CHAPTER 19

3D CANOPY MODELLING AS A TOOL IN REMOTE-SENSING RESEARCH

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Abstract. This chapter reviews the way in which 3D plant and canopy models have been used in the field of remote sensing. The focus of the chapter is on remote sensing of crops at microwave and optical wavelengths, although other applications are discussed. A brief review of remote sensing of crops is presented, followed by an evaluation of the motivation for using various types of 3D models with remote-sensing data. A discussion of current issues and areas requiring future work is provided.

REMOTE SENSING OF CROPS

Crop monitoring using earth observation (EO) is of major importance for its potential economic value to farm managers, levying or subsidizing bodies, and commodities and futures markets. It is also of value because of the role crops and cropping practices play in wider scientific and societal issues such as the environmental impact of farm-chemical inputs and carbon sequestration (Schlesinger 1999; Robertson et al. 2000). In addition, crops serve as a useful, controlled environment in which to develop generic EO science of wider application.

The key capability of remote sensing in this context is to provide regular sets of spatial observations of radiometric properties of earth surface vegetation. EO instruments can be deployed in support of crop monitoring in a variety of ways, including in-field sensors, airborne systems and satellites, obtaining information at a variety of spatial and temporal scales. Deriving estimates of state and rate variables of vegetation canopies has long been a goal of remote-sensing science. Traditionally, this has been attempted on the basis of empirical relationships between remote observations and (measured or modelled) biophysical parameters. For radar applications, relationships are usually derived by calibrating observed quantities (leaf area index (LAI), biomass etc.) with backscatter. For optical measurements, similar quantities are often related to vegetation indices, in an

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attempt to dampen the influence of atmospheric or soil moisture variations on the signal. Among the major disadvantages of such an approach are: (i) relationships retain sensitivity to multiple parameters – only partial success is often achieved because of parameter coupling for particular cover types; (ii) the relationships lack generality and require recalibration for different vegetation types and sensor or environmental influences; and (iii) sub-optimal use is made of multi-channel observations.

A more generic, flexible, and potentially more accurate approach is to use physically-based 'forward models' of scattering of electromagnetic (EM) radiation by canopies. This allows sensitivity to physical parameters to be explored and proof of concept studies for new sensors, supplementing information available from typically limited field and airborne trials. The models can also be used directly in inversion strategies to derive estimates of (biophysical) parameters. For many years, attempts at using traditional compute-intensive iterative inversion schemes held up the application of this approach, but recent work using artificial neural networks (ANNs) or the more flexible look-up tables (LUTs) (Kimes et al. 2000) has made using such methods feasible and practical (Knyazikhin et al. 1998). For many applications, however, uncertainties associated with the EO measurements and the impact of assumptions underlying the models lead to the inverse problem in remote sensing being 'ill posed' (Combal et al. 2003). For this reason, it is advantageous to supplement the observations and EO model with prior estimates of the model state variables. There are various frameworks for the optimal combination of such data, one of the more promising and practical being data assimilation (Weiss et al. 2001). One source of prior estimates is through the use of crop growth models. Such models can be generally grouped into two main categories: empirical and functional (mechanistic) models. This is essentially a distinction between top-down (analytic) and bottom-up (synthetic) approaches (Prusinkiewicz 1998). We can make two further distinctions between model types for remote sensing applications, based on their level of spatial organization – those that operate at the plant or plant organ level ('structural') and those that operate at the canopy level ('canopy'). In the structural approach, a canopy is modelled as an ensemble of individual plants.

In remote-sensing models of canopy scattering, vegetation is generally described through: (i) factors affecting scattering at the leaf (or other plant organ) level and lower (soil, snow etc.) boundary at appropriate wavelengths; and (ii) volumetric definitions of canopy structure, such as LAI and leaf angle distribution functions. The sub-models required for organ-level and lower-boundary scattering are relatively mature. Typical examples at optical wavelengths are: PROSPECT, which describes the reflectance and transmittance of leaves across the solar spectrum (Jacquemoud and Baret 1990), and the spectral bidirectional model of soil reflectance of Jacquemoud et al. (1992). At microwave wavelengths, typical sub-models are: the dual-dispersion leaf dielectric model of Ulaby and El-Rayes (1987), the 'thin scatterer' model of Karam et al. (1988) and the soil dielectric and texture model of Hallikainen et al. (1985) and Dobson et al. (1985).

