On the Nature of Models in Remote Sensing

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An explicit framework can provide a better understanding of remote sensing models and their interrelationships. This framework distinguishes between the scene, which is real and exists on the ground, and the image, which is a collection of spatially arranged measurements drawn from the scene. The scene model generalizes and parameterizes the essential qualities of the scene. Scene models may be discrete, in which the scene model consists of discrete elements with boundaries, or continuous, in which matter and energy flows are taken to be continuous and there are no clear or sharp boundaries in the scene. In the discrete case, there are two possibilities for models: *H*- and *L*-resolution. In the *H*-resolution case, the resolution cells of the image are smaller than the elements, and thus the elements may be individually resolved. In the *L*-resolution case, the resolution cells are larger than the elements and cannot be resolved. Most canopy models are *L*-resolution, deterministic, and noninvertible in nature; image processing models, however, tend to be *H*-resolution, empirical, and invertible. This taxonomy helps add insight to the development of remote sensing theory and point the way to new, productive areas of research.

Introduction

As remote sensing has developed over the last two decades, it has been primarily oriented to providing information about the Earth and its resources. This need has arisen from the broad realization that our planet is finite, and if the human race is to survive beyond the immediate present, careful management of Earth resources will be necessary.

Although the driving force for this development has been the generation of information about Earth resources, much work in the field has not been directly concerned with furnishing data for resource managers. Consider, for example, the new edition of the *Manual of Remote Sensing* (Colwell, 1983). Only half of this reference is devoted to *Interpretation and Applications* (Vol. II). The remainder consists of *Theory, Instruments and Techniques* (Vol. I). The primary thrust of work in the latter area has been to develop a better understanding of how electromagnetic radiation and matter interact, not only in the context of the scene being sensed, but also in the theory and design of sensors and sensing systems.

These two areas have tended to draw researchers into remote sensing with quite

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different backgrounds. On one hand are geologists, geographers, foresters, agronomists, and the like, who also work with statisticians to use remote sensing as a tool to study the earth. On the other hand, are researchers trained in electrical engineering and physics, who use functional mathematics to study processes involved with the complex physical problems that arise in understanding the flux of energy to and from the earth's surface. These groups typically have very different viewpoints and approaches to studying scientific problems; yet when they interact, the resulting synergism can be not only highly productive, but intellectually exciting as well.

Over the last several years, the authors have been fortunate to participate in a number of workshops, conferences, and symposia that have exposed us to the broad range of scientific activities in remote sensing. In a continuing dialogue among us, some truths seem to have emerged about a common viewpoint and framework that can unite lines of scientific inquiry as diverse as pattern recognition and microwave scattering. The primary objective of this paper is to develop and demonstrate that framework. It takes the form of a discussion of the nature of remote sensing models and the application of a taxonomy of models to existing work in theory and applications of remote sensing. The discussion is geared towards remote sensing techniques which ultimately result in some form of an image, although some aspects are relevant to other modes also, e.g., laser attenuation through sulfur dioxide plumes.

Model Setting

Before we can begin to discuss the nature of remote sensing models, it is important to define some relevant terms and concepts explicitly, so that our discussion can proceed carefully and precisely.* A *sensor* can be defined as a device which measures the intensity of electromagnetic radiation. We use the term here in a broad sense to include not only the specific sensing element, but also its associated parts and systems, such as optical apparatus and electronic circuitry. A sensor has an *instantaneous field of view* from which it senses energy fluxes. The *point spread function* defines how the energy flux is integrated over the field of view; the *spectral response function* defines how the sensor integrates energy to which it is exposed over the spectral domain; and the *temporal response function* defines how the sensor averages the energy it absorbs over time. A *measurement* is the output of a sensor in response to the above integrations. Measurements may be *analog*, recorded as continuously varying signals, or *digital*, recorded as single numeric values associated with the sensor's output as sampled and averaged over discrete time intervals.

A *scene* is defined as the spatial and temporal distribution of matter and energy fluxes from which the sensor draws measurements. An *image* is a collection of measurements from a sensor that are arrayed in a systematic fashion. Images may also be analog (e.g., photographic) or digital. Associated with a digital image are the concepts of the *resolution cell*, defined as the average area within the scene associated with each measurement in the image, and the *pixel* (picture element), which is either an individual mea-

*Although the following two paragraphs may appear overly basic, they are necessary for the rigorous definition of other concepts and terms to follow.

surement or its associated manifestation in a displayed digital image. Typically, the resolution cell is characterized by a particular size and shape. In a well-designed sensor system, the resolution cell will approximate the instantaneous field of view of the instrument.

