

Potential and Limitations of Information Extraction on the Terrestrial Biosphere from Satellite Remote Sensing

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The extraction of information on terrestrial environments from satellite observations requires the use of quantitative models to interpret the radiation data collected in space. Several approaches are feasible, ranging from the development of models capable of explaining the nature of the measured physical signal or of characterizing the state of the system under observation, to the establishment of empirical correlations between the variables of interest and the remote measurements. The premises and implications of these approaches are discussed with special emphasis on the mathematical and numerical requirements. Findings are condensed in 10 formal propositions, in the hope of clarifying the nature and domain of applicability of remote sensing. © Elsevier Science Inc., 1996.

INTRODUCTION

A number of potential climate change and degradation issues in terrestrial environments have been identified and studied over the past decades (e.g., pollution, drought and desertification, deforestation, ozone hole, etc). Various international committees have identified satellite remote sensing as a unique and essential tool to repetitively acquire global environmental data at spatial, temporal, and spectral resolutions appropriate to investigate these issues (NASA, 1983; OIES, 1988; IGBP, 1992). The reports they produced, as well as many other publications on operational remote sensing applications (e.g., agricultural monitoring), list an impressive series

of terrestrial and atmospheric variables that would be of great interest, and often suggest or claim that these can actually be derived from such data (e.g., vegetation type and amount, soil type and properties, surface temperature and roughness, biomass and primary productivity, surface fluxes of matter and energy, precipitations, etc).

Although much effort has been spent on applying remote sensing techniques in many different thematic fields, relatively sporadic work has been done to evaluate the actual suitability and range of applicability of the tools used in the interpretation of these data (Colwell, 1983; Strahler et al., 1986; Goel, 1988), perhaps because it appears empirically possible to retrieve useful information on the environment. Indeed, a wide variety of applications are currently based at least partly on remote sensing data, from cartography to geological exploration, from weather forecasting to ocean monitoring, and from agricultural yield prediction to disaster management.

In this article, we propose a conceptual framework to discuss the potential and limitations of the tools used to extract information from remote sensing data. After a general review of the nature of the problem, we compare the various approaches that have been proposed to extract quantitative information on terrestrial environments from such data, and highlight the premises and implications of adopting one particular approach or another. In the process, we attempt to establish what information can reasonably be expected to be retrieved from an analysis of remote sensing data, and to clarify the role of the different types of variables involved. We hope this discussion may shed some light on the setting of priorities for resource allocation in future model and instrument development, a crucial issue at a time when the National Aeronautics and Space Administration (NASA), the European Space Agency (ESA), and the Japanese National Space Development

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Received 18 February 1995; revised 8 April 1996.

Agency (NASDA), in collaboration with many other national space agencies, universities, and commercial companies, are heavily involved in the design and implementation of new polar platforms focused on Earth observation.

The following sections are framed in the context of the observation of terrestrial environments using remote sensing methods in the solar spectral range, but most of the arguments could be extended to other environments (e.g., the oceans) or spectral ranges (thermal infrared or microwaves). Similarly, we discuss only the interpretation of radiant intensity measurements, but additional radiative characteristics, such as the polarization and phase of the electromagnetic waves, could provide useful additional information and be considered as additional dimensions of the data. The next section provides an overview of the fundamental problem of remote sensing. This is followed by a discussion of the role of physically based models and the problems associated with their inversion against observed data. The next two sections review the role, potential, and limitations of spectral (and in particular of vegetation) indices, and of parametric directional models, respectively.

To provide as clear and objective as possible a framework to address these issues, we have expressed the principal arguments in a formal way. The "propositions" that follow are not intended to suggest a dogmatic view of remote sensing, but, rather, to state the conditions under which a particular technique may or may not be used. Our objective is not to establish a hierarchy of value or a rating among the various methods used to interpret remote sensing data, but to establish the advantages and drawbacks of each of these approaches. In any case, the tools of data analysis are intimately linked to the nature of and conditions in which these data were taken. We hope that these statements will stimulate discussions, result in a greater understanding of the opportunities and limitations of this technology, and generate ever better research and applications.

FUNDAMENTALS OF REMOTE SENSING

In principle, space-based observation systems can provide rather unique opportunities for monitoring our environment. Depending on the particular needs, data can be acquired over a range of spatial scales from local to global, with a spatial resolution of 10 m to 100 km. Some of these data have been acquired over a period of many years with a temporal resolution from hours to a few weeks, in a variety of spectral bands. Although detailed measurements could and should be acquired *in situ*, remote sensing from space platforms appears to be the only economically feasible way to repetitively gather information over large areas with a high spatial, spectral, and temporal resolution.

Indeed, satellite remote sensing techniques have raised the expectations of users of data and information.

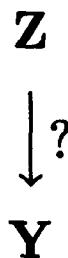


Figure 1. Graphical representation of the initial goal of remote sensing.

Typical applications include mapping, event detection, support to agriculture, forestry and fishing, weather forecasting, military surveillance, and the monitoring of the impacts of unpredictable events, resulting either from human activities (deforestation) or from natural disasters. Most of these applications hinge on the timely availability of data on the state and evolution of the system of interest, and of a panoply of tools and techniques for the proper interpretation of these data in terms of useful information.

However, satellite remote sensing observations are merely radiation measurements made hundreds of kilometers away from the targets of interest. Most users of these data are ultimately interested in some form of high level information, such as the temporal evolution of the spatial distribution of biomass, the fluxes of water, energy, and carbon between terrestrial environments and the atmosphere averaged over some suitably defined grid, the state and productivity of agricultural crops, etc. The fundamental problem of remote sensing is to establish to what extent the radiation measurements made in space can in fact provide useful information for these and other applications, and to design the tools and techniques to extract such information from these data. The implementation of these tools and techniques, in turn, depends on the existence of a body of knowledge on the fundamental processes that control or affect the emission of radiation at the source, its transfer within the relevant media, and its absorption in the detector.

