Crop Growth Modelling and
Architectural Models for Crops

Report on Workpackage 10
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1 INTRODUCTION

This document provides a summary of the current state-of-the-art in canopy and plant growth modelling for crops. It is focussed on applications within a remote sensing modelling context for deriving canopy state parameterisations from data at optical and microwave wavelengths, and aims to provide information to permit recommendations for future model implementation. As the crop selected for study is wheat, examples emphasise wheat growth modelling where possible, with some exploration of different crop types and potential methods for modelling.

This report complements one written on tree models. As much of the background, methods and models involved have a large degree of similarity for both crops and trees, material generic to both is covered in this report.

1.1 Motivation for the use of Plant/Canopy Growth Models

A remote sensing canopy model can be stated as a relationship between remotely observable quantities such as scattering (reflectance at optical wavelengths), emittance, or some transformation of a combination of these as a function of canopy state variables. We can term such a simulation tool a 'forward model'. The motivation for forward modelling can be varied, but is typically either to provide an understanding of the sensitivity of the remote sensing signal to variations in canopy state, or to provide an expectation of the remote sensing signal for comparison with measurement and potential model inversion (determination of canopy state given a set of remote observations). We can distinguish two main approaches to this, being based on empirical ('descriptive') approaches or physical ('mechanistic') principles. A similar distinction will be made in other areas of this report, so it is worthwhile emphasising here that the main benefits of a physically-based approach, following a reductionist line, are the generality of the solution, that they contribute to understanding of the process of interest, and that they integrate underlying mechanisms (e.g., Prusinkiewicz, 1998). Empirical approaches, on the other hand, provide a convenient description of apparent relationships and permit interpolation, but they fail in providing a clear path to integration of model sub-components, in furthering understanding, and in their generality. Whilst attempts can be made to reduce sensitivity to the observation to extraneous influences, such as angular, atmospheric or topographic variations e.g. through transformations such as vegetation indices (Vis), significant residual sensitivity to such effects can remain (e.g. Burgess et al., 1995).

There is not the scope within this report to review remote sensing simulation models, as this will be covered in the outputs of Task 4. A range of empirical models are used at both optical and microwave wavelengths, which are generally of a simple invertible analytical form (linear, exponential), relating reflectance, radar backscatter or Vis to a range of biophysical state variables, principally, (green) Leaf Area Index (LAI), the fraction of absorbed photosynthetically active radiation (fAPAR), and biomass. Baret and Guyot (1991) reviewed the potentials and limitations of some of the VI approaches, and Verstraete and Pinty (1996) provide a framework for designing optimal Vis aimed at particular compensating effects and particular state variables. Goel (1988) provides a comprehensive review of physically-based approaches to optical reflectance modelling, with an update by Goel and Thompson (2000) covering the main categories of models in use. Saich et al. (1995) have reviewed options in microwave canopy modelling. A key ability of the current range of optical and microwave simulation models is that of providing analytical solutions for simple canopy structural definitions (e.g. radiative transfer approaches or geometric optical approaches), as well as numerical solutions for radiation scattering from more complex structural descriptions based on volumetric cell representations or discrete representations of complex groups of simple geometric primitives (Disney et al., 2000). We return to issues of complexity of structural representation below.

Model inversion provides a route to the mapping of canopy state variables from remote sensing observations, and can be seen as one of the main aims of remote sensing in its attempt
to provide spatial datasets of continuous state variables. There are many examples of inverting both empirical and physically based models in the literature. For example, Walthall et al. (1985), Nilson and Kuusk (1989), Pinty et al. (1990). Inversion requires first a statement of a forward model. A typical empirical example is given by Ikeda et al., (1999):

$$ VI = \frac{\ln(Y) - a}{b} $$

where $Y$, the canopy state variable, represents aboveground phytomass, and VI, derived from the remote sensing observations, is a vegetation index, such as the Normalised Difference Vegetation Index (NDVI). The model parameters $a$ and $b$, assumed constant over time, are estimated simply using multilinear regression for a set of observations of NDVI and $Y$ (the model is 'calibrated'), and it is then assumed that observations of VI can be used to predict $Y$. In the more general case, and particularly for highly non-linear physically based models, numerical methods must be used for model inversion (Kimes et al., 2000). Most applications of remote sensing of vegetation require the monitoring of vegetation state over time, e.g. for yield prediction, burn scar detection, or canopy carbon uptake (Goetz et al., 2000; Ichii et al., 2001). This can be achieved by multiple applications of the inverse model to discrete sets of observations to provide mappings of canopy state at the times of the remote sensing measurements. However, these data cannot be interpolated or extrapolated without the addition of some form of model of the temporal dynamics of the state variables. Ikeda et al. use another empirical model for this:

$$ Y_t = Y_0 e^{-rt} $$

to describe the development of $Y$ at time $t$, $Y_t$, in terms of a constant growth rate, $r$, and an initial phytomass value at time $t = 0$. Again, the constant parameters of the combination of this empirical model with the remote sensing model ($a$, $b$, $r$) can be found from multilinear regression, but parameter estimation is more complex in the general case.

A temporal model of canopy state development (canopy growth model) can be used in many ways, either in its own right (e.g. crop yield prediction or change detection) or as a sub-component of 'process models' dealing with a range of processes, such as ecosystem models (Nouvellon et al., 2000) or Soil-Vegetation-Atmosphere Transfer Schemes (SVATS) (Cayrol et al., 2000). Whilst the crop growth model prediction tools are not always accurate (Delécolle et al., 1992), they provide a viable alternative to costly direct measurement. Early research efforts in the 1970s and 1980s, such as LACIE (Erickson, 1984) and AgRISTARS demonstrated the potential for the integration of remote sensing data with other measurements and models for crop production monitoring. More recently, the MARS (Monitoring Agriculture with Remote Sensing) programme of the EU (Meyer-Roux, 1990) has provided information on crop area estimates. This operational monitoring system currently uses remote sensing data only for area estimates, and not directly in the assessment of crop activity or yield estimates (Delécolle et al., 1992; Moulin et al., 1998), although experiments have been conducted under the project to investigate the potential for crop yield monitoring using remote sensing data (Genovese et al., 2001).

It should be noted that empirical models have been used to attempt to go directly from single or multiple data remotely sensed observations to products of vegetative growth such as yield. Examples of single date applications include studies by Hatfield (1983) and Murthy et al. (1996), relating potential yield to a VI at a particular growth stage. Tucker et al. (1985) related biomass to cumulative VI values through a multi-date empirical model, although as will be seen below, there is some process-based evidence for such a relationship. None of these models, however, use any explicit form of canopy growth model - the empirical
relationships derived by bypasses this. Although perhaps encapsulating an overall general relationship and providing rapid and simple monitoring of the estimated variable, the relationships derived cannot be applied directly to other locations or scales, and do not contribute to an understanding of the underlying processes.

1.2 Categories of Canopy Growth Models

Many models of vegetative growth exist (WWW1), but they can be generally grouped into two main categories: empirical and functional (mechanistic) models (Thornley and Johnson, 1990). 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 organisation, those that operate at the plant or plant organ level, and those that operate at the canopy level. We can term the former ‘canopy’ models, and the latter ‘structural’. In the structural approach, the canopy is modelled as an ensemble of individual plants. The following sections (2 and 3) will review options for empirical and functional crop growth models. Both canopy and structural models exist in empirical or functional forms, providing four model ‘types’. Before proceeding to the review, the role of canopy structure and general methods for its modelling will be considered.

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 PAR by a canopy. Varying row spacing and orientation in crops has a direct impact on light interception and competition. Dhingra et al. (1986) note an average increase of around 5% in wheat grain and straw yield for North-South planted rows than for East-West for a study in the Punjab, India, as a result of greater PAR interception. Bi-directional sowing, with an additional increase in PAR interception, gave additional yield of a similar magnitude over the North-South planting. Despite such known structural impacts, most canopy growth models, and many remote sensing models, assume a random distribution of vegetative elements in a turbid medium when calculating radiation scattering and 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) demonstrate in a modelling study that canopy border effects and 3D leaf area distribution strongly affect optical reflectance, by as much as 40% in some cases for their test canopy of a fallow field. Luquet et al. (1998) show errors of up to 10% in modelling the visible reflectance of a semi-arid grassland scene using a radiative transfer model assuming horizontal and vertical homogeneity rather than scattering from discrete 3D structures.