The measurements produced by a sensor are primarily a function of the energy flux from the scene which is exitant in the direction of the sensor. This flux is dependent on the spatial, temporal, and angular distribution of energy fluxes entering the scene, and the spatial arrangement and properties of the types of matter within the scene. Also influencing the sensor's measurements are the scattering, absorption, and emission of energy that occur in the atmosphere between the radiation source and scene, and the scene and sensor. Of course, the characteristics of the sensor itself (instantaneous field of view, spectral and temporal response functions, polarization sensitivity, etc.) also influence the measurements. Thus, a *remote sensing model* may be generalized as having three components: a *scene model*, which specifies the form and nature of the energy and matter within the scene and their spatial and temporal order; an *atmospheric model*, which describes the interaction between the atmosphere and the energy entering and being emitted from the scene; and a *sensor model*, which describes the behavior of the sensor in responding to the energy fluxes incident upon it and in producing the measurements that constitute the image. This paper will focus primarily on the scene model, although occasional reference to atmospheric and sensor models will be made.

Real scenes are not chaotic or random, but manifest spatial and temporal order. In general, the remote sensing problem can be presented as *inferring the order in the properties and distributions of matter and energy in the scene from the set of measurements comprising the image.* Whether explicit or not, scene inference implies the application of a remote sensing model, in that assumptions must always be made concerning the ground scene, atmosphere, and sensor. The problem of scene inference, then, becomes a problem of model inversion in which the order in the scene is reconstructed from the image and the remote sensing model.

Scene models may be of two types: discrete or continuous. In the *discrete* model, the matter in the scene is taken to consist of discrete objects. In other words, the discrete model assumes that there are boundaries or discontinuities where the properties of matter change abruptly over space or through time. This model therefore implies that the energy fluxes exiting from the scene must also change abruptly. By detecting the discontinuities in energy flux and parametrizing the homogeneous features they delineate, it is possible to identify the objects in the scene and locate them in space or time.

In contrast to the discrete model is the *continuous* model, in which the changes in matter (and therefore exitance of energy flux) are taken to be everywhere continuous in space or time. If the energy incident upon the scene is similarly smoothly varying, then the exiting energy fluxes must also vary continuously. Once a relationship between the variation in the energy flux and the variation in the matter in the scene is established, it may be possible to estimate the properties of the matter in each resolution cell in a continuous fashion. Further, the relationship may be extended to measurements of whole scenes or subscenes over time and space to estimate the bulk properties of the scene within the entire spatial or temporal interval.

Discrete Models

At this point, it will be helpful to examine the components of the discrete scene model in more detail. (We will return to the continuous model later.) In the discrete model, the scene is perceived as consisting of objects on a background. A scene-model *element* is an abstraction of a real object in the scene that can be regarded as having uniform properties or parameters. *Properties* are taken to be fundamental and invariant; these are typically associated with pure substances. Heat capacity, conductivity, and emissivity are examples. If the properties are stochastic in nature, that is, characterized by distributions, *parameters* may be used to summarize these distributions. Elements may be unique or of one or more *classes*. All elements of the same class are taken to be characterized by the same set of properties and/or parameters. The elements and classes of elements in a scene can vary widely according to the interests of the interpreter. Several examples of scene elements and/or classes are: leaf, branch, plant, crop row, tree, field, stand; lawn, car, street, garden, house; airplane, building, runway, truck, airport. In addition to these elements, which correspond to discrete objects, a particular type of element, the background, should be recognized. The *background* is usually assumed to be spatially continuous with uniform properties and/or parameters and is typically partially obscured by other elements in the scene. More than one type of background may be present in a scene. Soil, rock, snow, and understory are examples of background elements.

It may also prove useful to distinguish between simple and complex discrete-scene models. *Simple* models are those which contain only one class of element and the background, whereas *complex* models are those which include more than one class of element as well as a background. *Nested models* are also possible. In such models, elements, along with their properties and parameters, are used to derive the properties of larger elements that are aggregated from the smaller ones. A canopy model composed of layers of leaves is an example—both the layers and leaves serve as elements within the same nested model.

Just as the elements in a scene model are characterized by properties and parameters, so are the electromagnetic fluxes reaching the scene. Energy flux properties and parameters may include such information as the angular distribution of incident radiation (and/or its polarization or coherence) as a function of wavelength. For active sensing systems, the position of the radiation source with respect to the sensor is also important, and is typically considered as an invariant property of the sensing system. Just as the spatial pattern of elements varies in the scene, so the spatial distribution of incoming energy fluxes can vary throughout the scene. In active systems, this flux may be related to the distance between the element and the sensor; in passive energy systems, typically the assumption is a spatially uniform energy flux into the scene.

The specification of the properties and parameters of energy fluxes into the scene is an important part of the scene model. Neither the objects in the scene nor the energy flux into the scene remains constant with time. However, the temporal response function of the remote sensor is typically chosen so that the energy fluxes may be regarded as stationary within the imaged scene. If the energy flux distribution is not stationary over the response time, then the remote sensing model will need to include parameters of magnitude, frequency, and even spatial variation in the incoming energy flux.