MOTIVATION FOR 3D PLANT MODELLING

The remote-sensing signal is a function of canopy and plant structure

Plant and canopy structure plays a key role in radiative scattering and absorption, and thus affects both the modelling of a remote-sensing signal and the absorption of light by a canopy. Varying row spacing and orientation in crops is seen to have a direct impact on light interception and competition. Dhingra et al. (1986) noted an average increase of around 5% in wheat yield for North-South planted rows compared with East-West planted rows as a result of greater PAR interception. Structural effects due to ‘clumping’ at various spatial scales have a major impact on apparent LAI at optical wavelengths (Chen and Cihlar 1995; Chen 1996). Demarez et al. (2000) showed that canopy border effects and 3D leaf area distribution can strongly affect optical reflectance by as much as 40%. Luquet et al. (1998) showed errors of up to 10% in modelling the visible reflectance of a semi-arid grassland using a radiative-transfer model assuming a turbid medium rather than scattering from discrete 3D structures. Clumping arises in vegetation canopies due to such factors as nutrient or water distribution, shade avoidance, tropism, etc. Functional-structural plant models (FSPMs) are capable of modelling such effects and so including such clumping as a result of a model process. Structural plant models (SPMs) are capable of expressing the various forms of clumping (e.g. shoots on a pine tree), even though the structure is not directly generated through a model process.

A particular feature of canopy reflectance at optical wavelengths that arises *through* canopy structure is the ‘hot spot’ phenomenon (Myneni et al. 1995). This is a local peak in reflectance as a function of angle in the region of the retro-reflection direction. The peak exists at viewing and illumination angles for which no shadowing occurs. The angular width of this peak is seen to be sensitive to the ratio of scatterer (leaf) size to canopy height. Canopy reflectance models based on 1D radiative transfer are not capable of simulating this effect without modification to the theory. The effect is implicitly included in 3D numerical solutions to radiative transport such as ray tracing or radiosity, when used with explicit 3D objects.

Structural effects on microwave backscatter have been demonstrated through various measurement and modelling studies over forests (e.g. Zoughi et al. 1986; Mougin et al. 1993). Canopy macrostructure characteristics, such as row orientation, have been studied and modelled for crops (Whitt and Ulaby 1994), but most crop canopies are more generally subjected to simple (e.g. homogeneous radiative transfer) modelling approaches due to their assumed structural simplicity at the scales of interest. Stiles and Sarabandi (2000) argue for a more complex treatment of grasses and cereals such as wheat and barley. They suggest that such grass stems do not lend themselves to treatment as equivalent point scatterers, and leaves and other plant constituents are not conveniently modelled by simple geometric primitives on which much of the subject is based. In addition, the long, thin elements within a grass canopy are subject to variable illumination over the vertical extent of the canopy and elements are illuminated by a non-uniform (in intensity) coherent wave, meaning that current popular methods of treating such objects as attenuated versions of scattering in free space do not apply. As with trees, the 3D structure of the plant becomes important in understanding and modelling its response.

Common 3D structure as a route for model and data synergy

Effective systems for monitoring crop dynamics are likely to require multiple types of sensors. The principal reasons for this are: (i) whilst optical (particularly multi-angular, hyperspectral) data typically have a high information content for many monitoring tasks, clouds limit the temporal sampling available; (ii) radar data from current and near-future sensors, whilst less affected by cloud, have only limited channels of information and cannot be used to estimate all canopy and soil variables to which the signal is sensitive; and (iii) different EO measurements have sensitivities to different components of the canopy. Similar arguments apply to other vegetation-monitoring tasks, though temporal sampling requirements vary. Both optical and radar models can be phrased in terms of apparently common variables, e.g. LAI, and this has formed the basis of previous 'physically-based' efforts at model and data synergy. However, whilst there is clearly overlap between the parameters to which measurements in these domains are sensitive, in a general sense the mechanisms of EM interaction are often somewhat different. Optical measurements are sensitive to LAI, but radar is generally sensitive to both leaf size and scatterer number density. Both optical and radar can be sensitive to leaf thickness and leaf water content, but the impact of variations in these parameters is very different. Analytical models used at optical and microwave wavelengths are based on (geometric and other) abstractions made for mathematical convenience, rather than with an aim of maintaining consistent responses across the two regions: there is no guarantee that any derived ('equivalent') parameters will be consistent from such models.