Structural effects on microwave backscatter have been demonstrated through various measurement and modelling studies over forest (e.g. Zoughi et al., 1986; Mougin et al., 1993; Martinez et al., 2000). 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 at microwave wavelength due to their assumed structural simplicity at the scales of interest. Stiles and Sarabandi (2000) argue for a more complex treatment of grasses and cultural grasses 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, 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 freespace do not apply. As with trees, the 3D structure of the plant becomes important in understanding and modelling its response.

One additional advantage of being able to model the detailed (3D) structure of vegetation is that simulations can be undertaken of signals strongly known to be related to particular
canopy structural conditions, such as radar interferometry (Sarabandi and Lin, 2000; Sarabandi and Wilson, 2000) and LiDAR (Govaerts, 1996; Lewis, 1999).

Canopy-scale crop growth models do not contain both structural and topological information, and rarely contain any level of detail on structure of individual plants. On the whole then, canopy-scale models can neither explain, nor be used to explore, structural effects in plant or canopy growth. Neither can they be easily interfaced to remote sensing models which are driven by structural information.

Prusinkiewicz (1998) reviews the history of structural models of individual plants in detail. Two significant schools of modelling have developed over the last 30 years, namely, Lindemayer Systems (L-systems) (Prusinkiewicz and Lindenmayer, 1990) and AMAP models (de Reffye et al., 1997). Over the last few years, research has focussed on functional-structural modelling of plants (FSMPs) in these and other groups (e.g. Sievänen et al., 2000) and there is a recent move towards integration of model components and sharing of databases and models within a concept known as a Plant Architecture Information System (PAIS) (PAIS, 2001). Although current and earlier models have made appearances in remote sensing simulation studies (reviewed below), and there is some hope to integrate remote sensing monitoring and applications within PAIS concepts over the next few years (EuroPAIS, 2001), this is beyond the scope of this project. PAIS/FSPM developments will be briefly reviewed below to point the way for future developments in this field.

One major issue with using and developing detailed structural models of individual plants is obtaining sufficient measurements. This is briefly reviewed by Sinoquet et al. (1997) and Prusinkiewicz (1998) with some aspects regarding photogrammetric measurement examined by Lewis (1999).

2 Empirical Canopy Growth Models

Empirical canopy-scale models may have some grounding in consideration of process, but they ultimately rely on a set of observations to 'calibrate' the model parameters for a particular experiment. They fundamentally attempt only to provide an approximate expression of correlative effects. They are useful in describing and interpolating relationships, as well as form making practical predictions (Delécolle et al., 1992). The use of empirical-structural models is often somewhat different to canopy scale models, in that calibration of the supposed relationships governing structural development is often difficult to achieve, and many applications therefore simply study sensitivity around parameterisations that produce visually feasible structural representations.

Many variants of empirical models exist, either proposing simple relationships with time such as the exponential example given in section 1, or attempting to account for variations in the fundamental model parameters as a function of other variables. Ikeda et al., (1999), for example, modify the time relationship in their exponential model so as to be driven by accumulated temperature above a base threshold ('thermal time' in degree days) rather than actual time. This is based on the observation that the specific growth rate operates at a maximum within defined temperature limits, at least for C3 crops, where photosynthetic rate is dependent on temperature (Goetz et al., 1999). As with the remote sensing models, empirical canopy-scale growth models are simple to use and invert ('calibrate'), but they suffer from the traditional defects of such an approach noted above. As noted above, empirical-structural models are often difficult to calibrate, as they generally require large amounts of information in this process. A particular problem with the generality of empirical model is that the relationships encompassed in the model are limited to the climatic conditions under which the model was 'calibrated' as well as the particular plant species or varieties used. Thus, for example, they cannot be readily applied to other geographic regions,
for long-term monitoring or prediction under a changing climate, or for different plant
varieties. Delécolle et al. (1992) note that the relationships established will be scale
dependent, making their application to different spatial scales complicated.

2.1 Empirical Canopy-Scale Growth Models

There have been many attempts at defining suitable forms for empirical relationships of
canopy growth (Thornley and Johnson, 1990). Delécolle et al. (1992) and Moulin et al. (1998)
distinguish between 'statistical' models, based solely on multiple regression methods, and
'semi-empirical' models which encapsulate some concept of understanding process using
parameterised equations and statistical relationships (e.g. Monteith, 1977). For the purposes
of this review, we consider both of these model types as 'empirical' models.

Whether implicitly or explicitly, relationships defined for biomass or leaf area are often
considered through a first-order differential equation describing increase in e.g. biomass
$W$ with time $t$:

$$\frac{dW}{dt} = RW$$

where $R$, the specific growth rate typically operates at a maximum for early stages of
growth. The equation is simply an expression of the fact that the rate of growth is generally
sensitive to the current amount of biomass used in resource capture (Monteith, 2000). $R$
is seen to decline with competition for (e.g. light) resources, until the rate of biomass increase
essentially becomes independent of $W$. The exponential model used by Ikeda et al., (1999) is
an equivalent expression of this relationship which they apply to the early stages of canopy
development. A more flexible expression covering a the phase for which absolute growth rate,
$C$, is independent of $W$ is an expolinear model such as that developed by Goudriaan and
Monteith (1990) and reformulated in a non-dimensional form by Monteith (2000):

$$W^* (t) = \ln \left\{ 1 + e^{rt} \right\}$$

where $W^* = \{W(t) - W(0)\}(R_m/C_m)$ is a non-dimensional biomass term and
$t^* = R_m (t - t_1)$ is a non-dimensional time. Subscript $m$ refers to maximum values of the
variables concerned, and $t_1$ is an intercept on the time axis of the linear portion of a biomass
versus time plot.

Another way of expressing growth in biomass is the so-called 'production efficiency model'
(PEM) (Monteith, 1977):

$$W(t) = \varepsilon_e \int_{j=0}^{j=t} \varepsilon_i (j) \varepsilon_b (j) I(j) dt$$

where:
- $W(t)$ is the canopy standing biomass (dry matter) at time $t$;
- $I(j)$ is the incident global radiation;
- $\varepsilon_e$ is the proportion of Photosynthetically-active radiation (PAR) in $I(j)$ which is
generally taken to be 0.48 (Moulin et al., 1998);
- $\varepsilon_i (j)$ is the PAR interception efficiency of the canopy which depends on canopy density
and structure as well as leaf pigmentation. It is also termed the 'fraction of absorbed
photosynthetically-active radiation' (fAPAR);
and $\varepsilon_b(j)$ which is the efficiency of conversion of PAR to dry matter. $\varepsilon_b(j)$ has been claimed to be almost constant for a given crop type, being between 2.2 and 2.8 g of dry matter per MJ of absorbed PAR (Kumar and Monteith, 1983) for UK arable crops, at least as a seasonal mean value. However, $\varepsilon_b(j)$ may be variable over time and crop type, and will vary with metabolic pathway (C3, C4), phenological stage and environmental factors such as nutrient availability (Rasmussen, 1997). The effect of slight or moderate stress is found to be primarily in its reduction of leaf expansion, thereby reducing $\varepsilon_i(j)$.

The equation essentially expresses the rate of change of biomass with time as $\varepsilon_c\varepsilon_i(j)\varepsilon_b(j)I(j)$, which we can relate to $RW$ above by noting that $\varepsilon_i(t)$ will increase with increasing biomass, at least over the early stages of canopy development. As a (semi-)empirical model, it is an improvement on the 'calibration' equation above in that it more explicitly accounts for variable inputs such as incident radiation and allows for sub-models to be used to account for aspects of the fundamental processes of dry matter accumulation, namely radiation interception, photosynthesis, and assimilation.

The PEM has found widespread application in remote sensing, particularly through the use of VIs at optical wavelengths, since for a given crop type, there is an approximately linear relationship between several indices based on red/PAR and near infrared ratios such as the NDVI and fAPAR (Kumar and Monteith, 1983; Hall et al., 1992). Effectively then, if $\varepsilon_b$ and $\varepsilon_iI$ are assumed constant, $\varepsilon_c$ (fAPAR), which approximately equals NDVI provides a measure of plant productivity through temporal integration (Sellers, 1985, Tucker and Sellers, 1986).