H- and *L*-resolution scene models

It will prove useful for later discussion to break down scene models into two types, depending on the relationship between the size of the elements in the scene model and the resolution cell of the sensor. An *H-resolution model* is defined as one in which the elements in the scene are larger than the resolution cells; the *L-resolution model* presents the opposite case.† In the *H*-resolution model, the spatial arrangement of the elements in the scene can be detected directly because individual elements can be identified. In the *L*-resolution case, the elements are smaller than the resolution cells and are not individually detectable. Thus, their spatial distribution within a resolution cell may require parametrization. The *L*-resolution model also typically assumes two-dimensional stationarity—that is, the spatial process that distributes elements within resolution cells remains constant from one cell to the next.

Note that when the sizes of the element and resolution cell are similar, it may be difficult to characterize the model as *H*- or *L*-resolution. Detection of the spatial arrangement of objects, which is the essential feature implicit in the *H*-resolution model, may require a resolution cell size several times smaller than the size of an element. Similarly, to regard a resolution cell as including several elements on a background, which is the essential feature of the *L*-resolution model, a cell size several times larger than that of the scene element may be needed. Thus, the spatial domain containing the transition from *H*- to *L*-resolution models may require the formulation of models specific to the actual sizes of elements and resolution cells.

Another important point to note concerns spatial autocorrelation. Without some kind of spatial structure, an image would consist of random noise; therefore, there is some form of spatial autocorrelation in all images that are of interest to remote sensing. However, the spatial autocorrelation is produced by two different phenomena in the cases of *H*- and *L*-resolution models. In the *H*-resolution case, the resolution cells are smaller than the objects in the scene. Each resolution cell will thus tend to resemble its neighbor, since both are likely to fall within the same homogeneous object. The degree of autocorrelation will then be related to the size and shape of the objects in the scene as compared to the size and shape of the resolution cells of the image. In the *L*-resolution case, objects are smaller than resolution cells, so there is no *a priori* reason to assume that one pixel will resemble its neighbor. However, the spacing functions that distribute objects are often likely to be stationary over areas consisting of many resolution cells, and thus spatial autocorrelation in the image is usually a

† The terms "high" and "low" resolution are avoided because they tend to be associated with absolute measurement scales rather than the relative size of elements.

characteristic of an *L*-resolution model as well.

Although it will not be developed strongly in this paper, the concept of *H*- and *L*-resolution models can be extended to time as well as space. Between successive images, objects can move, appear, or disappear; their properties or parameters may also change slowly or abruptly through time. *H*-resolution in time implies that changes are slow and therefore the properties or parameters of elements remain relatively constant from image to image. Thus, a boundary in time can be sensed. *L*-resolution in time implies that the sensor's repeat time is too slow to keep time boundaries from being sensed. Images are then "snapshots" of the state of the ground scene, and undetected change occurs between snapshots.

Continuous Models

As the size of objects in the scene becomes increasingly small relative to the resolution cell size, it may no longer be necessary to consider objects individually. Instead, each measurement can be treated as a sum of interactions between various classes of scene elements as weighted by their concentrations or relative proportions. As an example, consider a layered atmospheric model in which absorption of incoming radiation is modeled as a function of the concentrations of various absorptive gases within each layer. Although this example could be treated as an *L*-resolution model in which the objects are individual molecules, it is more straightforward to treat this model as continuous in nature, driven by concentrations of the gases. Similarly, radiative interactions for optically thick media may often be mathematically described as a diffusion process.

In some situations, a continuous model deals with proportions instead of concentrations. This type of model is therefore a mixture model, in which the measurement is modeled as a function of the mixture of element classes within a resolution cell. Some *L*-resolution models can be regarded as mixture models as well, in which case the proportions are functions of the sizes and shapes of the elements in the scene model and their relative densities within the resolution cell.

Other Characteristics of Models

Remote sensing models can be contrasted another way, as being either deterministic or empirical. A *deterministic* remote sensing model utilizes basic physical laws concerning electromagnetic radiation and matter; its formulation specifies terms that include properties and parameters of elements and describe real processes of energy and matter interaction. Typically, such models include emissivity, scattering, and absorption of elements as properties or parameters, as well as statements utilizing the principles of conservation of energy and matter and the laws of thermodynamics. Scene, atmospheric, and sensor models may all be formulated in a deterministic fashion.

An *empirical* remote sensing model associates observed sensor measurements with scene elements, typically in a statistical fashion. In the simplest empirical remote sensing models, real objects are identified in the scene and compared with their manifestations in the image. By repeated sampling of like objects in the scene, the distribution of measurements associated with each class of scene element is determined. Scene inference occurs when the properties or parameters of the elements or classes of elements in the scene are estimated from measurements in the same or a different image.

In reality, the terms deterministic and empirical describe endpoints of a continuum of models. Models that are basically deterministic are often formulated with empirical components, and vice-versa. The advantage of deterministic models is that they lead to a more direct understanding of the nature of the scene, sensor, and atmosphere, and their joint interactions. Empirical models, however, do serve the useful purpose of data exploration, suggesting relationships that can be refined further by models with more deterministic components; and, when exercised under conditions for which they have been calibrated, empirical models can produce very accurate scene inference.