This state of affairs, symbolically depicted in Figure 1, can be formally expressed as follows: If remote sensing data is denoted *Z* (italic letters refer to single values, while bold symbols represent vectors or matrices), and if the variables of interest to the users of remote sensing are collectively denoted *Y*, it will be seen that the meaningful use of remote sensing hinges on the following conjecture:

Radiative data Z collected on board remote sensing platforms in space can be interpreted quantitatively in terms of the variables of interest Y.

The primary goal of remote sensing research is therefore to establish the existence and nature of the formal relation(s) postulated by this conjecture, to determine

the best algorithms to extract the desired information, and to produce operational tools for the exploitation of these data. Clearly, the only way to ascertain exactly what information can be retrieved from these data (and therefore to determine the range of applicability of remote sensing) is to understand the physical processes that control these observations. This knowledge can then, in turn, be exploited to design optimal tools for the interpretation of these data.

In general, measurements Z in space are not controlled exclusively, or even directly by the variables of interest Y at the surface, but, rather, by the state variables S of the radiative transfer problem, that is, the fundamental measurable quantities necessary for the description of the physical interactions between the incoming radiation and the media in which this radiation propagates. Formally, the physical models describing the radiative processes controlling a single observation Z can be written

$$Z = f(S) \quad (1)$$

The state variables S are the smallest set of variables which are needed to fully describe the physical state of the system under consideration at the scale at which it is observed. In the specific case of the radiation transfer problem addressed here, they include the geometric properties of the media (atmosphere, vegetation, soil) with which the radiation interacts (e.g., position, size, shape, orientation, or density of the objects constituting these media), and the physical properties of the scatterers (e.g., aerosol phase function, leaf reflectance and transmittance, pigment concentration). Since remote sensing measurements are entirely controlled by the radiative processes that determine the interactions of the electromagnetic waves with the intervening media, it should be clear *a priori* that the strict interpretation of these data can only provide information on these variables. This point is encapsulated in the following proposition:

Proposition 1: *A physical interpretation of electromagnetic measurements Z obtained from remote sensing can provide reliable quantitative information only on the radiative state variables S that control the emission of radiation from its source and its interaction with all intervening media and the detector.*

This is not to say that remote sensing techniques are useless in all but radiative applications. Rather, this proposition suggests that only radiative variables can be explicitly retrieved from an analysis of remote sensing signals and that any further interpretation of the results should be based on relations between the variables of interest and these radiative variables. In other words, if physicists and engineers can determine the full set of radiative state variables S that determine the measured signals, as well as the accuracy with which these can be retrieved, then users of remote sensing data can

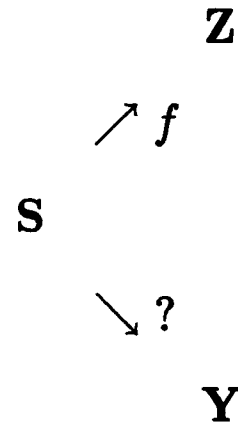


Figure 2. The goal of remote sensing when the existence of the radiative state variables has been recognized.

focus exclusively on establishing to what extent the variables of interest Y can be estimated on the basis of the radiative variables S (Fig. 2). One advantage of this approach is to make the potential user more aware of the nature of the information that is actually retrievable from remote sensing, as expressed by the reciprocal of the previous proposition:

Reciprocal: *If a variable of interest Y does not directly affect the transfer of radiation (i.e., is not one of the state variables S), no reliable quantitative information can be retrieved on that variable specifically from a physical interpretation of the corresponding remote sensing measurements alone.*

and it is understood that partial information on Y could be gained if and only if this variable is strongly related to one or more of the state variables S , and if these state variables can be accurately retrieved from the remote sensing data.

Historically, remote sensing techniques have been used in many different terrestrial applications to generate information on a wide variety of variables of interest (agricultural yield, environmental monitoring, land cover change, etc). Yet, few of these can be considered state variables of the radiation transfer problem. In many cases, the usefulness of remote sensing techniques in these applications resulted from an assumed or implied relation between the variables of interest and the state variables. It is important to note, however, that a significant amount of additional information is brought in the analysis through other sources, or from *a priori* knowledge, or by limiting the analysis to very particular situations. For instance, it is reasonable to expect that the rooting depth of plants has no direct influence on the reflectance of the canopy and should therefore not be directly retrievable from remote sensing data alone. However, there is likely to be some relation between rooting depth and the size of the plants above ground,

and larger plants tend to absorb more photosynthetically active radiation (PAR) and appear darker than smaller ones. It is thus possible that rooting depth is somewhat correlated with remote sensing data. Pine stands and tropical forests in general have generally shallow root systems and constitute significant exceptions to this biological relation, so that the assumed relation may appear to improve when the analysis is limited to deciduous forests. The important point here is that remote sensing data may provide only a small contribution to the information on rooting depth, which would be mostly conditioned by *a priori* knowledge brought into the analysis through geographical constraints, knowledge of the type of canopy, etc.

Physicists have accumulated extensive experience on the problem of radiation transfer, and recent reviews of the models available in the optical domain have been published (Goel, 1988; Asrar, 1989; Myneni and Ross, 1991; Hapke, 1993; Myneni et al., 1995b). Two types of radiation transfer models can be distinguished at this stage, depending on whether they can be practically inverted on an operational basis or not. In practice, the reliability of the results obtained by inversion is linked to the number of free parameters that need to be estimated, and the smaller this number, the better. Typically, radiatively simple scenes may require only one-dimensional models for an accurate description of their reflectance field, while more complex heterogeneous targets will necessitate complex three-dimensional models. In this latter case, the number of independent free parameters is very high, and the inversion can be envisaged only if additional assumptions can be made, or if ancillary information is available from other sources. The main constraint on the development of these three-dimensional models is to represent as faithfully as possible the physics involved; the conceptual or computational complexity of these models is of secondary importance, because they are used almost exclusively in direct mode, that is, to estimate the exitance or reflectance of a system which is otherwise fully characterized. Examples of these models include ray tracing techniques (Ross and Marshak, 1991; Govaerts and Verstraete, 1995), radiosity models (Borel et al., 1991), and discrete ordinate methods (Shultis and Myneni, 1988; Myneni et al., 1991). The importance of these models results from the deeper understanding they provide and the opportunity they offer to define and test simplifications and assumptions, or to design reliable parameterizations for use in more operational models.