An example of coupling the PEM to remote sensing data is given by Steven et al. (1997) in examining yield prediction of sugarbeet in the UK using high spatial (low temporal) resolution satellite data. In this approach, $\varepsilon_b(j)$ is assumed constant and the crop yield is related to biomass at harvest through a constant harvesting index. Since the NDVI-fAPAR relationship can be affected by (among other factors) soil brightness variations, they use a soil-adjusted index (OSAVI, Rondeaux et al., 1996) to derive estimates of fAPAR. Since the remote sensing data are only at sparse temporal samples, the fAPAR derived is interpolated (and extrapolated) by fitting the observations to an empirical growth model of initial sigmoidal shape with a subsequent logistic-log exponential form.

Rasmussen (1997) uses a simple version of the PEM, essentially relating yield to integrated NDVI in Senegal, in much the same way as Tucker et al. (1985), except that modifications are made to the yield relationship to account for pre-crop NDVI levels using an empirical linear model.

A 'semi-empirical' modification of the PEM can be achieved through (e.g. Prince 1991):

$$W(t) = \varepsilon_c \int_{j=0}^{j=t} \sigma \varepsilon_i(j)\varepsilon_{b\max}(j)Y_g(j)Y_m(j)I(j)dt$$

where:

- $\sigma$, effectively a 'stress' factor, describes the departure from maximum efficiency caused by physiological responses to limiting environmental conditions;
- $\varepsilon_{b\max}$ is the maximum efficiency of energy conversion;
- $Y_m$ is the proportion of total assimilate not used in maintenance respiration;
There are various developments around this theme. Nouvellon et al. (2000) utilise a similar idea in developing a PEM sub-model in an ecosystem model by defining $\varepsilon_{p_{\text{max}}}$ as a maximum energy conversion efficiency which is reduced for sub-optimal leaf temperature, water stress and leaf ageing. Goetz et al. (1999) derive models for $\sigma$ to account for variations in air temperature, vapour pressure deficit and surface soil moisture. They also account for a loss of assimilate through autotrophic respiration, which is a function of standing biomass and air temperature. Although still a (semi-)empirical model, the compartmentalisation of these processes within this extended PEM model provides a clear route for the integration of various types of remote sensing and other data. Hanan et al. (1997) alter the modified form of the PEM above to replace $Y_m$ to better account for maintenance respiration and develop various sub-models to provide linkage with field measurements.

Another stream of semi-empirical modelling is based on the CO$_2$ supply function model, which is compared to the PEM by Hanan et al. (1997) for Sahelian cover types with high light intensity. The essential difference between the two approaches is that the PEM assumes limitation by PAR and PAR conversion efficiency, whereas the CO$_2$ supply function model assumes light saturation but limitation by CO$_2$ availability. Hanan et al. suggest that this model and the PEM models are able to explain observed production to a similar degree over a 10 day period for the four Sahelian cover types examined. Since work on this contract will examine the use of crop growth models for European crops, we do not take this analysis of CO$_2$ supply function models further here.

In summary, whilst simple empirical function fits (exponential, sigmoidal etc.) to observed developmental relationships for crop canopies have been used in remote sensing applications, they suffer from all of the traditional drawbacks of such approaches, such as lack of generality and being difficult to scale. Empirical models which utilise a level of compartmentalisation of physiological responses (semi-empirical’ models), such as the PEM, provide a growth modelling framework which can be adapted to varying degrees of sophistication, generally through empirical modelling of the energy conversion efficiency term. Although the PEM is empirical in the sense that it needs to be driven by calibrated coefficients, it can in another sense be considered a 'functional' model, as it is parameterised by functional variables such as fAPAR. This has received a good deal of attention and application from optical remote sensing, largely due to the convenience and ease with which an estimate of this quantity can be derived from simple methods such as NDVI models. There is no direct route, however, to estimate this variable from microwave data. In addition, models such as the PEM lack a clear description of the physiological and biological mechanisms controlling growth and development.

Physically-based models of canopy reflectance and scattering of remote sensing modelling are becoming increasingly feasible as an operational alternative to VIs. Such models are driven by (typically generalised) ‘structural’ descriptions such as vegetation cover, gap fraction, LAI and orientation (Goel and Thompson, 2000) and consideration of physical laws of radiation interactions (to various degrees of abstraction). Such models provide many advantages over empirical approaches to information such as those using VIs, as they are more generic in nature, are based on an understanding of physical principles, and can be used to model a wider range of conditions (e.g. varying illumination and viewing angles, varying wavelength etc.). Whilst models such as the PEM can be driven by ‘structural’ variables such as LAI, which can potentially be derived from physically-based approaches from both optical and microwave, this requires the use of a radiation interception model to calculate fAPAR which may often involve a different set of assumptions about the nature of the canopy from that used in the remote sensing. The model integration therefore suffers from having a further level of
abstraction and modelling between the remote sensing model and the canopy growth model. One way around this is to use a synergistic physically-based approach to the estimation of LAI and fAPAR, as described by Knyazikhin et al. (1998) for operational use with MODIS and MISR data.

2.2 Empirical Structural Growth Models

Prusinkiewicz (1998) examines the different types of empirical structural models that have been developed. They will be briefly covered here, with an emphasis on those that have potential or actual application to remote sensing. He distinguishes empirical models of plant structure and empirical models of plant development. The former are essentially static representations of plant architecture, and are thus not technically growth models, although a series of static representations can be used to examine aspects of dynamics. They are of particular relevance because of their use in remote sensing (and other fields) in understanding the impact of structure on simulations.

The categories of empirical model of plant structure of major relevance are: reconstruction models; curve fitting; self-similarity. These are discussed in section 2.1.1. Prusinkiewicz (1998) conveniently packages most concepts in the empirical simulation of plant development within L-system concepts. A discussion of this is briefly reviewed in section 2.2.2, although variations used in remote sensing simulations of crops will also be discussed.

2.2.1 Empirical models of plant structure

Reconstruction models involve direct simulation of plant architecture from a set of measurements. Various examples of this can be found in the remote sensing literature. Andrieu et al. (1995) measure the detailed location of each leaf and stem element in a maize canopy using layered destructive sampling and stereo photogrammetry. The resultant model data were not structured in any topological sense, but the model was demonstrated to have a very detailed representation of the canopy through comparison with hemispherical photography obtained within the canopy. The model/data were used to analyse single and conditional gap fractions as a function of canopy depth. Single gap fraction controls light interception by the canopy, whereas conditional gap fractions control the joint probability of photons arriving from above the canopy, travelling along a free path to a given depth, and being able to travel along a free path to escape from the canopy in an upward direction. It can be considered the main structural control to first-order scattering at optical wavelengths from a canopy, and was shown to be strongly dependent on structure for the maize canopy. Being a reconstruction model, however, no further analysis could be made of the influence of gap fraction of changing canopy parameters. One particular role of such detailed measurement studies, however, which impacts the ability to move from static to dynamic studies, is the exploration of descriptions of plant and leaf structures and their interrelationships. Thus, the work of Andrieu et al. (1995) can be seen to form the basis of further developments of a dynamic maize model by Fournier and Andrieu (1999).

Lewis and Disney (1998) use a reconstruction model of a barley canopy at various growth stages to study the nature of multiple scattering from a structured medium at optical wavelengths. Measurements were based on a set of manual key plant parameters, describing the topology, and leaf and inter-node lengths of the main stem and tillers of a sample set of plants in a canopy, along with characterisations of leaf insertion and tip angles (Lewis, 1999). Having sampled a number of plants at different growth stages allowed the study to examine some aspects of growth stage on multiple scattering, but this could only be achieved for reconstructions of the measured canopies.

Curve-fitting models take advantage of multiple measurements of individual plants or plant organs to provide best-fit or stochastic variations around these. They are therefore capable of
providing more variability than a simple reconstruction model, but do not appear to have found application in remote sensing.