Remote sensing models may also be either invertible or noninvertible. An *invertible* model is one in which some of the properties or parameters that characterize the elements are unknown, but can be inferred from the remotely sensed measurements either singly or taken as an image. In a *noninvertible* model, such estimation of the parameters is not possible. An invertible model must be a complete remote sensing model in that scene, atmosphere, and sensor models are required even if they are not explicitly specified. This arises because scene inference begins with the measurements and ends with the scene. Models that are not used for scene inference, i.e., are not inverted, do not have to be carried all the way through to the measurement, and therefore do not necessarily have to specify all three submodels. However, if measurements are used to verify the outputs of a model, then atmospheric and sensor models are implicit.

As with the distinction between deterministic and empirical models, the distinction between invertible and noninvertible models may be somewhat arbitrary. This arises because modern analytical techniques allow inversion of rather complex models that are driven by many parameters—given appropriate side constraints, such as least squares or maximum likelihood. Thus, models that are not explicitly formulated to be invertible can often be inverted under proper conditions.

Within invertible models, another useful distinction differentiates direct and indirect methods of inversion. In *direct inference*, a continuous quantitative relationship is formulated between the measurements in the image and some characteristic of the elements in the scene. Scene inference (or inversion) occurs when the measurements for a resolution cell are evaluated with respect to this relationship to produce an estimate of the properties of the elements in the scene. As an example, consider estimating forest biomass from brightness values of AVHRR pixels. The absorption in the red band and reflectance in the infrared band are directly proportional to the amount of forest-covered land within the pixel and therefore to the biomass (Logan, 1983). Thus, the biomass can be estimated through direct inference from the brightness values using a linear or curvilinear function. Since inversion through direct inference assumes a continuous relationship, it usually implies a continuous scene model, or at least an L-resolution model with the objects much smaller than the resolution cell size.

Unlike direct inference, which requires an explicit quantitative relationship between the measurement and the property or properties of the object, inversion through *indirect inference* may only require a qualitative relationship. The only assumption required is that the different classes of elements in the scene have different properties that in turn influence the measurements received by a sensor. For inversion, the measurements must be sufficiently different that a given measurement or range of measurements can be associated with a particular property. If so, a one-to-one relationship can be formulated to estimate the property of the element from the measurements associated with it in the image. Typically, the property will be a simple label (e.g., crop type, land-use category), as in a classification procedure. However, the property inferred can also be a quantitative measurement (e.g., timber volume for a particular type of forest) if that measurement has been associated with the label by some sampling or experimental procedure.

Most remote sensing models fall into either of two categories: deterministic, noninvertible models, or empirical, invertible models. Further, deterministic, noninvertible models typically exhibit L-resolution or continuous scene models, whereas empirical, invertible models typically include scene models of the H-resolution type. This distinction comes about because H-resolution scene models do not require the parametrization of the spatial distribution of objects, since the objects can be resolved directly. Thus, it is possible to establish a direct relationship between a class of scene elements and a sensor's measurements, and thereby constitute a simple, empirical, and usually invertible remote sensing model. On the other hand, L-resolution models are typically deterministic and not explicitly formulated to be invertible. This is because the purpose of the model is usually to predict the electromagnetic intensity received at a sensor, rather than to infer scene properties. However, as noted above, such models are often invertible through the addition of additional constraining equations or relationships.

Existing Remote Sensing Models

To explore the concept of the remote sensing model further, some existing remote sensing models will be reviewed in the context of the framework presented in the last section. Obviously, a large number of models are in use in remote sensing today, and it is not possible to discuss them all. Instead, we have selected a number for discussion that we feel are typical or that illustrate particular types of models which are of special interest. Our selection also reflects our considerable biases, in that it emphasizes image processing and optical, reflective and thermal canopy modeling. However, we hope that the discussion will be useful to colleagues with different biases by offering examples of how our modeling framework may be profitably extended into other areas. We begin by examining some of the models that are used in image processing.

Image processing models

Our discussion of image processing models begins with supervised and unsupervised classification. Typically, classification procedures are not explicitly formulated with a scene model in mind. However, the implicit scene models that underlie such procedures are always revealed on careful examination. In a routine application of supervised classification (e.g., Landsat data processing), the elements of the scene model (classes) are determined *a priori*; then, objects typifying these elements (training fields) are identified on the ground and located in the image. The measurements in the image associated with the objects in the scene are then processed to yield a distribution of values characterizing each class of element in the scene model. If the parameters of the distributions for each class of element are sufficiently different, then the model may be inverted. Inversion takes place when individual measurements are classified, i.e., processed to assign each to a class of scene element. The classifier typically assumes multivariate normality and uses a maximum likelihood constraint in the decision rule to ensure invertibility. Since there is a one-to-one empirical association of classes with measurements, identification of classes within the scene constitutes indirect inference as described in earlier pages.