A preferable route for model and data synergy is to adopt a common explicit (3D) structural basis for both domains, using appropriate numerical models to compute radiation transport. Numerical solutions are preferred as: (i) they do not require significant geometric abstraction; and (ii) the compute-intensive forward-modelling task can in any case be separated from run-time inversion task using ANNs and LUTs. This approach has been adopted by Lewis et al. (2003), Saich et al. (2002; 2003) and Disney et al. (2003; 2006) and shows much promise for application to crops and forests. Numerical EO radiation models developed are driven by explicit geometric representations of leaves, stems etc. Radiation transport at optical wavelengths can be modelled with Monte Carlo or radiosity methods (Disney et al. 2000) and coherent addition models (Saich et al. 2002) for microwaves. One additional advantage of being able to model the detailed (3D) structure of vegetation is that simulations can be undertaken of signals known to be strongly related to particular canopy structural conditions, such as radar interferometry (Sarabandi and Lin 2000) and LiDAR (Govaerts 1996; Lewis 1999). There would seem to be much promise in further developing this approach to thermal remote-sensing observations, although this has not yet received any great attention. The majority of current research in linking observations from different EM domains or different types of measurements (e.g. distance/time resolved) is still however very much empirical (e.g. Kimes et al. 2006).

3D modelling as a constraint on inversion using remote-sensing data

Kimes et al. (2002) demonstrated the feasibility of inverting parameters such as canopy cover, LAI and soil 'brightness' using synthetic EO data for forest canopies via a complex (voxel-based) description of canopy architecture and a numerical solution to scattering at optical wavelengths. An important aspect of having an explicitly-defined 3D description of *plant* architecture within a canopy is that it can be used to reduce effectively the parameter space in the inversion algorithm. In effect, by using a 3D representation of a particular plant (or set of plants) we are defining constraints on the inversion. Further, if the 3D model is dynamic in a way that can be related to the time interval between sets of remote-sensing observations, then *time development* can be used as a further constraint. Saich et al. (2002; 2003) and Lewis et al. (2005) show how such an approach can be used with 3D dynamic models to invert the 'effective age' and time development of forest and wheat canopies using optical and microwave observations. For a Scots pine forest model, canopy structural development is defined as a function of time (in years). For the wheat model, development is defined as a function of integrated thermal time (the sum of degree days from appearance). Simulations are produced of the structural models and numerical solutions to radiation transport used to simulate the EO data. These simulations are stored in a LUT and a merit function defined to relate the simulations to the observations. Although much further work is required to develop these ideas fully, these studies indicate the feasibility of using the dynamics of 3D plant architecture as a strong constraint to remote-sensing inversion.

The 3D dynamic models noted above are not 'functional-structural' models, in that even those that describe the typical development of the plants being modelled do not link plant growth and development to the function of plant organs. Thus, the controls on the plants of resource limitation (light, heat, water, nutrients) are not considered and the models require some form of calibration to simulate specific conditions. Should the field of functional-structural plant modelling further develop, one can envisage opportunities to link such models of botanical process to EO data using methods such as data assimilation.

3D models for understanding the radiation regime of vegetation

The widest use of 3D models of plants and canopies in remote sensing, particularly in the optical domain, is currently in understanding features of the radiation regime of vegetation and the sensitivity of EO data to various parameters. Within such models, we can distinguish what have been termed 'hybrid' models (those which represent plant architecture macrostructure and assume vegetation to be a turbid medium within the bounds of the macrostructure envelope) and those which use explicit 3D representations of all plant elements modelled. A variation on the 'hybrid' theme (effectively a discretization of the approach) is the representation of the canopy as voxels with assumed turbid-medium scattering within each cell. Kimes and Kirchner (1982) provide an example of a hybrid model that is used to examine the impact of 3D row structure effects on canopy reflectance and demonstrates the importance of this feature of canopy geometry. An example of a voxel optical model is that of Gastellu-Etchegorry et al. (1996). The model has been used for a wide range of studies of the influence of heterogeneity and other properties on the remote-sensing signal. The model of Sun and Ranson (1995) operates at microwave wavelengths with a similar form of canopy representation.