Self-similarity is a particular feature of fractal models, the application of which can be found in several remote sensing studies of trees (there appear to be no crop studies). Fractal models have proved popular for such applications as they can simply produce tree-like representations, although they cannot easily be made to model any real form of development, and remain essentially static representations. Borel and McIntosh (1986) used fractal objects to examine millimeter wave backscatter from deciduous trees. They justified the use of the model as it produced visually similar results to real trees, and were able to study the effects of leaf orientation. This early work was able to exploit key features of having a 3D representation, such as more realistic leaf azimuth distributions than are possible in the usual statistical models, as well as to demonstrate the role of tree-like architecture of millimeter wave backscatter. Lin and Sarabandi (1999a) developed a coherent scattering simulation model with tree structure driven by a fractal-based architecture within an L-system. The ‘growth’ of the trees is simulated in their model through iterations through the L-system rewriting rules. This actually produces a development in complexity of the tree-like structure or a simple change in structural parameters such as trunk width (Sarabandi and Wilson, 2000), rather than simulating any more realistic form of growth. It does at least allow for a simple parameterisation through initial conditions, length ‘growth’ rates, and branching angles, the variation of which provides a range of ‘realistic’ tree-like structures for study. The resultant objects have the additional advantage for simple microwave modelling of being defined as a set of simple geometric primitives for which scattering can be calculated analytically at an equivalent scattering centre and summed coherently over each tree object. Other studies using fractal 3D tree models include that of Xiande et al. (1999), who examined the effect of tilting ground on the radar bistatic scattering coefficient and demonstrated that the using a coherent addition model could have a very large impact at lower frequencies (P band) but a relatively small effect at higher frequencies (C band).

2.2.2  Empirical models of plant development

Many models implemented within L-systems are of the empirical-structural variety. An L-system (Prusinkiewicz and Lindenmayer, 1990) is a grammar re-writing system which can be applied to whole plants or plant organs. The basis of plant representation is a bracketed L-system, which represents a branching structure as a string of symbols corresponding to plant modules. Bracketing within the string represents branching topology. In empirical L-system models in particular, it is common to incorporate turtle interpretations within this bracketed string. Turtle symbols are essentially graphic rotation and translation commands which describe the tracing of the plant architecture. They operate in 3D to generate 3D plant architectures. An L-system comprises an initial configuration string (the ‘axiom’) and a set of re-writing (‘production’) rules which specify a parallel replacement of string symbols at each iteration. They are seen to be a simple and compact representation of forms of plant development.

Various advances on the original L-system concepts have been developed, notably: parametric L-systems, which allow the association of a set of parameters with each string symbol and the variation of continuous geometric or other parameters (such as branch length or width); and stochastic L-systems, which permit the application of different rules according to given probabilities within a stochastic simulator. This latter point allows for stochastic variation in plant architectures from a small rule set, which is often used in empirical modelling of state change to account for unknown, supposedly unmodellable, or unmeasured mechanisms. This concept incorporates discrete Markov processes (Prusinkiewicz, 1998). The re-writing system allows L-systems to model the development of plants, rather than just static representations. This can be a simple development in complexity, as used by Lin and Sarabandi (1999a) or more complex empirical growth and development functions. A wide
range of empirical L-system models have been developed for crops, trees, and other plants and plant organs (see Prusinkiewicz, 1998, p. 124).

Not all empirical developmental models are implemented within L-systems, although most can be, which has added to the growing popularity of L-systems modelling and the re-use of tools developed. One example of a model developed outside of an L-system is the maize structural model developed by Prévot et al. (1991). This is based on a relatively simple geometric representation of leaf form and a set of empirical relationships between various structural properties, namely: relative leaf insertion height is related to the difference in height between subsequent leaves; leaf length is related to leaf width; leaf length is related to relative leaf insertion height; and various other calibrated relationships with known means and variance values. The model is seen to be able to reproduce observed forms and leaf surface area well, and as (non-forage) maize grown under agronomic conditions does not produce tillers, has a simple topology. Even a 'calibrated' empirical model such as this, however, could quite simply be implemented within an L-system.

España (1997) and España et al. (1998) studied a wide range of relationships between structural and developmental measures of maize plants and derived empirical relationships to permit the dynamic reconstruction of a canopy. Plant structure development was modelled using normalised data from a modelling of the structural dependencies. The resultant model is simply parameterised by the phenological stage (defined by phyllochron, which can be parameterised as a function of degree days), planting density, and cumulative leaf area index and canopy height at a given time (e.g. final states). The approach has the advantage of being able to directly extrapolate canopy state from a single set of structural measurements (España et al., 1998). Note that the canopy driving variables in this case are not generalised parameters such as LAI, rather they are the ‘genetic’ of parameters describing the evolution of leaf length, insertion distances etc. over time, and that the simple set of state parameters provide modelling of the detailed 3D descriptions the plant. Using this approach, generalised canopy parameters such as LAI and leaf angle distributions can be calculated from this representation for input to more generalised remote sensing models. In addition, other generalised structural terms such as canopy clumping and canopy cover can be directly derived from the 3D structural representation. If the canopy state is defined in terms of generalised parameters, as in canopy-level models, these cannot directly be used to infer structural representations. The model is very much from the empirical school of modelling, being limited in its consideration of light interception and temperature effects to encompassing their effects through canopy state development as a function of thermal time. It does not, for instance, deal explicitly with photosynthesis. Whilst the various structural relationships derived provide useful information for other maize structural studies, the model is not implemented within a generic framework such as L-systems, requiring re-coding for adaption and further development. Importantly for linkage with remote sensing models, España also investigated the temporal evolution of water and chlorophyll over time for maize leaves, allowing multi-temporal modelling of the optical reflectance and transmittance properties of the leaves using the PROSPECT model (Jacquemoud and Baret, 1990). The major trends were a gradual decrease in chlorophyll and specific leaf water content over time, and a slight increase in leaf structural complexity. The model was used to study, among other issues, the difference between ‘true’ (3D model-based) and (radiative transfer equivalent) effective leaf angle distribution and LAI by comparison with SAIL model simulations. One important feature of a dynamic 3D model noted is the ability to provide simultaneous estimations of expectations of all structural parameters and their inter-dependence for a particular canopy type, rather than having to estimate individual temporal trajectories. This feature of temporal structural expectation will be returned to below.

Helbert (1996) and Boissard et al. (1997) developed a parameterised architectural model (Simblé) for the tillering stage of wheat. A key feature of the model is the use of detailed photogrammetric measurements of plant structure in developing the model. This allowed detailed models inclination and twisting angles to be used in modelling the 3D geometry of wheat leaves. Simple empirical models were developed to fit a set of key defining characteristics of the plant (twist angles,
insertions angles etc.) to describe the development of plant structure over integrated thermal time. Variability observed in the measured plants was introduced by stochastic variation of the model parameters.

There have been a number of studies using empirical development models within L-systems for remote sensing applications. We can group these into studies using L-systems simply for a convenient structural representation, and those dealing more explicitly with modelling plant development. The former ‘static’ models should technically be included in the previous section, as was the fractal model of Lin and Sarabandi (1999a), but since L-systems have the potential to model plant dynamics, they are considered here. The primary aim in ‘static’ models is to have a route for representing ‘realistic’ complex forms of plant structure. This essentially allows improved modelling of gap probabilities at optical wavelengths and object location for studying coherence effects at microwave with a simple parameterisation. An additional advantage of a parameterised model providing a complex structural definition is that it implicitly models plausible structural inter-relationships between canopy variables such as canopy cover, LAI, leaf/branch angle distribution, as well as branch length and radius distributions. These latter terms are particularly important for microwave modelling. This is a particular advantage for remote sensing simulation models, as it provides a more restricted but ‘realistic’ parameter space for modelling plant interactions than e.g. allowing LAI, leaf angle distribution, branch length and radius etc. to vary independently.

Tsang et al. (1994, 1995) Chen et al. (1995) developed a stochastic L-system/coherent microwave scattering model of ‘tree-like’ objects. Ma et al. (2000) develop a similar microwave model with an L-system representation of rice and maize. Zhang and Tsang (1996) combined scattering from tree models generated with L-systems with scattering models for grass and rough soil to create a so-called ‘scene model’, and whilst this is a very interesting example of using such models for up-scaling, their paper is singularly lacking in detail. At optical wavelengths, Goel et al. (1991) use a radiosity approach to the simulation of canopy reflectance using L-system modelled maize plants to investigate plant spacing effects. Govaerts (1996) used Monte Carlo ray tracing of various L-system canopies to simulate reflectance from such structured canopies.