On the other hand, there is also a need for physically-based models capable of describing the radiation transfer in terms of a small number of state variables, whose values can be retrieved by inverting these models against the observations (Goel and Thompson, 1984; Goel and Deering, 1985; Nilson and Kuusk, 1989; Verstraete et al., 1990; Pinty et al., 1990; Iaquineta and

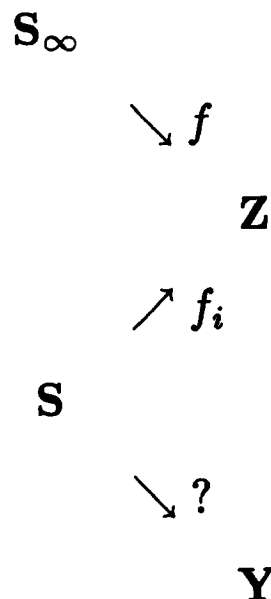


Figure 3. Two kinds of physical models can be distinguished in remote sensing: those that are used mostly in direct mode, and those that can be routinely inverted to retrieve the values of the state variables.

Pinty, 1994). These simpler models are usually based on specific hypotheses, such as the plane-parallel assumption, or two-stream approximations, but their development is further constrained by the need to keep the number of model parameters (state variables) as limited as possible. Indeed, the larger the number of free parameters, the more difficult it is to guarantee that a unique solution exists and can be found by optimization. More free parameters also increase the computational cost of the inversion procedures. Figure 3 shows these two approaches, where f designates the complex and possibly computationally expensive models, S_{∞} stands for the potentially very large number of state variables used to describe the various aspects of the real world, while f_i stands for the economically invertible physically based models.

In this context, we use the phrase "model inversion against a data set" to designate the numerical process whereby the parameters of the model are estimated on the basis of the information contained in the observations, using an optimization procedure and a figure of merit function. In the case of the physical models described here, the model parameters are the state variables of the radiative transfer problem, so that they are measurable quantities, and this feature allows the validation of the model (Pinty and Verstraete, 1992b). The inversion procedure is investigated in the next section; for the time being, it is sufficient to know that this approach implies that the number of model parameters must be as small as feasible while main-

taining both a realistic representation of the physical processes and an accurate description of the measurements.

After such a model f_i has been inverted against the observations and the model parameters S have been retrieved, a further scientific goal is to establish quantitative relations g_s between the variables of interest Y and the state variables S just obtained. Strictly speaking, this falls outside the scope of remote sensing *per se*. However, the development of these models $Y = g_s(S)$ contributes directly to a better understanding of the basic processes that control the environment, justifies the use of remote sensing as a source of data and of the radiation transfer models as the tools to assess the state variables of the system, and permits objective identification of the variables of interest that can realistically be retrieved from remote sensing with sufficient reliability and accuracy, as will be seen below. In the end, the problem of remote sensing can therefore be conceptually divided in two tasks: The first consists in exploiting the physical understanding of the measured signals Z to retrieve the values of the state variables S that control the observations, and the second refers to the interpretation of these state variables, often in conjunction with many other sources of data and *a priori* information, to determine the variables of interest Y . However, it will be seen that this distinction is not always obvious, especially when more empirical methods such as spectral indices are used.

RETRIEVING INFORMATION BY INVERTING PHYSICAL MODELS

Because of the importance of the inversion procedure to estimate the state variables and ultimately to characterize the system under observation, we investigate further some of the requirements and implications of this approach. As long as the model $Z = f(S)$ requires only one state variable S to explain a single measurement Z , this equation can be analytically or numerically inverted to yield the value $S = f^{-1}(Z)$. Such a situation would occur, for instance, if a surface reflected light equally in all directions. In that case, the surface is isotropic, and its reflectance is the only parameter that needs to be estimated. This can be done on the basis of any single measurement.

However, natural surfaces are not isotropic, and the models f used to represent their reflectance require more than one state variable to describe the remote sensing observations Z . Such models then cannot be analytically inverted (or, equivalently, the values of S cannot be uniquely estimated through symbolic manipulations of Z only) because the problem is underdetermined: We have multiple unknowns and only one equation. The standard approach consists in taking M measurements, and leads to the following system of equations:

$$\begin{aligned} Z_1 &= f(S_1^1, S_2^1, \dots, S_m^1) \\ Z_2 &= f(S_1^2, S_2^2, \dots, S_m^2) \\ &\vdots \\ Z_M &= f(S_1^M, S_2^M, \dots, S_m^M) \end{aligned} \quad (2)$$

where it has been assumed that the same model f is applicable to all measurements. This does not help, however, because either all Z_k are identical (within the errors of measurements), and no additional information is gained by multiplying them, or they are different, but then these differences in the observations must result from differences in the state variables S . This means that the system has changed between observations, and there is no way its state can be uniquely characterized on the basis of these measurements alone. This difficulty cannot be resolved without introducing yet another set of variables:

Proposition 2: *A model f describing remote sensing measurements Z in terms of more than one state variable S cannot reliably be inverted unless it expresses the variability of Z as a function of at least one measurable independent variable X .*

Ignoring the polarization of electromagnetic waves, four sets of independent variables have been found useful in remote sensing, corresponding to the spatial (\vec{r}), temporal (t), spectral (λ), and directional (Ω) dimensions (Gerstl, 1990). Many models use more than one independent variable simultaneously. For instance, bidirectional reflectance factor (BRF) models describe the variability of the measured reflectances in terms of the zenith and azimuth angles characterizing the directions of illumination and observation.