Unsupervised classification follows a similar *H*-resolution model, but it is formulated somewhat differently. Measurements are assumed to be random samples that are subject to error and are drawn from objects comprising an unknown set of elements and classes of elements existing in the scene model. If the parameters of each element or class are sufficiently different, then the measurements will fall into groups or clusters in measurement space that can be identified through clustering or histograming techniques. There remains only to associate an element or class of element with each measurement cluster, a process which may be problematical if the elements or classes desired are not well separated by the sensor's measurements or the clustering technique.

Classification is nearly always based on an *H*-resolution model—the measurements are assumed to be samples of energy exiting from objects that are larger than resolution cells. Typically, each measurement is classified independently of the others; however, as noted earlier, spatial autocorrelation is an inherent feature of *H*-resolution images. Where spatial autocorrelation is ignored, significant biases can be introduced that reduce the accuracy of areal inventory. On the other hand, there are several widely used classification models that do utilize the spatial autocorrelation inherent in an *H*-resolution model. The BLOB classifier of Kauth and Richardson (1977) uses an unsupervised algorithm that incorporates the measurement's spatial coordinates in the image as additional values. Clustering proceeds using both spectral and spatial variables to identify spatially homogeneous objects (blobs). Postprocessing joins adjacent blobs, allowing the delineation of agricultural fields, timber stands, etc. Thus, this classification procedure utilizes an *H*-resolution, empirical model that explicitly provides for multipixel objects.

Two other classification models that accommodate the spatial autocorrelation inherent in the *H*-resolution model are ECHO (Landgrebe, 1980) and AMOEBA (Bryant, 1979). The former operates by checking adjacent measurements to see if they are statistically significantly different. If not, they are classified in the aggregate. If so, they are classified individually. The latter functions by region growing. Like the BLOB algorithm, these approaches imply a minimum size and minimum spectral separability for elements in the scene model.

Haralick's facet model (1980) is another *H*-resolution scene model used in image processing. In this model, the scene elements are multipixel facets. The facets do not need to correspond to objects in the real scene, although they may. Within each facet, measurements vary as a simple function of their spatial position. In the flat facet model, the measurements in each facet are assumed to be uniform, subject to random error. In the sloped facet model, measurements are a simple linear function (again, subject to measurement error) of the measurement's x, y position within the facet. Haralick provides several methods for enhancing images to accentuate facets. On its face, the facet model is not invertible; rather, it simply specifies the form of functions that characterize elements. However, it is useful for segmenting an image into uniform areas that may correspond with objects in the scene. The facet model is thus an *H*-resolution, noninvertible, empirical model that specifies the form of the reflectance function of scene elements.

A last group of image processing models includes those of the *L*-resolution type. Since a primary objective of scene inference is often to estimate the total area within a region devoted to a particular class of elements, it is possible to formulate models explicitly for proportion estimation. Many of these derive from the first "pixel splitting" models of Nalepka et al. (1972), which conceived of each pixel as a mixture of a few types of areal components. Because each component has a different mean brightness vector, the measurement associated with each resolution cell is then the sum of the mean vectors for each component as weighted by its areal proportion within the resolution cell. This model is empirical in character, since the mean vectors are indirectly inferred from measurements of "pure" classes within the image. An alternative approach of Adams et al. (1982) uses spectral measurements made on the ground to develop the distribution of brightness values used to characterize each class. The values are transformed using an explicit atmospheric model to predict the spectral reflectance as it might be measured from spacecraft or high-altitude aircraft. Another mixture model, termed CLASSY (Lennington et al., 1984), is of the *H*-resolution type. It estimates proportions of unknown classes within an entire image by maximizing the fit of a mixture of multivariate normal distributions to the observed image data. This model does not require specifying either the number of classes or the range of measurements associated with them—just that the measurements will be of multivariate normal distribution. Since each measurement is assumed to be a realization of one of a few, different, random processes, an *H*-resolution scene model is implicit in this approach.

Canopy models

In contrast to image processing procedures, canopy models are typically formulated explicitly to conform to a particular physical or biological abstraction. A close examination usually reveals a structure that can be described in the terms of our discussion above. Most canopy models are *L*-resolution scene models that utilize radiative transfer theory and energy budget relationships; they may or may not include coupled atmospheric and/or sensor models. Many canopy models are plane-parallel in formulation, specifying a vertical distribution of layers (elements) in a continuous, uniform, horizontal extent. Nearly all are one-dimensional, therefore assuming spatial homogeneity in the plane. In such a case, the measurements in an image are treated as replications, and their spatial positions are unimportant to the model.

Canopy models are usually not invertible, since they are not formulated primarily for scene inference. Typically, a canopy model is validated by comparing measurements of exitant flux with values of flux calculated by the model. If the instrument is well calibrated and accurate, and the distance which the radiation travels through the atmosphere is short, then atmospheric and sensor models can be assumed to be null, and deviations of predicted values from observed are attributed to inadequacies of the model. Improvements to the model then lead to better scene abstractions and improved understanding of the interaction of electromagnetic radiation with scene elements.