Ross and Marshak (1988) present a simple structural model of vegetation represented by disk leaves on cylindrical stems to simulate optical canopy reflectance. Borel and Gerstl (1994) use a radiosity method to investigate factors such as the non-linear spectral mixing in a canopy composed of 3D walnut trees. Castel et al. (2001) combine 3D AMAP tree models with SIR-C radar observations to investigate the retrieval of forest parameters, including terrain effects. Heyder (2005) uses explicit representations of Scots pine trees in a stand to investigate the impact of terrain slope and other factors on ICESat LiDAR signals. An L-systems-based model of various cover types in a semi-desert area is used by Qin and Gerstl (2000) to produce ‘scene models’ at optical wavelengths.

The list of applications given above using ‘hybrid’ and ‘structural’ 3D representations of vegetation structure is far from exhaustive, but provides a flavour of the range of modelling work within the remote-sensing literature within which details of 3D plant or plant macrostructure geometry has proven important to the understanding of the remote-sensing signal. It is likely that the range of such applications will extend in the future as tools and models become more readily available. A major motivation for much of the work cited is to be able to account for the influence of structure on the simulations. Although the computational cost of such simulations is generally significantly higher than using simpler analytical or numerical models, the advantage is that structural influences can be explicitly investigated: the derivation of models is no longer reliant on making assumptions purely for mathematical convenience.

Modelling of high-resolution imagery and image texture

Unlike 1D radiation models, 3D representations can be used to provide spatially explicit simulations which can be used to simulate measures such as image texture. Although there are many measures of image texture in use (Atkinson and Lewis 2000), some of the most useful for linking to radiometric simulations and measurements are geostatistical measures relating to the image semivariogram and related spatial-variance terms. The former are typically used for analyses where the average spatial extent of the vegetation is larger than the imaging spatial resolution, the latter where the object size is smaller than the imaging resolution. Measures related to these concepts are found to contain important and unique information on the spatial macrostructure of vegetation canopies, and the behaviour of variance and semivariograms with changes in viewing in illumination and viewing geometries can be seen as an additional dimension of information from EO data.

Most models use simple geometric representations of plant macrostructure (no variation within the bounds of the plant is assumed), which can provide a useful indication of the major influences on the ‘directional’ signature of spatial texture (Ni and Jupp 2000). There are several papers that use more complex representations of plant structure to investigate textural parameters. Examples using ‘hybrid’ models include DART (Bruniquel-Pinel and Gastellu-Etchegorry 1998), which is used to simulate texture in high-resolution imagery. Izzawati et al. (1998) used the model of

Sun and Ranson (1995) to examine textural features of high-resolution radar imagery through 3D modelling of oil-palm canopies. There are few examples of 3D structural models of plants being used to examine image texture, one being the simulation of very-high-resolution image texture in a canopy (Lewis et al. 1999) using 3D representations of barley plants. The main reason for this lack of activity is most likely due to the fact that the texture measures require the simulation of high-spatial-resolution images of plant canopies. This puts greater emphasis on the details of the geometric representation than other more spatially aggregated simulations, and the computer-processing cost is significantly higher. There are many potential advantages of this approach to modelling however, particularly for close-range applications such as understanding texture from tractor-mounted imaging systems targeted at agricultural monitoring in precision farming or weed detection.

In summary, since the 3D nature of plant canopies impacts the spatial variation of canopy reflectance, radar backscatter and other radiometric quantities, variations in 3D structure lead to changes in local image variance and other measures of texture. 1D models of canopy reflectance are not able to simulate such effects, but 3D models which represent individual plants are well-suited to this task.