The physical model describing the observed signal is now formally expressed as $Z = f(X, S)$, and to avoid acquiring the same observation over and over again even though the system does not change ($S = \text{cst}$), we adopt an observing strategy designed to change one or more of these independent variables between each observation. The system of equations becomes

$$\begin{aligned} Z_1 &= f(X_{11}, X_{21}, \dots, X_{n1}, S_1, S_2, \dots, S_m) + \varepsilon_1, \\ Z_2 &= f(X_{12}, X_{22}, \dots, X_{n2}, S_1, S_2, \dots, S_m) + \varepsilon_2, \\ &\vdots \\ Z_M &= f(X_{1M}, X_{2M}, \dots, X_{nM}, S_1, S_2, \dots, S_m) + \varepsilon_M, \end{aligned} \quad (3)$$

where X_{ik} stands for the value of the independent variable X_i ($i = 1, 2, \dots, n$) corresponding to the conditions of observations prevailing when the measurement Z_k ($k = 1, 2, \dots, M$) was acquired. The state variables S_j ($j = 1, 2, \dots, m$) are kept constant for all observations, and ε_k represents all the remaining discrepancies (e.g., errors of measurement and model limitations).

As before, if $M < m$, there is no solution because the system is underdetermined. When $M = m$, there

is usually no solution, because of nonzero errors of measurements ε_k in Z (or in X), or because of limitations of the model f . And if $M > m$, there is no analytical solution because the system is overdetermined. We are once more forced to change objective. Rather than searching for the unique "true" solution of this system, we seek the "best" solution, that is, the best estimate of the values of the state variables: Those that, together with the model f , optimally describe the observations Z and their variance with respect to the independent variables.

This implies that a criterion must be selected to evaluate the "goodness" of a particular solution. A figure of merit function is used for this purpose, and the least mean square estimate is usually chosen:

$$\delta^2 = \sum_{k=1}^M W_k [Z_k - f(X_{1k}, X_{2k}, \dots, X_{nk}; S_1, S_2, \dots, S_m)]^2, \quad (4)$$

where W_k is the weight given to observation Z_k . The problem is solved by searching, among the set of possible solution vectors S , the one that minimizes the figure of merit function δ^2 . Standard numerical algorithms exist to solve this optimization problem, provided that the function f is sufficiently well behaved and the data set Z provides enough variance to constrain the inversion procedure. The following two propositions make explicit these requirements:

Proposition 3: *In order to invert a model $f(X, S)$ against a data set of M remote sensing observations Z_k and retrieve the m values of S , 1) the model must be mathematically "well behaved" and require as few parameters S as possible, 2) a figure of merit function must be defined, 3) an inversion procedure must exist and implement an algorithm capable of finding the absolute extremum of the figure of merit function if it exists, and 4) more observations must be collected than there are parameters in the model ($M > m$).*

The smaller the number m of parameters a model needs, and the larger the number of measurements M can be explained by the model, the more confidence we can place in this model's capability to represent the variance of the measurements. We know from experience that an arbitrarily large fraction of the variance of a particular data set can always be "explained" by a given model if enough free parameters are allowed. However, the more there are parameters, the less likely their values will be retrievable with other data sets or meaningful in other situations. Also, the reliability of the model formulation and of the inversion procedure is increased if the values of the state variables S retrieved from inverting the model against a number of data sets agree with those resulting from actual independent measurements in the environment being observed (Pinty and Verstraete, 1992b).

Not all state variables S can be retrieved from an inversion with respect to any given independent variable. In fact, there is a strong association between the nature of the state variables S and the type of independent variables X that are appropriate for the retrieval of these state variables. For example, the chemical composition of the materials in the observed medium can only be retrieved from the spectral variations of the measurements. Similarly, it would be meaningless to try to retrieve information on the structure of a plant canopy from the time evolution of measured signals, as structure affects mostly the directional signature of the target. For this reason, it is useful to partition the set S into disjoint classes S^j of state variables which must be retrieved simultaneously, that is, which are physically associated with disjoint classes X^i of independent variables (for instance, spectral and directional), and it is advantageous, both from the observational, mathematical, and computational standpoints to keep these classes X^i as small as possible.

Two consequences result from the fact that the independent variables have only to do with the way the system is being observed, not with the state of the system itself: 1) The physics of the problem and hence the mathematical form of the physical model f (that describes the measurements Z) determine which independent variables X are relevant for the retrieval of each of the state variables S , and 2) the observation strategies should be designed to effectively provide sufficient variability in the appropriate independent variables. The following proposition formalizes these statements by specifying the conditions required for the successful retrieval of such a class of state variables:

Proposition 4: *To reliably and accurately retrieve the state variables S^j by inverting a physical model $f(X, S)$ against a data set Z , 1) the model must be sensitive to the values of S^j , 2) the model must be inverted with respect to the appropriate class of independent variables X^j , 3) the measurements must be acquired by varying only the independent variables in X^j while maintaining S and all other independent variables X^i (where $i \neq j$) constant, and 4) the observational sampling in X^j must be extensive and dense enough to generate sufficient variance in Z and constrain the inversion.*

In effect, this proposition implies that if a model parameter S_j plays a minor role in the determination of the variance present in the data for the particular range of values of the independent variables X^j , it may be difficult or impossible to retrieve the value of this parameter. If this parameter S_j never really affects the measurements, one could argue that it should not be included as a variable of the model. However, the effect of that state variable may not be noticeable because of the particular sampling strategy followed in the acquisition of a given data set. A case in point is provided by the

structural parameter describing the shape of the hot spot in the reflectance of rough surfaces. This parameter strongly influences the reflectance field in a limited range of illumination and viewing angles, but does affect the reflectance field everywhere. A reliable and accurate retrieval of this parameter is strongly dependent on the availability of measurements in the appropriate angular regions. A similar situation arises when a parameter normally significantly affects the measurements but does not do so for a particular type of surface.

It also follows that if the data Z are acquired while varying only the independent variables appropriate for the retrieval of S^j , then only those state variables belonging to that subset can be retrieved from such an inversion against these data. For instance, it would be inappropriate to claim the direct retrieval of surface structural information from an analysis of spectral variations if the structure controls the directional variability of the signal and that variability is not observed. Intuitively, this proposition implies that the observational sampling strategy should be designed to provide higher densities of observations where the model f is most variable with respect to the independent variables appropriate for the inversion.