Most canopy models illustrate well the concept of nested models. At one level, the leaves are the elements of the model. The properties of leaves as individual scatters are specified, as are their spatial distributions. The properties and spatial distributions of the leaves are then used to parametrize canopy layers, and the layers serve in turn as elements used to model reflectance of the canopy as an aggregate.

Of existing canopy models, the Suits model (1972) is probably the most familiar. In this model, the elements are randomly distributed leaf facets; these are further organized into horizontal canopy layers. A background underlies the canopy layers. Leaves have fixed properties of hemispherical reflectance and transmittance, and, further, are regarded as Lambertian (diffuse) reflectors. A key element in the Suits model is the assumption that all leaves in each layer are either horizontal or vertical, with the horizontal and vertical leaf areas known and parametrized by single values. This assumption simplifies the mathematics of the model significantly, and allows either a closed-form solution for a single layer (Bunnik, 1978) or an iterative solution in the case of multiple layers for angular canopy reflectance as a function of incident beam and diffuse radiation. Note that, as an *L*-resolution model, the Suits model must describe the spatial position of leaves as elements and layers as elements. For the leaves, this is simply the horizontal and vertical projected areas; for the layers, it is simply their relative position in the vertical stack. The SAIL model of Verhoef and Bunnik (1981) and the Suits prime model of Youkhana (1983) extend the Suits model to accommodate any discrete distribution of leaf angles. In our modeling framework, this extension simply serves to increase the number of parameters that describe the spatial positions of the leaves as elements.

Other canopy models may also be viewed as discrete, *L*-resolution, deterministic models. The Ross and Nilson model (1975) treats individual leaves within a canopy as the basic elements. The full leaf orientation distribution is presumed to be known, as is the phase function which describes the scattering of a single leaf. From these latter two distributions, the bidirectional reflectance distribution function of the canopy can be derived. An iterative solution accounts for multiple scattering and includes a correction for downwelling flux that is not intercepted by leaves. The model of Cooper et al. (1982) is conceptually quite similar, in that it also specifies one or more plane-parallel canopy layers over a background. The leaf angle distribution and the leaf gap probability function are specified. Reflectance and transmittance of each leaf are assumed to be different for dorsal and ventral sides. The authors use the Adding method of van de Hulst (1980) to calculate bidirectional canopy reflectance.

Another vegetation scene model of interest is the Markov model of Tucker and Garratt (1977). In this model, the elements are not leaves, but interfaces within an idealized leaf. These are stacked vertically and in a fixed sequence. Examples are the atmosphere–cuticle boundary, cuticle–palisade parenchyma boundary, and the palisade parenchyma–spongy mesophyll boundary. Each boundary exhibits characteristic values for reflectance and transmittance, which are expressed in the form of transition probabilities of photons in passing from one boundary to the next. The probabilities are determined from measurements of the thickness, structure, pigment composition, and water content of each anatomical layer within the leaf, and are calculated for wavelengths between 0.40 and 2.50 μm at 0.01-μm increments. Each transition probability matrix is powered until it converges on a steady state, which yields total hemispherical reflectance and transmittance as a function of wavelength for the leaf being simulated. The scene that the Tucker and Garratt model implies is simply a single leaf of infinite size that may be sensed from above or below. Although this model is unrealistic when compared to real scenes, it could be used to parametrize reflectance and transmittance for leaves in a multilayer canopy model. Such an application would yield a triply-nested structure, with interfaces within leaves within canopy layers as elements.

Although plane-parallel canopy models are not directly formulated to be invertible, Goel and Strebel (1983), Goel et al. (1984), and Goel and Thompson (1984a–c) have shown that it is possible to solve for driving parameters given brightness measurements by introducing side constraints and using numerical methods. They have applied their techniques to invert both Suits- and SAIL-model canopies using multiple (25–50) reflectance measurements taken over different solar illumination and viewing directions. As applied to real crop canopies, their studies have shown that remote estimation of leaf area index and leaf angle distribution are quite sensitive to measurement errors and to the departures of real canopies from their models.

In contrast to the plane-parallel canopy models described above, Strahler and Li (1981; Li and Strahler, 1985) developed an *L*-resolution, explicitly invertible canopy model that is of a geometric-optical character. The model is applied to conifer forests and treats conifers as three-dimensional cones of fixed shape but varying size. The cones (elements) are distributed randomly on a contrasting background, and are illuminated at a given solar zenith angle sufficient to create shadows. Resolution cell size is assumed to be sufficiently large that several dozens of cones are distributed within each resolution cell. Size and spacing functions for the cones are specified explicitly as log-normal and one- or twoparameter Poisson distributions, respectively. By applying calibrations and corrections derived from field data, the model can be inverted explicitly through pixel-to-pixel variance to yield direct estimates of the height and spacing parameters for the cones from Landsat data. It is thus an *L*-resolution, deterministic, invertible model.