Prusinkiewicz and Lindemayer (1990) propose the concept of a ‘virtual laboratory’ for investigation of various effects on plant architecture, and L-systems as a particular modelling framework for performing them. The addition of 3D optical and microwave models to this allows a wide ranging virtual laboratory for exploring factors affecting the remote sensing signal. Empirical structural models of the sort considered here have the advantage of allowing the investigation of structural effects using a small number of parameters to generate a range of plant forms. Empirical L-system and fractal models used tend not to be linked to direct measurements of structure, but used to explore the impacts of model parameterisations and the reasonable structural representations they produce on optical and microwave signals. The vast majority of such studies have used essentially static representations of canopies, rather than exploring the temporal dynamics of the parameters and remote sensing signal. Other models developed outside of L-systems, such as that of España (1997) tend to be based on extensive sets of field measurements and are more obviously dynamic models. It should be noted that, with the exception of the work of Lin and Sarabandi (1999b), none of the structural models (empirical or mechanistic) have been used to attempt to invert a remote sensing signal to obtain canopy parameterisations – they have all been used in the ‘forward modelling’ sense.

3 **Functional Growth Models**

Mechanistic or 'functional' growth models are designed to simulate the development of canopy state variables and fluxes of energy, carbon, water, and nutrients over time (Moulin et
al., 1998). They can be held to generally model the processes governing canopy growth in a mechanistic manner. A generic mechanistic crop simulation model is defined by a set of state and rate variables. Rate variables are calculated from the current system state and derived (e.g. LAI from number and size of leaves) and environmental factors (e.g. solar radiation). Modelling involving rate variables utilises underlying an understanding physical, physiological and biochemical processes. If this knowledge is lacking, statistical relationships may be used (Bouman et al., 1996). Prusinkiewicz (1998) distinguishes a class of models which we will include here, which he calls 'casual', whereby change of state occurs in response to some form of information transfer, such as as response to environmental conditions or an internal 'signal' propagated through the plant.

For generalised canopy-scale models, the state variables include LAI, and the dimensions and biomass of plant organs. Whilst these can, in a sense be labelled 'structural' variables, they are not generally assigned to a specific location in a canopy, and the variable descriptions exist only as volumetric averages. We may call this a 'functional canopy scale' model. A functional-structural model, on the other hand, involves generally mechanistic modelling of processes (where the mechanism is understood) for plant organs which exist at a specific location in space, and which have a defined topology grouping individual organs into a plant (Prusinkiewicz, 1998). Given the selection of wheat as an exemplar model within this contract, examples will focus on wheat and other crops where appropriate.

3.1 Functional Canopy-scale Growth models

A wide range of mechanistic models of the growth and development of canopy-scale state variables have been developed (WWW1). Rather than review all such models, it is preferable to point out the general structure of such models and to discuss the various options that exist within the model components. The discussion will be exemplified with crop models from three main groups aimed at wheat modelling, namely, the SUCROS models from Wageningen University (Spitters et al., 1989; van Laar et al., 1992), the CERES models, initially developed by the USDA-ARS (Ritchie and Godwin, Ritchie and Otter, 1985), and the AFRCWHEAT models (Porter, 1993). Whilst agronomic models are developed for a range of uses, we concentrate here on those with potential application to remote sensing monitoring. It is however, worth noting that functional models have found particular application studying likely crop growth and development under climate change scenarios (e.g. Peris et al., 1996).

Bouman et al. (1996) note a scheme of model development in the 'de Wit school', whereby an initial model (production situation 1) is developed considering potential production, with growth rates determined by solar radiation and temperature. Subsequent stages (2-4) of development move on to consider growth rate reduction based on water, nitrogen and nutrient limitations. In section 3.1.1, we describe the basis of a generic mechanistic growth model, to demonstrate the differences to empirical approaches and illustrate the common components of a stage 1 model and some of the options that are available. In section 3.1.2 we examine the current and potential role of these models in combination with remote sensing data.

3.1.1 Framework for a Mechanistic Growth Model

Most canopy-scale growth models consist of a similar structure. In the past, it has not been straightforward to integrate components from different model implementations, although there have been efforts to co-ordinate a modular approach through the IBSNAT/ICASA since 1982 (WWW2). As opposed to the PEM discussed above, most mechanistic models are 'photosynthesis-based'. A 'stage 1 model' is limited only by light and temperature, although mechanisms for other limiting factors are relatively easily introduced within a modular framework. Such models are therefore driven by: (i) a set of (supposed) genetic inputs, describing the way in which the crop responds to its conditions; (ii) a set of management data (planting density, sowing depth etc.); and (iii) environmental factors, such as incident direct
and diffuse solar radiation and temperature, which will vary over time and space. Porter et al. (1993) compared results from three ‘stage 1’ versions of wheat models including AFRCWHEAT2 and CERES-wheat. Differences in model outputs and variations from field measurements were attributed to varying assumptions as to the effects of daylength and temperature on growth and development. Jamieson et al. (1998) reviewed the differences in the way in which variants of the models considered deal with stage 2 processes (water), and note the divergence of assumptions made about root distribution and soil dryness effects, initiation of water stress effects on leaf area development, and light use efficiency. They found these three models to compare favourably in prediction of yield and its response to drought, but model predictions of amounts and time profiles of aboveground biomass, LAI and evapotranspiration varied considerably between models under water stress.

(a) PAR interception
Most mechanistic models of canopy growth (e.g. CERES, ARFCWHEAT) are driven primarily by light interception, as this provides the energy source for photosynthesis. Any other factors, such as temperature or water stresses, can be considered as additional limiting factors. The vast majority of canopy growth models make very simplistic assumptions concerning the canopy in calculating radiation absorption. It is generally reasonable to assume that that only first order interaction effects are significant, as PAR involves only the shorter optical wavelengths, which are heavily absorbed by leaf pigments in photosynthesis. A more restricting assumption that is generally made is that a simple application of Beer’s Law, assuming a simple turbid medium, is sufficient to model light intensity at various depths throughout the canopy. Such an approach takes no account of the structural arrangement of a canopy, which has been shown to be important for many cases and can lead to significant errors in calculating PAR absorption (Dauzat et al., 1988; Diaz-Ambroona, 1998).

Various models which incorporate some description of structure have been considered (see review by Chelle and Andrieu, 1999), but these have not generally been interfaced to canopy scale models. One such model that has is that of van Kraalingen (1989), which treats PAR absorption throughout a gridded voxel 3D space, assuming a local exponential absorption. Assimilation and light attenuation is then considered for each cell, assuming a connectivity to the plant. The assimilation module is then linked to the SUCROS model to simulate development of canopies with strong structural heterogeneity, such as row crops or some tree canopies.

A more flexible approach, operating on a plant-by-plant basis with surface representations of plane elements can be achieved by representing the structure of individual plants using Monte Carlo ray tracing (Dauzat et al., 1988; Govaerts, 1996) or projection/radiosity methods (Chelle and Adrieu, 1998). Using such models, important issues such as local competition for light resources can be easily modelled (Edmeades and Danyard, 1979). Practically, PAR modelling requires only consideration of first order effects. However, linking a synergistic remote sensing optical model with a PAR interception model requires treatment of multiple scattering, particularly in the near infrared. Further flexibility can be gained by linking local (plant) light (or other environmental variables, such as temperature) regimes in a functional-structural modelling environment (Fournier and Andrieu, 1999).

(b) Dry matter accumulation, partitioning and structural growth
Similarly to the PEM, a model such as SUCROS (Spitters et al., 1989) is based around consideration of a dry matter growth rate, $\frac{dW}{dt}$, which is the conversion of assimilates $A$, minus losses due to respiration $R_m$, converted at a given efficiency $C_f$:

$$\frac{dW}{dt} = C_f (A - R_m)$$
We mainly follow the generic aspects of SUCROS in describing the stage 1 components of a generic mechanistic growth model. SUCROS has been used to model (among other crops) winter wheat, maize, potato and sugarbeet.

Dry matter produced over some time step (typically one day) is then partitioned among the plant organs at rates determined by the plant phenological stage. A particular problem in verifying empirical values used for partitioning is the difficulty in measuring the weight of roots (Ritchie and Godwin).