The accuracy of the numerical values of the model parameters S^j retrieved by inversion depends on the particular figure of merit function, the noise level in both the independent variables X^j and the measurements Z , and the implementation and performance of the optimization procedure. Specifically, the latter should be robust (noise-insensitive), reliable (capable of finding the absolute minimum despite the presence of local minima) and computationally cheap if this approach is to be used operationally. Clearly, all model parameters in S^j should be retrieved simultaneously. Of course, these parameters must *a priori* be independent of the X^j used in the inversion.

Proposition 5: *If the data set Z has been acquired by varying independent variables in two disjoint classes (X^{j1} and X^{j2}), and if the corresponding classes of state variables (S^{j1} and S^{j2}) are independent of each other, then two separate models $Z = f_1(X^{j1}, S^{j1})$ and $Z = f_2(X^{j2}, S^{j2})$ can be defined and inverted independently on the same data set.*

In other words, each class of state variables can be retrieved directly by inversion of the appropriate model with respect to the relevant independent variables.

Corollary: *If some of the state variables in S^{j1} depend on S^{j2} , then there exists a causal model $Z = f_1(X^{j1}, S^{j1})$ describing the observations Z in terms of the state variables S^{j1} and a set of causal models of the type $S_{j1} = f_2(X^{j2}, S^{j2})$ describing the values of the state variables S^{j1} in terms of the state variables S^{j2} . If, in addition, the associated subsets of independent variables X^{j1} and X^{j2} are*

disjoint, then the model f_1 must be repeatedly inverted against Z with respect to X^{j1} for various values of X^{j2} , and the models f_2 must be inverted against the newly obtained sets of state variables S^{j1} with respect to X^{j2} to retrieve the state variables S^{j2} .

In this case, the model describing the measurements could be formally written $Z = f_1[X^{j1}, S^{j1}, (X^{j2}, S^{j2})]$. This discussion occurs because the remote sensing instruments on board space platforms typically used to investigate surface processes acquire data for particular directions of illumination and observation in a number of spectral bands. As indicated earlier, this results in data variability with respect to the directional and spectral independent variables, and current models associate these disjoint subsets of independent variables to distinct subsets of state variables. However, some of the state variables of the radiative transfer problem, which describe the directional variance of the signal (typically the reflectance and transmittance of the scatterers, which contribute to the anisotropy of the surface), are functions of the state variables which can be retrieved by inversion with respect to the spectral independent variable.

Specifically, in the solar spectral range, i) the inversion of a BRDF model f_1 capable of describing the physics of the measured signal in terms of the structural and optical properties of the medium should preferably be performed before the analysis of the spectral variance, and ii) the latter, executed through the inversion of a spectral model f_2 , can then focus exclusively on those state variables which are spectrally dependent. This satisfies Proposition 3 by minimizing the number of free model parameters at any one step, and takes advantage of the causal relationship between the state variables. From a numerical point of view, a higher confidence may be placed in the estimates of the state variables, since the higher the number of model parameters, the higher the probability the optimization procedure may find a local minimum.

The inversion of a physically based model f against a data set Z acquired by varying an independent variable X results in the retrieval of model parameters that are independent of that independent variable. Hence, when starting with remote sensing data that are intrinsically functions of all four sets of independent variables $Z(\bar{r}, t, \lambda, \Omega)$, one must be careful in which order the inversions are applied. If a spectral model is inverted first, the retrieved model parameters (such as the transmittance and reflectance of leaves, for instance), would be independent of λ , but still functions of the particular angles of illumination and viewing. This may increase the complexity or even prevent the proper interpretation of the results. On the other hand, if a bidirectional reflectance model is inverted first against these data, the retrieved parameters (e.g., single scattering albedo

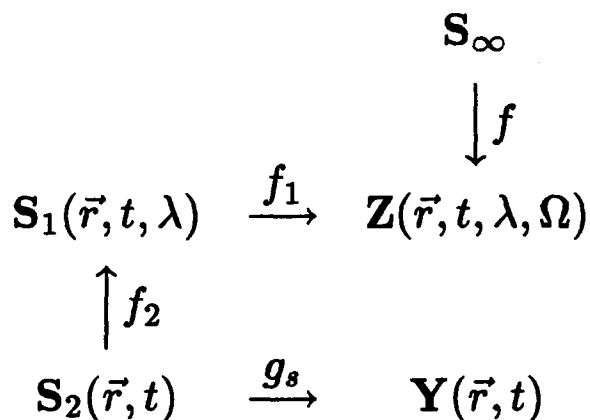


Figure 4. The interpretation of remote sensing data on the basis of physically based models should proceed first with the inversion of BRF models against directional data, then with the inversion of spectral models against multiple spectral values of the appropriate state variables.

and phase function, or reflectance and transmittance of the scatterers) remain spectral function but are now independent of the particular geometry of the measurements. By repeating this procedure at multiple wavelengths, the spectral variations of these physical variables can be documented, and interpreted in terms of the chemical composition of the medium.

This nesting of models no doubt results from the fact that the fields of view of all current and planned airborne and space instruments (as well as those of the vast majority of laboratory and field instruments) are sensitive to a large number of scatterers at any one time. Remote sensing measurements are therefore intrinsically characteristic of the medium under observation, and not only of the individual scatterers. The separation of the two effects must be performed before a meaningful spectral analysis can be carried out.

The new situation resulting from this discussion is shown in Figure 4. Overviews of the BRF models (f_1) currently available exist in the literature (Goel, 1988; Strahler, 1994). Similarly, specific models (f_2) have been proposed to exploit the spectral variations of the leaf properties to estimate the chlorophyll and water content, as well as a leaf structural parameter N (Jacquemoud and Baret, 1990).