A geometric approach has also been used by Norman and Welles (1983) to model orchards and wide-row crops as collections of discrete ellipsoids containing bulk canopy material. The directional reflection, absorption, and scattering properties of the aggregate canopy are a function of the properties of the bulk canopy material weighted by the path length of radiation through one or more ellipsoids. Recently, Norman et al. (1985) have extended this model to include directional reflectance of the soil. The soil submodel assumes that the soil consists of small opaque cubes that cast shadows, and the directional reflectance is thus a function of the surface-to-shadow ratio for given illumination and viewing angles. Although not directly formulated to be invertible, the geometric ellipsoidal part of the model has been inverted by Goel (personal communication) using methods cited earlier.

A more general three-dimensional canopy simulation model has been presented by Kimes and Kirchner (1982) and extended by Kimes et al. (1985; 1986). In this model, the canopy elements are cubic cells, each parametrized by its own leaf absorption coefficient, leaf gap distribution, and anisotropic scattering function. Energy flow from cell to cell is regularized by directional sectors. Absorption and non-Lambertian reflectance of the soil substrate are also accomodated. Radiation escaping from the cell matrix is tabulated by directional sector to produce directional reflectance factors. If a single direct source of illumination is simulated, the result is a bidirectional reflectance distribution function. Since the exiting energy flux is summed for either the upper or entire surface of the cell matrix, the model can be regarded as an *L*-resolution, deterministic, noninvertible model.

Thermal models

Plane-parallel models of the vegetation canopy have been developed for the thermal domain as well. Thermal canopy models usually include an optical shortwave model at some resolution for energy budget calculations (Kimes et al., 1981). The density and angular distribution of leaves within each layer is required for view factor calculations, since gap probability functions are needed to determine the extinction and exitance of radiation as a function of the view angle. In addition to the optical properties of leaves, various thermal coefficients are assigned to the canopy and soil elements, as well as meteorological coupling coefficients. Examples of layered thermal canopy models include that of Kimes et al. (1981) and its extension by Smith et al. (1981). Both models feature three layers and tabulate radiation flux between layers in discrete directional sectors. Like the canopy models they resemble, these models are of the nested, *L*-resolution, noninvertible type.

Plane-parallel models are one-dimensional, although they yield estimates of reflected or emitted radiation by angle and azimuth. Recently, Kimes (1983) has developed a thermal model for row crops that is two-dimensional in character. In this model, the scene is taken as a series of crop rows that are rectangular in cross section, regularly spaced, and extend infinitely in the plane. Kimes models the thermal exitance of the scene at a given viewing angle as a linear function of the proportion of soil, crop, shadowed soil, and shadowed crop visible at that angle. Thus, the model for this scene includes four elements: soil, crop, shadowed soil, and shadowed crop. From repeated measurements at varying angles, it is possible to invert the model and recover the temperatures of the four types of surfaces as well as the ratios of row height and width to row spacing. The concept is similar to pixel splitting, as described in a preceding section. The measurements are assumed to be made without significant atmospheric attenuation using a well-calibrated instrument. The remote sensing model, then, is of the *L*-resolution, deterministic, invertible type.

Kahle's method (1977) for estimating thermal inertia of soil and rock substrates using remotely sensed diurnal temperature differences provides an example of a continuous, invertible remote sensing model. The technique uses an energy budget equation that describes thermal equilibrium at the atmosphere–surface interface. Since the energy budget equation is a complicated, nonlinear expression, Kahle uses a finite difference technique for its solution. The finite difference formulation calculates heat flux as a function of time for thin layers of substrate between the surface and a fixed depth below which heat flow is assumed to be negligible. Note, however, that the layered structure implied by the finite difference technique is simply a convenience used to solve the energy budget equation. The layers are not necessarily presumed to have different properties, as are layers in a plane-parallel model. To invert the model and infer thermal inertia remotely, Kahle solves the energy budget equation over a range of values for surface albedo, slope, slope azimuth, and thermal inertia to yield predicted diurnal temperature differences. These values are incorporated into a lookup table which is restructured to provide thermal inertia as a function of albedo, slope, azimuth, and diurnal temperature difference. The scene is therefore modeled as a surface that continuously varies in albedo, slope, azimuth, and thermal inertia.

Microwave models

Although we lack expertise in microwave modeling, we believe that our framework may be applied productively to this area. At the risk of appearing presumptuous, we attempt the following brief discussion of how active-sensing microwave models might fit into our taxonomy.

Microwave models differ significantly from other types of models used in remote sensing primarily because they are usually derived for active sensors emitting coherent, polarized radiation; thus any formulation modeling the backscatter of an object must take surface characteristics and geometry of the target and sensor into account. Modeling the return of a target begins with considering the radar equation (Fung and Ulaby, 1983). Holding hardware factors constant, the return will be proportional to the distance between the target and sensor and the target's radar cross section. For targets larger than resolution cells, the radar cross section will be determined by the scattering coefficient of the material irradiated. The scattering coefficient, in turn, will be sensitive to the wavelength of the radiation as it interacts with the surface shape and discontinuities within the volume of the target. The dielectric and conductive properties of the target will also be of major importance, since they determine the depth of penetration and the differential volumetric absorption of the incident microwave radiation. Thus, a complete radar model for earth remote sensing must usually include both surface scattering, related to the geometry of the element, and volume scattering, related to its dielectric constant and conductivity.