Under optimal conditions, light intensity and temperature are the main factors affecting leaf area growth, with temperature being the overriding factor in early growth stages (Spitters et al., 1989). Light intensity affects the photosynthetic rate and therefore the supply of assimilates, and so light attenuation in the canopy is usually considered (see above). Temperature affects cell division and extension rates. The leaf area per plant, \( L_t \), can be modelled for early growth (\( D < 0.3 \) in SUCROS) as an exponential expressing a demand-driven approach:

\[
L_t = L_0 e^{R_L t}
\]

where:
- \( L_0 \) is the leaf area at emergence;
- \( R_L \) is the relative growth rate of leaf area.

\( R_L \) is a function of temperature, and can generally be defined per degree day, rather than per day. For later growth stages which are assimilate-restricted, a specific leaf area is used to calculate leaf area growth in SUCROS (supply-driven). AFRCWHEAT2 incorporates a model of temperature response in leaf area development, but is also assimilate-limited. In the CERES-wheat model, leaf and stem expansion are calculated from assimilate growth for all stages. A leaf death rate is also typically modelled to account for senescence, and is related to the current area of green leaves and a (constant) relative death rate. Mechanisms for leaf senescence due to shading can also be incorporated. Since the appearance and death of leaves are important factors in the plant development, the models keep track of the number and dimensions of individual leaves. Note, however, that they have no further locational (other than 1-D layer) or geometric characteristics (such as angular orientation).

(b) Photosynthesis and Rates of Gross Assimilation

Rates of gross assimilation are calculated from absorbed light energy and the photosynthesis-light response of individual leaves. Because of the non-linear response of leaves to light intensity, it is considered important to consider the variation in light intensity over the day rather than taking a daily average value. Radiation interception is calculated in a radiation interception module (above). The module would typically calculate radiation for both sunlit and shaded leaves in a 1-D layer representation of a canopy. The absorbed radiation at layer \( L \) in the canopy, \( I_{al} \), is calculated in most of the SUCROS models using an exponential relationship to describe the instantaneous assimilation rate for each leaf layer, \( A_L \):

\[
A_L = A_m (1 - e^{-I_{dl}/A_m})
\]

where:
A_m is the (maximum) gross assimilation rate at light saturation (c.f. the CO_2 supply function model discussed above);

and \( \varepsilon \) is the initial slope of light use efficiency.

Total canopy assimilation is calculated by summing \( A_L \) over all layers for radiation absorbed over the day. The particular attention paid to using variation in light intensity over the day and throughout the canopy is a major distinction between this approach and the PEM, as, it is claimed the latter will tend to over-estimate assimilation rate by using average values. Note that unlike the other models, CERES-wheat assumes a constant light use efficiency over all phenological stages.

(c) Maintenance and Growth Respiration
There are various ways in which the loss of carbohydrates formed in respiration to give energy to maintain existing plant structures can be modelled. In SUCROS, a maintenance rate is calculated from weightings of the green plant organ biomass values, which is used to calculate maintenance respiration as a function of temperature above a threshold temperature to account for a reduction in metabolic activity and maintenance requirements with age. This is an example of an empirical component in this otherwise mainly physiologically-based model.

In the conversion of net primary assimilates into structural plant material, CO_2 and H_2O are lost, resulting in an effective growth respiration loss. This can be calculated from consideration of the assimilate required to form and transport particular compounds that make up the plant organs.

(d) Phenological Development
Plant development is considered as a progression through phenological stages, characterised by the formation rates of vegetative and reproductive organs and their order of appearance. The duration of different growth phases is known as phasic development, which is affected primarily by genetic and environmental factors. Plant morphology (expressed for a canopy-scale model as the appearance of leaves on the main stem, and the number of tillers and grains on a plant) is directly controlled by phenology. For many annual crops, the dimensionless development stage, \( D \) (0 - seedling emergence; 1 - flowering; 2 - maturity in SUCROS; 1 - emergence, 2 - terminal spikelet, 3 - end of leaf growth, 4 - end of pre-anthesis ear growth, 5 - beginning of grain filling, 6 - end of grain filling to harvest, 7 - fallow/pre-sowing, 8 - sowing, 9 - germination in CERES-wheat) can be expressed simply as an integral of development rate, \( D_r \), which is mainly controlled by temperature. For non-extreme temperatures in SUCROS, this is expressed as:

\[
D_r = \sum \frac{T - T_b}{\sum (T - T_b)}
\]

where:

\( T \) is the average daily temperature;

\( T_b \) is the base temperature below which the plant does not develop further;

\( \sum (T - T_b) \) is time integral of mean temperature above the base temperature (degree days).

Some variation in phenological development and growth responses to temperature is observed between different studies and varieties, but variations in these ‘cardinal temperatures’ appear to be relatively small for many phases and processes for wheat (Porter and Gawith, 1999).
The phenological stage defines, among other terms, the dry matter partitioning weights for different organs, although this is achieved with an empirical module in most crop models. In the CERES-wheat model, for example, shoots have higher priority than roots for assimilates (in the absence of water or nutrient limitations, when the opposite is true) during the vegetative growth stage. During grain filling, the grains take the largest proportion of new assimilates as well as utilising stored assimilates (this is not greatly affected by water and nutrient limitations).

For CERES-wheat, stage 7 is used to calculate initial soil water conditions. Stage 8 is usually rapid (within one day, unless limited by temperature or lack of soil moisture). Stage 9 is controlled by temperature and sowing depth, the length of which in thermal time (with 0C and 26C bounds) can be modelled as a linear function of soil depth. The duration of phase 1 can vary considerably by leaf appearance, based on thermal time per leaf, and the initialisation of flowering, based on vernalisation and photoperiod and modelled as having an impact on accumulated thermal time. Wheat genetic varieties cover a wide range of sensitivities to photoperiod and vernalisation. Stage 2 to 5 developments are mainly controlled by temperature. Stage 6 is not typically used in the model, but is included for completeness and to analyse the crop in the absence of harvesting.

The CERES-wheat model also accounts for winter hardiness and winter kill. This is calculated for low temperature situations and for snow cover.

Jamieson et al. (1998a) comment that a the definition of growth stages plays a critical role in understanding and modelling plant development, and can cause confusion as to potential genetic influences/varietal variations in parameters. They propose an alternative framework for the mechanisms based on the rate of production and numbers of leaves/leaf primordia on the main stem apex and the co-ordination of leaf and leaf primordium appearance, which provides a simpler route for describing wheat phenological response to daylength and temperature.

3.1.2 Scaling and application of functional-canopy-scale models

Moulin et al. (1992) note that mechanistic models of crop development are strictly only valid at the field scale. The question of scale and knowledge of specific inputs required to drive varietal-specific mechanistic models needs careful examination when considering the application of these models to broad-scale monitoring using remote sensing where the specific varietal and management parameters driving the models may not be available and environmental factors may only be available as spatial and/or temporal averages. Harrison et al. (2000) examine the scaling-up of the AFRCWHEAT2 model to the European scale. They examine the sensitivity of model outputs to a number of simplifying assumptions. Their main findings are: (i) although daily temperatures are required to drive the models, these can be adequately estimated from monthly averages, at least for Europe; (ii) spatial variations in crop suitability and sowing dates can be estimated from mean climatic data and consideration of the time when vernalisation will be most effective; (iii) the range of responses to different cultivars can be estimated at the broad scale, although there can be significant differences between them; (iv) the scaled-up model can be applied to the study of future climate scenarios. Harrison et al. provide both qualitative and quantitative assessments of their results, the latter through comparisons with regionally-averaged harvest dates. They suggest that the level of agreement found is likely to be due to the reasonable broad-scale modelling of light and temperature environmental responses, which, although with error, operate in a cumulative fashion in phenological development, reducing the sensitivity of the final result to any errors. They also note that scaling-up responses such as water stress, which rely on soil conditions and discrete weather events will be more problematical. Porter (1984) notes that although these models operate in a generally mechanistic manner, canopy development and
assimilation operate through empirical sub-models and the use of inaccurate coefficients may lead to significant error.