The following outstanding issues remain and should be underscored: i) Physically based models need to be validated before they are used extensively. This issue has been addressed in the literature (Pinty and Verstraete, 1992b), but much more effort should be expended to validate and intercompare models than has been done in the past. ii) Perhaps the major obstacle to the validation of models is the lack of simultaneous remote sensing, field, and laboratory data acquisitions, although

this approach raises scale issues when comparing local measurements to space observations. The advent of instruments such as the PARABOLA (Deering and Leonoe, 1986; Deering, 1989; Deering et al., 1995) offers new opportunities, but significant effort will be needed to collect the relevant ancillary data sets. iii) The identification of the minimal number of angular observations and of the optimal illumination and viewing geometries for inverting BRF models and of the minimal number of spectral bands necessary to retrieve the biochemical state variables remains a research issue. Work is currently under way in this area (Maggion, 1995), but significant progress will probably still take time. iv) Better results may be expected with improved figure of merit functions, and in particular with the use of weights to differentiate the contribution of each data item to the knowledge of the desired state variable. In the same vein, improvements in optimization procedures and a better understanding of the impact of noise in the data or the independent variables should help extract more reliable products from remote sensing data. v) Last but not least, the importance of establishing relations $Y = g_s(S)$ between the parameters of interest Y and the state variables S cannot be overstated, even though this effort is, strictly speaking, outside the scope of remote sensing. A typical example is the need to derive information on plant productivity from physical and biochemical information on the state of the canopy. Ultimately, the existence and establishment of these relations justify the use of remote sensing techniques.

RETRIEVING INFORMATION FROM EMPIRICAL METHODS

The inversion of physical models against remote sensing data clearly constitutes a sound but scientifically involved approach. We can reasonably ask whether it would not be possible to assess the values of the variables of interest Y more directly by establishing empirical relations of the type $Y = g(Z)$. The answer appears to be yes, since a large number of algorithms are routinely used to retrieve information on terrestrial surfaces from direct manipulations of the measured signals. These methods are based on the analysis of images (pattern recognition, local variance, image structure), time variations (change detection), or the exploitation of spectral contrasts, as is done with all vegetation indices. Of course, the values of the variables of interest Y cannot be causally affected by the fact that the system is being observed, or by the numerical value of these measurements, so that it is clear from the outset that such a relation is of a different nature than the physical models described in the previous section. The objective of setting up such relations is also clearly to estimate the values of the variables of interest Y , not to provide

any new understanding of the physical processes that control the measurements.

We now analyze the meaning and implications of this alternative approach to the estimation of Y . Three categories of variables of interest can be distinguished for this purpose: Those that are state variables of the radiative transfer problem (i.e., the variables S of the previous sections), those that can be entirely determined as a function of these state variables, and those that depend on at least one other variable, not related to the radiative processes discussed above.

Since there is an explicit physical or biochemical (causal) relation between the state variables S and the measurements Z , for example, through the models f_1 and f_2 described above, we know *a priori* that these quantities are related to those observations, and we expect that relations of the type $Y = g(Z)$ can be established for any of these state variables. However, since i) multiple state variables S are necessary to physically describe each of the measured values Z and ii) only an optimal (but not perfect) estimation of the state variables S can be retrieved through the numerical inversion of physical models against the data Z , we cannot expect that a relation linking multiple measurements to a single state variable provides a perfect deterministic estimation of the state variable of interest. Hence, this relation will be empirical, even if there is ample theoretical ground to justify its establishment. It is also worth noting that even if the variable of interest Y happens to be a state variable, that does not guarantee that a relation $Y = g(Z)$ is reliable or useful. Indeed, the leaf area index is a state variable of the radiation transfer problem, but it cannot be reliably estimated from vegetation indices when the canopy is deep enough.

The establishment of a relation to estimate the chlorophyll concentration $[cc]$ in the leaves from remote sensing measurements provides an example of this first category of variables. A relation can reasonably be established, since the presence of chlorophyll affects the spectral values of the reflectance and transmittance of these leaves, and these properties, in turn, affect the measurements. However, since the measurements are also influenced by other factors, such as the presence of an atmosphere, or the structure of the canopy, we can hardly guarantee that a single relation such as $[cc] = g(Z)$ could be used to accurately determine the chlorophyll concentration anywhere and at all times.

The case of the state variables of interest Y which can be computed explicitly and exclusively on the basis of the knowledge of the state variables S is very similar. However, if multiple state variables S_j are needed to estimate the variable of interest Y , the relation $Y = g(Z)$ is equivalent to establishing multiple relations $S_j = g_j(Z)$, and then computing Y on the basis of the model $Y = g_s(S_j)$, assuming that the latter relation exists. The accuracy of such a relation cannot be better than that

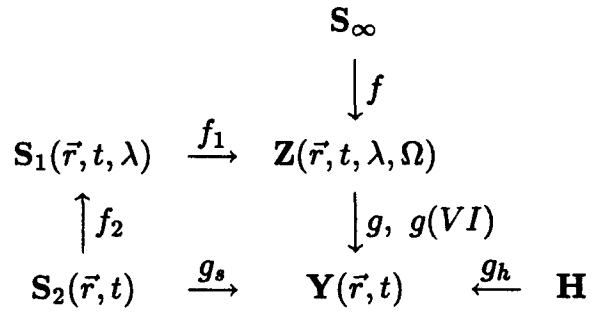


Figure 5. Hidden variables (factors which do not control the transfer of radiation and the remote sensing measurements) often largely control the variables of interest. When this occurs, the actual contribution of remote sensing to the desired information may be limited.

of any of the implied relations g_j , even if the model g_s is perfect. Again, there may be sound theoretical justification for seeking such a relation, but the final relation g will also be empirical and of limited reliability.

In the vast majority of cases where relations of the type $Y = g(Z)$ are developed and used, the variable of interest Y is an environmental or economic variable whose value is determined only partly by the state variables S . We will call "hidden variables" H all the variables that affect the value of Y , but which are not state variables of the radiative transfer problem and do not depend on them. These hidden variables include, for instance, all underground characteristics not accessible by optical methods (e.g., deep soil moisture, root depth), all physical, chemical or biological properties unrelated to the transfer of radiation in the spectral range considered here (e.g., the parameters that describe the competition of species), and all parameters describing human activities (e.g., amount of fertilizer and irrigation). Since hidden variables directly affect the variable of interest, but do not influence the remote sensing measurements, the latter may not include much information on the former and cannot provide, alone, the basis for a deterministic determination of the variable of interest. In fact, the more the variable of interest Y depends on hidden variables H and the less it is controlled by the state variables S , the less reliable the relation $Y = g(Z)$ will be.