OUTLOOK

Integrating aspects of plant and canopy growth with remote-sensing measurements has many attractions both for research directed at both fields, and for the joint development of practical monitoring systems. Remote sensing provides temporally sampled monitoring of the vegetation canopies. Whilst vegetation growth can be considered ‘gradual’, remote sensing may often not achieve sufficient sampling to monitor this sufficiently, particularly using single technologies (e.g. optical or microwave) for the various applications involved. Whilst canopy growth models can be calibrated or adapted to conditions at particular locations, they cannot be considered error-free, and will generally benefit from the addition of remote observations to constrain potential growth to actual (observed) dynamics. Whilst there are clearly still issues to be resolved in integrating crop growth models and remote-sensing measurements, the most integrative and flexible way forward on this would appear to be to use data assimilation with mechanistic canopy-functioning models and physically-based canopy reflectance and scattering models. The state of the art in this area is currently the work of Weiss et al. (2001).

FSPMs have many potential advantages over canopy scale models in this role, in particular in allowing improved modelling of canopy interactions of the main environmental drivers (light and temperature) with the canopy structure. In addition, both functional-structural and empirical-structural models provide ‘realistic’ ranges of structural representation for particular vegetation canopies, which can be used to restrict biophysical parameter spaces to feasible ranges of conditions and inherent dependencies between canopy structural variables. They also have great potential for the integration of optical and microwave remote-sensing data as they can provide a common structural basis for modelling in both regions of the electromagnetic spectrum. There is also promise for linking such measures to other sources of remote-sensing information such as radar interferometry, LiDAR, and texture measures.

Whilst empirical-structural models have received particular attention, neither they nor FSPMs have yet been used directly in remote-sensing assimilation studies. This is partly due to computer-processing requirements for simulating the remote-sensing signal but, as in other areas of detailed structural modelling, increased computational capacities allow much greater scope for such studies. An additional limitation has been that very few such models exist for crops, and those that do have not received the wide testing of canopy scale models. These are points that need to be addressed before the more general uptake of functional-structural plant modelling can take place in remote sensing.

There is much to be gained through the use of FSPMs, both in terms of generality if the main physiological processes are incorporated, and of providing structural expectations for remote-sensing modelling and inversion. However, the more recent ‘stream’ of functional-structural models have not yet been used in remote-sensing applications, with current uses being limited to more empirical structural models. Most remote-sensing applications have not made detailed use of the expectation of temporal evolution of structure to any great degree, but this is clearly an interesting and feasible avenue for research.

Some interesting questions that arise from the use of such models in remote sensing include: (i) what is the impact of the *detail* of the underlying 3D description? and (ii) what is the impact of the *specificity* of the 3D vegetation model? The first of these questions has received little attention to date in remote sensing. España et al. (1999) examine the impact of the number of triangles used to represent maize leaves in a 3D canopy representation on the optical signal. They find only marginal impact on canopy gap fractions and simulated bi-directional reflectance when using a degraded representation of the leaves. Further studies are required to explore other aspects of the impact of the degree of accuracy of representation needed to simulate canopy scattering accurately at different wavelengths. The most likely answer to this question is that there are breakpoints in scale critical to accurate simulation (thence important to inversion). An interpretation of the results of España et al. (1999) then is that a detailed representation of leaf shape and features such as undulations is relatively unimportant for simulations at the canopy scale. If the model were used to perform high-spatial-resolution texture simulations, the impact could be greater. This question of detail also applies to the detail with which plant and soil material directional reflectance needs to be simulated: in many models they both are assumed Lambertian. This is partly for ease of specification or lack of suitable data to parameterize such models, partly because Lambertian numerical simulations are more straightforward (particularly for radiosity methods), and partly out of a belief that all such angular effects will balance out to some equivalent Lambertian reflectance when averaged over all vegetation/soil elements. This is clearly an area requiring further study.

FSPM is a rapidly developing field, but still relatively new subject area and the use of such models in remote sensing is still in its infancy. It has been recognized for some time that the structure of vegetation canopies affects what is measured by remote-sensing instruments, and this chapter has attempted to show some of the ways in which structural concepts have been introduced into modelling and inversion. As EO instrument technology develops, the volume and range of measurements that can be made from satellites and aircraft increases. At the same time, methods for combining different forms of observations via models of vegetation dynamics are being explored (e.g. data assimilation). Many of these measurements, particularly radar interferometry and LiDAR, are affected by (and contain information on) canopy structure at relatively high spatial resolution. As the field of functional-structural plant modelling matures, it is most likely that increasing use will be made of such models in both informing information extraction from remote-sensing data and in being driven by information provided by this and other spatial information technologies.

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