Bouman et al. (1996) note that within the MARS project, yield predictions using a mechanistic canopy growth model made no significant impact on accuracy over regression modelling for most crops, aggregated at the country or primary administrative district level, although this is difficult to assess as the accuracy of official statistics used in the comparisons are unknown. However, they go on to stress the timely, objective, quantitative and spatially-consistent benefits of crop growth modelling in this application.

3.2 Functional-Structural Growth Models

In a structural plant model, a plant can be considered to be composed of a set of topologically-connected modules/organs. Prusinkiewicz (1998) cites a key feature of ‘casual’ structural models as being information passing between these modules (endogenic) and between modules and their environment (exogenic). Endogenic information passing (‘plant signals’) has been implemented in L-system modelling through context sensitive grammars, whereby the application of a production rule depends on the context of an operator within the L-system string (Prusinkiewicz and Lindenmayer, 1990). Such ‘signals’ can include the flow of water, hormones or nutrients. Exogenous information transfer includes information on light intensity for photosynthesis (Fournier and Andrieu, 1999) or local water availability for root growth (Mech and Prusinkiewicz, 1996).

Functional-structural models more generally, need to incorporate some concept of physiological process into the development of plant development. A good example of this is AMAP (de Reffye et al., 1988). As with L-systems, the AMAP model is based on a description of plant architecture in terms of topology and geometry. Topology is modelled as a result of the functioning of plant organs (growth, branching, dormancy and death). Dynamic modelling is considered in terms of ‘growth units’. Early AMAP models used stochastic models of organ functioning over time steps, but recent variants (as is the trend with other recent modelling efforts such as LIGNUM (Perttunen et al., 1998)), such as AMAPpara (de Reffye et al., 1997) have examined the incorporation of more physiological bases for plant functioning, such as water flow and transpiration. The integration of structure and functioning of plants in plant growth models is a focus of a range of current research (see e.g. Sinoquet and Le Roux, 2000). Whilst a good deal of understanding gained from gained by earlier work, and integrated into some canopy-scale functional models can be used inform this (e.g. light response curves and models at the leaf level), there are significant challenges ahead for this research area (EuroPAIS, 2001), based on integrating concepts, time scales, etc.. Hanan (1997), for example, discusses the integration of physiological models (based on real or thermal time) and architectural (‘structural’) models such as L-systems (based typically on time defined by organ appearance) and provides a simple example of their integration within L-system concepts.

The ADEL-maize model of Fournier and Andrieu (1999) is a state-of-the-art model in integrating functional and structural processes for a crop model. Boissard et al., (1997), Goel et al., (1990) and Diaz-Ambrona et al. (1998) all implement structural developmental models of crops as a function of thermal time, which is, in a sense modelling an interaction with the environment, but ADEL-maize is the first structural crop model to integrate physical process (radiation interception) with plant development and structural dynamics. The model has four components, dealing with: growth and development of individual organs (temperature and carbon-limited); dry matter production and partitioning to individual organs; (3D) parameterised organ shape models; and environmental interface (exogenic) models calculating light and temperature in the canopy. Potential growth under non carbon-limiting conditions uses a modification of the model of Prévot et al. (1991), with responses to temperature and carbon availability based on those in the CERES-maize canopy scale model. PAR interception is calculated for individual leaves within the canopy for first-order interactions, and a temperature balance model is used in the upper part of the plant to model organ temperature. Whilst there is clearly further work to be done in this area, the ADEL-maize succinctly demonstrates how components of canopy scale functional models can be integrated within a functional-structural model, making use of the explicit structural representation for light
and temperature calculations for each organ. A key advantage of the functional-structural approach being driven by light interception is that variability due to different light environments can be modelled explicitly, rather than treating this as stochastic variation and re-parameterising empirical models for different densities.

There have been a range of studies incorporating (earlier) functional-structural models and remote sensing models, although these do not yet make of recent advances in functional-structural modelling, relying mainly on stochastic models of functioning as in early AMAP models. As with empirical-structural models, the vast majority of such applications have been for forest canopies. Examples of this using AMAP tree models, include Castel et al. (2000, 2001). Grass and crop simulations using AMAP models include those of Dauzat and Hautecoeur (1991) for a millet canopy and Luquet et al. (1998) for a semi-arid grassland. The latter demonstrates the significant effect on optical reflectance modelling of incorporating structural information, particularly at visible wavelengths. An L-systems based model of various cover types in a semidesert area is used by Qin and Gerstl (2000) to produce ‘scene models’ at optical wavelengths. Scene models, such as this and the microwave model of Zhang and Tsang (1996), are particularly important in consideration of scaling, as features such as mixed cover types and topography (Burgess et al., 1995) can be consistently integrated into the modelling. Such models potentially provide complementary information to expensive intensive field and airborne campaigns for understanding the remote sensing signal, inversion strategies (Moulin et al., 1995) and validation of satellite products (Justice et al., 2000)

It is clear that there is much to be gained through the use of functional-structural models, both in terms of generality if the main physiological processes are incorporated, and in terms of providing structural expectations for remote sensing modelling. However, the new 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. The model of Fournier and Andrieu (1999) demonstrates the feasibility of ‘re-using’ components of canopy-scale functional models in functional-structural models, but much additional information on structure is required in developing such models.

4 Strategies for integration of crop growth models with remote sensing observations

Remote sensing data can be used in various ways in conjunction with canopy growth models or wider process models typically (i) to provide updates on growth model parameter estimation from a set of data which may include remotely-sensed observations through an inversion of a coupled canopy growth and remote sensing model (assimilation) (e.g. Weiss et al., 2001); (ii) to provide a spatial initialisation of surface state from which to run a temporal model for future predictions; (iii) to provide a method of checking the accuracy of model outputs or compare model-predicted potential state predictions with ‘actual’ measurements from remote sensing observations (e.g. Moulin et al., 1994; Franklin et al., 1997); (iv) to use the process models to understand the remotely sensed observations or calibrate empirical relationships (Ranson et al., 1997). Plummer (2000) provides a recent review of these approaches in the context of ecosystem modelling, and provides pertinent comment on the potentials and limitations of the various strategies and suggestions for future research. Moulin et al., (1998) provide a similar review for agricultural crop models. Case study uses of different types of growth model with remote sensing data are reviewed below. The application to which growth models will be put in this contract is to constrain remote sensing model inversions. This can be seen as a form of assimilation (application i), so particular attention is paid to the potentials for this.
Remote sensing applications have typically used canopy-level representations, of both functional and empirical categories, in coupling to or providing information for canopy growth models. This is for several reasons, including the computational load in using structural models, the growing preference for using functional models in data assimilation and other approaches, and the data and level of understanding required to create and drive functional-structural models.

Although there are a large number of unknowns in running all but the simplest forms of canopy growth models, there has been much interest in their integration with remote sensing data (see Wiegand et al., 1986; Moulin et al., 1992, 1998 for discussions and reviews). A subset of the applications given above are reviewed by Moulin et al. (1998) for agricultural crop models. These are phrased as: (i) the 'forcing strategy' using driving variables directly obtained from remote sensing data; (ii) the 're-initialisation/re-parameterisation' strategy whereby the growth model is set to run from updates provided by remote sensing data.

4.1 The forcing strategy
In this approach, at least one canopy growth state variable is derived directly from remote sensing data. As gaps in observations may exist, they are typically filled through local empirical curve fitting procedures. Moulin et al. (1992) provide many examples, but a typical application using satellite data is that of Delécolle and Guérif (1998) who derived estimates of LAI from high spatial resolution (low temporal resolution) SPOT/HRV data to drive the AFRCWHEAT mechanistic canopy-scale model (Weir et al., 1984). As the SPOT/HRV data provided only periodic estimates of LAI, daily values were interpolated using a simple interpolation model. It had been noted by the authors of the crop model that providing fieldscale periodic updates of LAI could reduce the error in yield estimates (re-initialisation). Delécolle and Guérif opted to drive the model with a temporally-continuous stream of LAI information and found that similar improvements could be made in yield estimation. Both of these results suggest problems with the modelling of LAI in the original AFRCWHEAT model: changing this for an external forcing parameter therefore circumvents errors associated with this. Moulin et al. (1998) suggest that a forcing mechanism of this sort helps improve the description of all processes in the model. Effectively, however, all it does is replace model components which utilise LAI (principally radiation interception) with an alternative 'model'. Another view of this approach is that although relatively simple and pragmatic, it introduces inconsistencies between the internal derivations of terms within the crop growth model and the values used for aspects of simulation. A more complete integration of the forcing variable (LAI) with the AFRCWHEAT model would involve re-balancing the internal parameters of the model (phenological stage, number or size of leaves etc.) to achieve consistency of description.