Figure 5 exhibits the place of these relations and the role of the hidden variables in the graphical scheme used before, and the following proposition identifies which variables of interest may in fact reasonably be expected to be estimated from remote sensing data on the basis of these empirical relations:

Proposition 6: A meaningful relation of the type $Y = g(Z)$ can be established only if the variable of interest Y is in fact one of the state variables S which control

the measurements Z , or a function of these variables. In the latter case, these state variables must affect the variable of interest more significantly than any other variable, in particular than the hidden variables.

It is important to note that this proposition places a necessary but not a sufficient condition for such a relation to be meaningful. We must therefore question and precisely document its range of applicability. Most of the relations $Y = g(Z)$ are traditionally established by correlating remote sensing measurements to field observations of the variable of interest. The fact that these *in situ* measurements take place at spatial and temporal scales different by 1 or more orders of magnitude from those of space observations should be of major concern. Strictly speaking, the validity of such statistical relations is limited to the set of conditions that are accurately sampled by these remote sensing measurements and field observations. The field of statistical inference defines the degree of confidence that can be placed in various statistical statements about a population, when information is available only about a sample. Nevertheless, the establishment of these empirical relations hinges on the availability of field measurements of the variable of interest Y , and their verification can only be achieved through the collection of more field data. The following proposition expresses this paradox between the conflicting needs to collect additional field data to evaluate the reliability of the relation, and to apply these statistical relations at places and times other than those where field observations are made, by exploiting remote sensing data as proxy for the variable of interest:

Proposition 7: *A relation $Y = g(Z)$, obtained by statistically correlating remote sensing measurements and field observations, is useful only for those locations and times others than those used to establish the correlation, that is, where and when the applicability and reliability of the relation is empirically justified by previous experiences with statistical extrapolation. By the same token, remote sensing does not provide any new information on the state of the environment for those places and times where local field observations of Y are already available.*

The reliability of these relations may be increased by allowing an explicit dependency on hidden variables: $Y = g(Z, H)$, provided that the values of these variables are available independently. If these relations are established for fixed values of these hidden variables, their applicability is even more reduced. This is typically the case when a relation is deemed applicable only to a certain location, season, type of ecosystem, for instance.

Another difficulty arises because of the role of the state variables S_j that affect the measured signal but are unrelated to the variable of interest Y . Although the relation g may still be useful in practical applications,

its precise interpretation may be difficult or impossible. The "contaminating" effects of the atmosphere and soils on the value of vegetation indices, and therefore on the variables of interest estimated from them, provide typical examples of such difficulties.

Vegetation indices (VI) have been used extensively for a wide variety of applications, and probably constitute the most common approach to the direct estimation of the variables of interest. They were initially designed as linear combinations of sensor spectral channels (for the most part, one in the red and one in the near-infrared), to exploit the spectral variations of the reflectance of plant canopies (Myneni et al., 1995a) around $0.7 \mu\text{m}$. Only minor attention was given to the perturbing factors $\partial VI / \partial S_j$. New vegetation indices (Huete, 1988; Kaufman and Tanré, 1992; Pinty and Verstraete, 1992a) or procedures [such as the maximum value composite proposed by Holben (1986)] were introduced when a better compromise was found between maximizing $\partial VI / \partial Y$, and minimizing $\partial VI / \partial S_j$. However, it is also only recently that these optimization constraints have been explicitly recognized as design criteria (Verstraete and Pinty, 1996). Significant further developments can be expected in this direction over the next few years.

Of course, any number of empirical relations of the type $Y = g(Z)$ may be established, one (or more) for each variable of interest Y . In fact, the literature abounds in correlations between vegetation indices and variables of interest, such as plant properties, ecosystem structure and functioning, soil characteristics, etc. In each of these applications, it must be remembered that the derivation and use of such a simple relation essentially assumes that the variable of interest is the main controlling factor of the observations, and that all other factors are assumed constant in that context. Since the same data are often repeatedly used to estimate a single vegetation index and derive different information in different applications, we must conclude that only one type of information is actually retrieved, even though it may be labeled differently by different authors:

Proposition 8: *If more than one variable of interest Y is correlated to a given vegetation index, or if more than n variables of interest are correlated with n independent remote sensing data items Z_k , these variables are correlated between themselves and no additional information is gained on the system, unless these relations also depend explicitly on additional and independently known hidden variables.*

Two more issues will be mentioned, although they would require a more detailed treatment than will be possible here. First, most of the empirical relations $Y = g(Z)$ already derived, say on the basis of data from one sensor (e.g., AVHRR), will not be easily transferable to other sensors, existing or under development. Indeed,

the numerical value of vegetation indices is different for each remote sensing instrument, even if they observe the same location at the same time. This is due to differences in the spectral responses of the sensor, as well as in spatial resolution and viewing geometries. As a result, vegetation indices are specific to the sensor, or class of similar sensors, for which they were designed. For instance, because the broad-band observations of the AVHRR instrument in the near-infrared channel span one of the atmospheric water vapor absorption bands, these measurements are rather strongly affected by the presence of a variable amount of this atmospheric constituent. More recent instruments, with much narrower bands, may avoid most if not all of this perturbation. Hence, none of the empirical relations derived on the basis of AVHRR data and ground measurements would be appropriate with these new instruments (whether they use vegetation indices or not).

The other (and perhaps more important) issue is expressed in the following proposition:

Proposition 9: *A vegetation index compresses the volume of remote sensing data by a factor equal to the number of channels used, but also significantly reduces the information contained in the original data set.*

This point has been addressed elsewhere (Verstraete, 1994) but can easily be demonstrated by pointing out that the mathematical process of computing a vegetation index is not reversible. From two spectral measurements, we can easily compute their sum and their difference. The latter could be used as a vegetation index, the former could be used to estimate the "albedo" of the target. Yet, it is not possible to estimate this albedo on the basis of that vegetation index alone.

