'greenhouse' warming, may accelerate global climate change. Similarly, Zeng et al. (1999) demonstrate the role of vegetation dynamics in enhancing regional climate variability at interannual and inter-decadal time scales, while presenting evidence to suggest that soil moisture stress on vegetation may contribute to the persistence of regional droughts. An enhanced understanding of these feedback mechanisms would greatly improve the 'skill' of climate model predictions and, hence, assessment of the actual and potential effects of climate change.

An assessment of variations in land surface properties and processes that are affected by climate oscillators, such as the El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), is also of paramount importance. Recent studies suggest that climate oscillators operating on different timescales interfere with one another, enhancing or negating each other's effect (Los et al. 2001). Understanding these interferences and interactions would assist in the development of improved land management strategies to cope with their adverse impacts and, perhaps, to make use of their beneficial effects.

The central role of Earth Observation in this context is to provide some of the dynamic, spatially-comprehensive data sets on the biosphere that are required as input to land surface parameterizations (LSPs) in Global and Regional Climate Models.

2 REPRESENTING LAND SURFACE–CLIMATE FEEDBACKS IN GCMS

In the 1980s, greatly improved LSPs were developed in which the transfer of mass, heat and momentum between the land surface and the atmosphere was linked with variations in biophysical properties in a integrated framework (Dickinson 1984; Sellers 1986). Thus, for example, changes in leaf area index (LAI) not only affected interception and transpiration, as had previously been the case, but also albedo and surface roughness, altering both the surface energy balance and momentum transfer. LSPs are regulated by a set of inter-dependent biophysical properties, the values of which were initially based on land cover classifications derived from conventional atlases (Matthews 1983) and existing ecological data sets. Because of their static nature, however, these data are unable to account for the full spatial and temporal variability of the biosphere, so that important within-class spatial heterogeneity, as well as interannual and longer-term (decadal to centennial) variations, cannot readily be modelled.

One way to obtain this information is to use Dynamic Vegetation Models (DVMs) (Friend et al. 1997; Cox et al. 2000). These calculate key biophysical properties as a function of climate, soils, and competition between species. DVMs are an attractive alternative to the use of prescribed biophysical properties because they can interact fully with the GCM and, hence, provide a means to explore the feedbacks between vegetation and climate. They enable plant growth and competition to be simulated interactively and the related land surface properties to be updated accordingly (Dickinson et al. 1998; Sellers et al. 1996). As a result, they can simulate the terrestrial carbon budget and the broad distribution of biomes across the globe. Even so, considerable uncertainties remain, notably in terms of plant and soil respiration, and soil water storage. Enhancements are also required to the representation of the surface radiation balance, sub-grid-scale spatial heterogeneity, as well as seasonal and regional vegetation patterns.

3 THE ROLE OF EARTH OBSERVATION

The representation of biophysical properties in current LSPs can be further improved through the use of Earth observation satellite-sensors (Potter et al. 1993), since these produce spatially comprehensive and temporally explicit information on the biosphere. This can be incorporated into LSPs through model initialization, forcing and validation, or by means of data assimilation (Knorr & Schulz 2001). Sellers et al. (1996) have, for example, adapted their Simple Biosphere (SiB) model to take advantage of satellite-sensor data by incorporating the photosynthesis formulations of Farqhuar, Berry and Collatz. The revised model, SiB2, uses f_{APAR} (fraction Absorbed Photosynthetically-Active Radiation) as the key parameter to calculate photosynthesis: it is also linked with LAI, roughness length and albedo. Estimates of f_{APAR} are obtained from satellite sensors such as NOAA/AVHRR (Sellers et al. 1996; Los et al. 2001).

The use of EO data in this context has been made possible by continuing increases in the computational power available to climate modelling, which have allowed the specification of finer spatial grids in both GCMs and RCMs. These are more appropriate to an analysis of land surface processes under changing environmental and climatic conditions. As a result, there is an increasing awareness of the sensitivity of spatially-averaged meteorological parameters to sub-grid-scale land-surface variability and of the need to incorporate such variability within climate models; for example, to improve seasonal to interannual forecasting (Cox et al. 1999). Indeed, a new generation of LSP has recently been developed that accounts for mixtures of vegetation types within a single grid box and that allows these components to interact with the overlying atmosphere (Cox et al. 1998). Although relatively crude at present, these models provide the framework for a more explicit description of sub-grid scale variability and feedback.