4.2 The 're-initialisation/re-parameterisation' strategy
Moulin et al. (1998) consider two approaches to this strategy: (a) using a remotely-sensed derived state variable; (b) direct use of the remotely sensed observation (assimilation). The former of these offers a refinement of the forcing strategy, in that the growth model is forced with a state variable (e.g. LAI) but the other state parameters are changed to provide an internally-consistent representation. To update the LAI variable, for example, an inversion of the day of emergence (alternatively, LAI on the day of emergence) is performed to fit with remote sensing state observations. An example of this is presented by Clevers and van Leeuwen (1996), who inverted the emergence date, a growth rate, light use efficiency, and maximum leaf area of the mechanistic canopy-scale SUCROS model (Spitters et al., 1989) to fit observations of LAI estimated from optical and microwave airborne measurements. Most such applications show an improvement over the forcing method, probably due to the more consistent parameter definitions within the model. A study by Steven et al. (1997), however, with a Production Efficiency model (see below) of sugarbeet found the accuracy of the yield forecast with remote sensing inputs to be not greatly improved over that obtained using a set
of ‘mean’ growth model parameters. This result was, however, assessed at an aggregated level.

A drawback of such work noted by Moulin et al. (1998) is that typically empirical methods (e.g., using VIs) are used in parameter estimation, which need to be locally re-calibrated. It can be argued, however, that even if more generic physically-based models were to be used (inverted against the remotely sensed observations) for parameter estimation, that this is a sub-optimal use of the models and observations. This is for several reasons, namely:

(a) Errors in biophysical parameter estimates will be propagated into the growth model re-parameterisation. If there are sufficient observations and the error is sufficiently small, the growth model inversion may still be robust to this. In practice, the number of observations is typically rather limited.
(b) Even if the growth model prediction of canopy state is in error, it will generally provide a reasonable initial estimate of the value to be derived from the remote sensing data.

The assimilation method, using remote sensing observations directly in updating the growth model, is generally preferable to using remote sensing-derived state variables. Using assimilation requires the statement of a forward remote sensing model as a function of canopy state variables. This is best achieved with a physically-based approach for both remote sensing and canopy growth modelling. Since remote sensing observations are sensitive to a range of canopy state parameters, this can be explicitly accounted for in the modelling. In addition, since the canopy state variables include parameter sets which drive remote sensing models at optical, microwave and thermal wavelengths, there is a clear route for the use of synergistic observations in determining canopy state. A potential drawback of the approach, however, is that it will be very reliant on the quality of the physically-based modelling and the consistency between the meaning of the parameters across the range of models used. Moulin et al. (1995) used the SAIL optical canopy reflectance model (Verhoef, 1984) and the AFRCWHEAT2 mechanistic canopy growth model (Porter, 1993) to demonstrate the ability of the coupled models to simulate reflectance at the field scale and both high (SPOT/HRV at 20x20 m²) and moderate (AVHRR, at 4x4 km²) spatial resolutions satellite data for wheat cereals. Reflectance profiles for other crops were obtained from ground measurements. The results were generally promising, particularly when the radiative transfer model was modified for fractional vegetation cover, suggesting that both sets of models may be adequate for assimilation. An interesting feature of the work is to note that they were able to explicitly account for the effects on reflectance of varying viewing and illumination geometries in the AVHRR data, which is not possible with simpler methods such as VIs. Another important aspect of the work is that they were able to explicitly produce simulations over a heterogeneous areas for the moderate resolution simulations by making assumptions about the underlying land cover types. This is likely to be preferable to any empirical methods attempting to deconvolve the signal for sub-pixel variations in cover type (Moulin et al., 1998).

A typical example of this method is given by Bouman (1992) who used SUCROS as a mechanistic growth model, with simple optical (EXTRAD, Goudriaan, 1977) and microwave (‘Water Cloud’, Attema and Ulaby, 1978) remote sensing models. Although all of these models have some grounding in physical/physiological mechanisms, they require calibration to greater or lesser degrees for different locations and conditions. This is particularly true of the water cloud model, which might be termed a ‘semi-empirical’ model of radar backscatter, but is also required, e.g. in assimilate partitioning proportions for SUCROS (see below). A model inversion was performed to minimise the error between observed and predicted remotely sensed observations, using data over the growing period, resulting in an ‘optimised’ set of growth model parameters. The results indicate an improvement in biomass estimation by integrating remote sensing data from field measurements, with seasonally averaged errors being reduced by around one third over running the growth model alone.
Moulin et al. (1994) compared the results of assimilation of four SPOT/HRV observations using a range of radiative transfer models including SAIL and EXTRAD. As with Moulin et al. (1995), they found that an incorporation of fractional vegetation cover to be an important parameter to consider for all models. They inverted the sowing date in the assimilation, and found that different models produced different results and estimated of biomass production. Whilst there study is of interest, and demonstrates the general feasibility of the assimilation approach, it further stresses the point that this approach is sensitive to the quality of the selected growth and radiation transport models.

Weiss et al. (2001) use a more complex form of the SAIL model in their data assimilation of a wheat canopy, which allows for scattering by different layers in the canopy to be more explicitly accounted for. This is of particular importance in monitoring crops such as wheat which can be considered to comprise ‘layers’ with varying optical and structural properties. Rather than just dealing with LAI as a driver for the canopy reflectance model, they are able to use the fuller layered description provided by the crop growth model they use (STICS, Brisson et al., 1998). They also link other growth model state variables to the radiative transfer model, such as surface soil moisture (changing the soil reflectance) and a representation of leaf nitrogen (being linked to chlorophyll, thence to leaf reflectance through the PROSPECT model (Jacquemoud and Baret, 1990)). Modelled reflectances were found to compare well with observed SPOT measurements, as do leaf and organ area indices derived from the assimilation in most cases.

5 DISCUSSION AND RECOMMENDATIONS

Integrating aspects of plant and canopy growth with remote sensing measurements have 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, particular 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. At the simplest level, a temporal model of vegetation development provides an expectation which can be compared to remotely-sensed observations or used to interpolate them. More complex uses of growth models and remote sensing permit updating estimates of canopy state variables, e.g. through assimilation within an ‘integrated’ modelling and monitoring environment.

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), but this builds on the experiences of Moulin, Bouman, their co-workers, and others. Integration of a range of remote sensing inputs (such as optical and microwave data) is possible, but applications are limited by:

(a) The quality of the remote sensing models used. Of particular concern are the consistency of representations of canopy parameters (particularly structural representations governing relationships between LAI and canopy cover among other terms) within optical and microwave synergistic modelling and between these and the canopy functioning models;
(b) The quality of certain aspects of the canopy functioning models, particularly their inconsistent treatment of water and the need for empirical calibration of assimilate partitioning;
(c) The selection of sensitive growth model parameters and model inversion is done in a relatively simplistic manner

Functional-structural models have many potential advantages over canopy scale models, 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. Whilst empirical-structural models have received particular attention in remote sensing, neither they not functional-structural models have 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.

No structural model has been developed specifically for wheat crops, other than the tillering stage model of Boissard et al. (1997). Fournier and Andrieu (1999) have demonstrated the potential route for integrating aspects of canopy scale models into functional-structural approaches for crops with detailed consideration of environmental drivers, which can be seen as a model for near-future development of applications. As with initial models of maize structure, it is recommended that near-future developments for wheat concentrate on providing data and representations for canopy structure over time, and that these models be later re-visited to further integrate functional-structural interactions. The approach of España (1997) and España et al. (1998) is one option for a simple and practical ‘calibration’ of an empirical structural model to local conditions that should be considered. Further developments should take place by integrating remote sensing models within current integrative approaches such as a PAIS. Following the ‘de Wit school’ of model development, it is further recommended that initial modelling efforts concentrate on modelling unstressed plant architectural development (‘stage 1 models’), particularly given the variable performance of current mechanistic canopy-scale ‘stage 2’ models.

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