Radar models are generally of the deterministic, noninvertible type. The simplest models are continuous in nature, modeling backscatter as a function of volume scattering in a medium with slowly changing or randomly varying dielectric properties (Brekhovskikh, 1960; Fung and Ulaby, 1983). Surface scattering can also be modeled continuously, as in the formulation of Fung (1967), for surfaces with horizontal roughness scales larger than the incident wavelength of the microwave radiation. More advanced models are of the complex, *L*-resolution type, such as that of Lang and Sidhu (1983). This model considers a vegetation canopy to be composed of a geometric mixture of disks and cylinders corresponding to leaves and stems; it provides for both surface and volume scattering by these elements. In a recent extension, Lang and Saleh (1985) have shown the model to be invertible given measurements of backscattering at a range of incidence angles. The model is thus of the *L*-resolution, deterministic, invertible type.

Concluding Remarks

As the discussion of existing models above has demonstrated, our general framework for remote sensing models is widely applicable. As our modeling sophistication increases, it is evident that various combinations of discrete and continuous, *L*- and *H*-, deterministic and empirical abstractions will be used at different levels within the same overall remote sensing model. Applying our framework to a model, however, helps to clarify its structure and leads to a careful examination of its assumptions and specifications, whether implicit or explicit. This, in turn, leads to a better understanding of the model itself as well as its relationships with other models.

Our framework may also be helpful in model formulation. Approaching a modeling problem from the viewpoint of the properties and parameters of objects in the scene and the nature and distribution of incoming radiation incident on the scene often leads to early critical thinking and analysis of the modeling problem. For example, in the early development of the invertible, coniferous-forest canopy-reflectance model by one of us (Strahler), it became obvious that the spatial distribution function for the trees would have to be specified because the model was of the *L*-resolution type. A literature search revealed little information on the spacing of conifers in natural stands, and thus early field work was planned to study spacing in real stands. Without the explicit formulation of a scene model, this realization might have occurred much later. This, in turn, might have led to missing a field season and/or working with incorrect distribution functions.

Using our model framework may also lead to new areas of inquiry. For example, consider the discrete scene model. Approaching a scene as a collection of objects arranged on a background leads immediately into a consideration of resolution—that is, whether the model will be *H*- or *L*-resolution. This, in turn, leads directly to thinking about images at varying resolutions and the transition between L- and H-resolution. One of us (Woodcock, 1986) has pursued this line of thought further, developing the concept of texture within the image as a function of the size and shape of the objects in the scene and the size of the resolution cell. He assembled a diverse array of images, drawn from forests, agricultural areas, and urban and suburban areas, which were acquired either by aircraft and spacecraft multispectral scanning or by scan-digitizing aerial transparencies. By collapsing these images through spatial averaging to yield increasingly coarser resolutions, he has shown that local image variance (spatial texture) is controlled by the geometric relationship between object and resolution cell.

Similarly, the realization that the spatial autocorrelation inherent in discrete-object H-resolution scenes is a function of the size, shape, and spacing of the objects has led to the exploration of one- and two-dimensional variograms of images as tools to reveal the size, shape, and spacing (Woodcock and Strahler, 1984; 1985). Current work by Strahler and Jupp (Strahler et al., 1984) is devoted to developing closed-form solutions to variograms of simple scenes consisting of randomly placed objects on a contrasting background. This line of research promises to enhance our theoretical understanding of image texture as it is controlled by the size, shape, and spacing of real objects in the scene.

Our framework also helps demonstrate the relationship between different types of models. For example, consider crop classification using Landsat data. Because the H-resolution model underlying classification leads easily to indirect inference through empirical relationships between measurements and crop types, it is invertible in that crops are identified remotely. However, the structural parameters of the crop canopy that reveal crop condition, such as leaf area index, leaf angle distribution, etc., can only be directly inferred from a deterministic, L-resolution, invertible canopy model. Because agricultural yield estimation involves not only determining the area planted to a crop but also its condition, it is only by coupling and exercising both types of models that the true potential of remote sensing for agricultural forecasting can be revealed.

Our model taxonomy also should help researchers working in diverse areas of the field to understand better the interrelationships among their areas. Nearly all workers in remote sensing are interested in inferring the intrinsic properties of a scene from remote measurements. However, the scene, atmosphere, and sensor models individual researchers are concerned with vary widely. The modeling framework we provide facilitates the comparison of models and provides a mechanism for grouping together models that are structurally similar, so that the common approaches and techniques they utilize can be easily transferred, regardless of the explicit modeling context.

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