Importantly, advances in climate modelling have been matched by developments in both the science and technology of Earth Observation. Specifically, the latest generation of satellite sensors produce data that are better calibrated, are more accurately geo-referenced, have finer spectral and spatial resolution and, hence, are more appropriate to the needs of the climate modelling community. At the same time, improvements in our understanding of, and ability to model, the physics of radiation transport at the Earth surface mean that we are now better able to convert remotely-sensed measurements of surface-leaving radiation into accurate estimates of the key land surface properties, or to assimilate EO data directly into LSPs. Moreover, the archive of EO data is now sufficiently long to detect and represent interannual cycles and trends in the global biosphere (Los et al. 2000).

Despite this, the full potential of EO data has yet to be realized. Most LSPs still obtain a substantial part of their input from land cover classifications, while satellite data are seldom used in studies with DVMs. Thus, it is only recently that climate-related, interannual variations in vegetation — readily detected in satellite-sensor data — have been investigated using LSPs. Similarly, few LSPs can exploit *directly* information on the episodic and seasonal changes in vegetation contained in EO data. Implementing these features in LSPs/DVMs would greatly increase their realism and would provide an additional means by which to validate the results produced by such models.

4 DERIVING LAND-SURFACE PROPERTIES FROM EARTH OBSERVATION DATA

Previous studies suggest that satellite remote sensing has the potential to provide information on a range of *state* and *rate* variables required to initialize, force and evaluate LSPs, or to be assimilated within them. These include measures of leaf and canopy biochemistry (e.g. chlorophyll and water content), vegetation amount/density (e.g. fractional ground cover, Leaf Area Index (LAI) and above-ground biomass) and radiation interception (e.g. f_{APAR} and canopy light-use efficiency) (Baret & Guyot 1991; Walter-shea et al. 1992; Myneni & Williams 1994; Begue & Myneni 1996; Barton & North 2001). Estimation of these properties has traditionally been founded on the use of linear combinations of data recorded in relatively broad spectral wavebands, typically centred on visible red and near-infrared (NIR) wavelengths, by near-nadir pointing sensors. These so-called vegetation indices (VIs) rely on the positive, asymptotic relationship that often exists between many vegetation properties and total canopy reflectance at NIR wavelengths, and the corresponding negative, asymptotic relationship at red wavelengths. By taking a ratio of these, VIs seek to linearize the relationship between the index and the surface property, while minimizing the influence of extraneous factors, such as soil brightness (Huete 1988; Qi et al. 1994), terrain slope, and atmospheric effects (Kaufman & Tanré 1992).

The principal advantages of VIs are their conceptual and computational simplicity. This no doubt explains their enduring attraction, despite their well-known limitations (Myneni et al. 1995; Verstraete et al. 1996). Specifically, broadband measurements of reflected radiation from soils and vegetation canopies are a composite function of several factors, including leaf and soil biochemistry, vegetation amount (LAI), leaf angle distribution, the spatial clumping of plants, and soil surface structure (Figure 1). Unfortunately, most VIs lack an explicit mechanism to account for the relative contributions of these factors to the total surface-leaving radiation. This explains why they must normally be 'tuned' (or calibrated) for data acquired by different sensors, over different vegetation types, or at different times of day/year. In other words, whenever their relative contributions change (e.g. because of phenological effects or other environmental influences), the form of the relationship between the VI and the property of interest also typically alters.

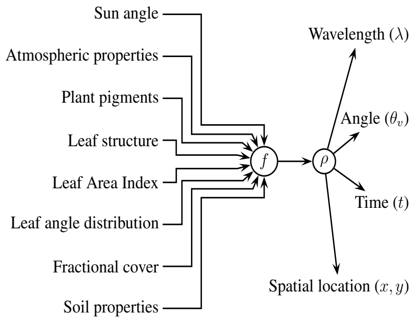

Figure 1: Functional relationship between vegetation canopy properties and detected reflectance.

5 THE ROLE OF HYPERSPECTRAL IMAGERS

One solution to the challenges outlined above, is to employ sensors that record data in a greater number of narrower spectral channels; that is, to use 'super-spectral' or 'hyperspectral' instruments, as opposed to multispectral devices. Careful selection of the most appropriate spectral channels can help to minimize the impact of extraneous environmental influences, while providing important information on key biochemical properties of the surface materials.

Peñuelas and others have, for example, demonstrated the use of narrow spectral wavebands in the red and NIR to estimate plant chlorophyll content, water status and biomass (Filella & Peñuelas 1994; Peñuelas et al. 1996). It is common in many such studies to calculate the first derivative of the detected spectral reflectance curve to derive estimates of the desired canopy biochemical properties. Particular attention is often given to the so-called 'Red-Edge Position' (REP) — the point of inflection on the spectral reflectance curve for vegetation between the local minimum around $680nm$ and the local maximum around $800nm$ — which appears to be a good indicator of changes in leaf and canopy biochemistry, most notably chlorophyll content (Boochs et al. 1990; Curran et al. 1995; Pinar & Curran 1996). To date most REP studies have been carried out on carefully

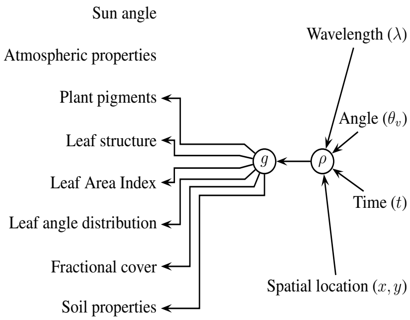

Figure 2: Inverse function used to estimate surface biophysical properties from sample measurements of spectral bidirectional reflectance.

controlled, often single species, vegetation canopies. There is evidence to suggest, however, that changes in canopy structure (e.g. leaf wilt) and other confounding factors (e.g. variations in ground cover/LAI, vegetation type and soil substrate) may place significant constraints on the straightforward application of this technique to data from spaceborne sensors (Zarco-Tejada & Miller 2001).

6 USE OF MULTI-ANGLE IMAGE DATA

The problem identified in the previous section essentially reduces down to the need for an independent assessment of the three-dimensional structure of the vegetation canopy and/or the soil substrate. This includes, but is not limited to, an evaluation of the fraction of ground covered by vegetation and its spatial distribution (i.e. clumping) within each pixel, as well as the size, shape, orientation and location of the plant elements (e.g. leaves, stems, stalks, branches and flowers) within the vegetation canopy, and the surface roughness of the soil below. In principle, bulk information on these properties for the vegetation canopy or soil surface as a whole can be obtained from an analysis of its bidirectional (or angular) reflectance characteristics; in other words, by measuring the apparent reflectance at different sensor view angles and solar illumination angles (Barnsley 1994).

A complete description of the bidirectional reflectance properties of a surface, for all possible viewing and illumination angles, is given by the Bidirectional Reflectance Distribution Function (BRDF). Unfortunately, the BRDF cannot be measured directly, not least because it is defined in terms of infinitesimal elements of solid angle (Nicodemus et al. 1977). It can, however, be represented by a mathematical model: many such models have been developed over the last 30 years (Goel 1987; Pinty & Verstraete 1992). If the model is founded in the physics of shortwave radiation transport and specified in terms of measurable biophysical properties, it is often possible to invert measurements of bidirectional reflectance, sampled over a range of Sun-target-sensor geometries, against the model — using numerical or analytical techniques — to yield estimates of the driving variables (Figure 2); in other words, the surface biophysical properties (Goel 1989; Antyufeev & Marshak 1990; Privette et al. 1996; Barnsley et al. 1997; Gao & Lesht 1997; Qiu et al. 1998).

7 BIOPHYSICAL PROPERTY ESTIMATION THROUGH BRDF MODEL INVERSION

BRDF model inversion techniques are currently being applied to estimate land surface biophysical properties from data acquired by a number of current and recent satellite sensors, including NOAA/AVHRR (Privette et al. 1996), ADEOS/POLDER (Deschamps et al. 1994; Roujean et al. 1997), ERS/ATSR (Flowerdew & Haigh 1997), Terra/MODIS and Terra/MISR (Wanner et al. 1997; Justice et al. 1998; Strahler et al. 1999). The characteristics common to each of these sensors are that (i) all are relatively coarse spatial resolution devices ($\sim 1km$; $\sim 7km$ for POLDER) and (ii) the intention is to derive global data sets. This raises a number of important issues:

1. Most BRDF models implicitly assume that the surface radiation scattering takes place within a spatially homogeneous medium, which is rarely the case at $1km$ resolution;

2. The standard numerical techniques used to solve inversion problems are typically too demanding in computational terms for application at the global scale and are not, in any case, very robust to the initial estimates of the model parameters, given the highly non-linear nature of many BRDF models; and

3. Validation of the derived data sets is problematic given the large difference in spatial scale between the image data and typical *in situ* measurements.

The first two of these have, to date, prompted something of a retreat from the use of more complex, physically-based BRDF models. The third remains an ongoing issue.

The practical solution adopted in most cases has been to try to 'linearize' the BRDF models by making a number of simplifying assumptions and approximations (Roujean et al. 1992; Wanner et al. 1995). This has a number of important ramifications, including implicit modelling of spatial heterogeneity and the ability to derive fast, analytical solutions to the model inversion problem. Unfortunately, the model abstraction performed during the linearization process makes the relationship between many of the derived model parameters and the corresponding surface properties less reliable, except perhaps close to the point in parameter space where the linearization is performed. In short, while one may be able to *describe* adequately the bidirectional reflectance properties of the land surface with such models, the relationships between the model outputs and the biophysical quantities of interest are more problematic.

In view of these issues, research in this field is currently focused on the use of Look-Up Table (LUT) and Artificial Neural Network (ANN) approaches to BRDF model inversion. The former, in particular, offers two very considerable benefits, namely that (i) a range of more sophisticated, physically-based BRDF models can be employed, and (ii) the bulk of the computational burden is transferred from the inversion stage to the generation of the LUT from the BRDF model, making viable operational application of this approach.

8 THE CHRIS/PROBA MISSION

In theory, it should be possible to separate the biochemical signal from the structural/biophysical effects by combining information from both the spectral and directional (angular) reflectance domains. Verhoef (2000), for example, has shown that it is theoretically possible to retrieve simultaneously two soil parameters (soil brightness and soil spectral slope), two leaf parameters (leaf chlorophyll concentration and leaf mesophyll structure), four canopy parameters (canopy LAI, average leaf angle, canopy hot spot parameter and leaf angle distribution) and three atmospheric parameters (visibility, aerosol Angstrom coefficient and aerosol single scattering albedo) by inverting a suitable BRDF model against hyperspectral measurements of bidirectional reflectance.

The necessary combination of a high spatial resolution, hyperspectral imager — capable of resolving in fine spectral detail the reflectance properties of Earth surface materials — and an agile satellite-platform — capable observing a fixed target from multiple view directions both along- and across-track — has been realized for the first time through the CHRIS/PROBA smallsat mission. The CHRIS (Compact High Spatial Resolution Imaging Spectrometer) instrument (Figure 3), developed by Sira Electro-optics Ltd, records data in either 19 or 63 narrow, user-selectable spectral channels between $410nm$ and $1050nm$ at approximately $18m$ or $36m$ spatial resolution, respectively. CHRIS is mounted on board the PROBA (Project for On Board Autonomy) platform, which was launched into a sun-synchronous, elliptical, near-polar orbit, with a mean altitude of about $600km$, from Sriharikota in India on 22 October 2001. Significantly, PROBA carries four reaction wheels which enable it can be tilted in orbit up to $\pm 55°$ off-nadir in the along-track direction and up to ± 36 in the across-track direction. Using this unique combination of a highly configurable hyperspectral imager and a small, agile satellite, it is possible to acquire hyperspectral data for a $14km \times 14km$ area on the ground at up to 5 different view angles from a single orbital overpass, and typically from up to three such orbits within a 7–10 day period, depending on the latitude of the site (Figure 4).

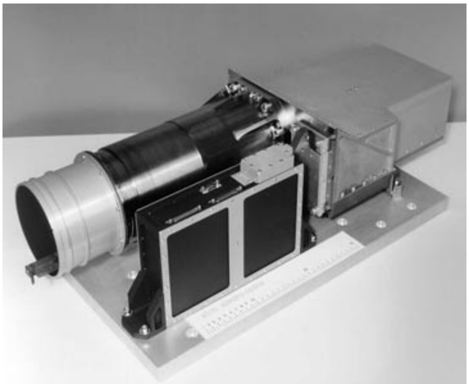

Figure 3: The Compact High Spatial Resolution Imaging Spectrometer (CHRIS), currently orbiting on the agile PROBA-1 satellite. Photograph courtesy of Sira Electro-Optics Ltd.

Data from CHRIS/PROBA can be used to invert complex, physically-based BRDF models, for which the relationship between the retrieved model parameters and the corresponding surface biophysical properties is well characterized and understood. Focusing of key sites of environmental and climatological significance around the world, this will not only improve our understanding of the detailed feedback mechanisms involved between the land surface and climate, but will also help to interpret and validate the results obtained from the suite of coarser spatial resolution, global imaging satellite-sensors.

9 CONCLUSIONS

Earth observation satellite-sensors offer considerable potential in terms of providing information on the spatial and temporal variations in the biophysical and biochemical properties of the Earth's land surface. This information is required as input to land surface parameterization schemes in Global and Regional Climate Models. In this context, new data processing techniques must be developed, based on a combined analysis of hyperspectral and multi-angle image data, with the aim of separating the effects of variations in the surface biophysical properties from the surface biochemical properties on the detected signal. These are likely to rely on the inversion of numerical models of surface radiation scattering against measurements of spectral bidirectional reflectance sampled at a range of different solar and sensor angles. A range of satellite-sensors is now operational which can provide data appropriate to this task, some geared toward global change studies, while others, such as the CHRIS/PROBA mission, are suited to more detailed, local investigations, but can also be used to validate the results obtained from the global imagers.

(a)

(b)

Figure 4: Two images of Long Beach, California recorded by CHRIS/PROBA at slightly different sensor view angles during a single orbital overpass.

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