Historically, vegetation indices have been used in a large number of applications. They obviously are sensitive to the state variables of the radiation transfer problem, but they also often appear related to other vegetation characteristics. As such, these indices have largely helped to promote remote sensing techniques and the development of better performing instruments. The lack of operational models and inversion procedures to analyze existing data, as well as the intrinsic limitations of these data (in particular, the systematic undersampling in the directional domain), have often prevented the use of more sophisticated methods. The main point of the propositions above is to warn the users of these empirical relations against an overinterpretation of the data in quantitative applications, which will in the end turn out to be counter-productive.

THE ROLE OF EMPIRICAL BRF MODELS

A final category of bidirectional reflectance models should be mentioned for completeness, namely, those that aim to describe the anisotropy of the surface with-

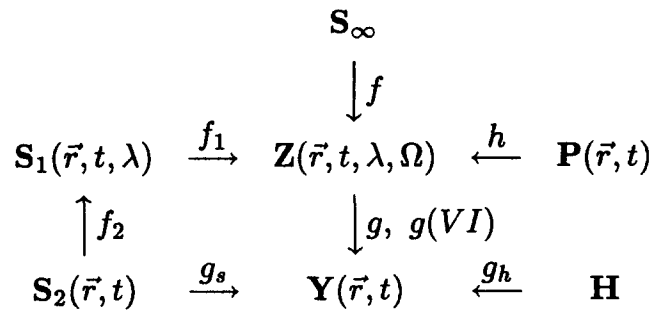


Figure 6. Empirical BRF models occupy a special niche in the exploitation of remote sensing data: They can represent the anisotropy of the surface and may be useful to estimate integral quantities such as the spectral directional hemispheric reflectance (albedo), but they also have significant limitations.

out imposing any constraint, other than being able to fit the given data Z as well as possible, on the analytical form of these models. Their parameters P can be adjusted to fit a wide range of conditions, but have no particular physical meaning. Formally, these models can be written $Z = h(X, P)$. This approach is schematically represented in Figure 6.

Empirical BRF models have been developed since early this century, in particular to characterize the directional reflectance of the surface of the Moon as observed from the Earth (Minnaert, 1941). Various models were recently proposed for Earth observation applications based on remote sensing data (Wathall et al., 1985; Roujean et al., 1992; Rahman et al., 1993; Wanner et al., 1995). These models may be useful to represent the overall effect of the anisotropy of the surface in specific applications. However, to the extent they focus on representing (rather than explaining) the shape of the BRF of the surface, they do not provide new insight into the problem of radiation transfer. These points are summarized in the next proposition:

Proposition 10: *In certain specific applications, it may be sufficient to represent the anisotropy of the surface with empirical BRF models of the type $Z = h(X, P)$. While these models may be used with some success to interpolate or even extrapolate directional measurements at angles other than those measured, or to estimate the albedo of the observed system, they cannot provide any understanding of the processes controlling Z , nor do they characterize the system in terms of the variables of interest Y .*

Why do we develop these models, since they do not provide an understanding of the processes controlling the measurements or characterize the observed system? Because these simple models can be used effectively in the following three specific applications: i) to provide the shape of the BRF as a lower boundary condition for atmospheric or vegetation models, ii) to generate the reflectances that would have been ob-

served under a different geometry of illumination and observation, and iii) to estimate the directional hemispherical reflectance (albedo) of the surface by integrating the sampled BRF over all viewing angles.

The use of an empirical BRF model in any one of these three applications presupposes that this model can reliably and accurately represent the bidirectional reflectance of the medium under arbitrary geometries of illumination and observation. In many cases, the usefulness of these models hinges on the reliability with which they can estimate realistic reflectances under illumination and viewing conditions other than those available in the sample of observations *Z*. Since these models cannot be validated in the strict sense advocated earlier (Pinty and Verstraete, 1992b), extra care must be given to the verification of their performance for a wide variety of angular conditions and surface types.

CONCLUSIONS

Various sectors of economic activity and scientific inquiry require repetitive, high spatial resolution data on the state and evolution of the environment. Sensors on board satellite platforms appear to provide the only economically feasible solution available today to collect relevant information at the regional to global scales with relatively high spatial resolution. The dichotomy between the natures of the measured signals and of the variables of interest prompted a discussion of the feasibility of retrieving useful information on the variables of interest from the space measurements. It was also argued that the physical understanding of the physics of the signal was necessary to develop and support practical applications, and to gain knowledge on the fundamental processes that govern the evolution of these environments.

A variety of approaches exist to exploit remote sensing data. Detailed physical models can incorporate much explicit knowledge of the structure and properties of complex media, but do not easily lend themselves to operational applications. Physical models describing radiatively simpler situations may be inverted against remote sensing data, but this process results in the retrieval of the state variables controlling the transfer of radiation in the medium, not necessarily in the desired information. All of these models embody our knowledge of the radiative transfer processes that control the measured signals. The inversion of such models also provides an objective way to estimate the state variables of the radiative transfer problem. The values of other variables of interest may be deduced, provided that they depend on one or more of these state variables. This same restriction also applies to direct empirical methods, including vegetation indices. These methods currently support many practical applications, but suffer from various intrinsic limitations. Finally, empirical BRF

models have been found useful only in very specific applications.

It may be that new developments will witness the emergence of yet other approaches. For example, expert systems (whether rule-based or using neural networks) may both integrate much of the knowledge gathered with the models described above and provide alternative ways to analyze remote sensing data as explained by Kimes et al (1994). The validation of the models and relations used in remote sensing remains a major challenge, mostly due to the lack of appropriate data sets. High priority should be given to combined laboratory and field campaigns, where both remote sensing and *in situ* data are collected from the same targets concurrently.

Last but not least, it has been argued that the spectral exploitation of the data cannot be done without taking the directional aspects into account. The lack of directional sampling in current data sets poses significant problems in the proper treatment of this issue. This has significant implications on the priorities for further research and the development of future sensors, especially because of the current focus on high spectral resolution. In this respect, the selection of MISR on NASA's EOS-AM platform and POLDER on Japan's ADEOS constitutes an original and most promising development.

The authors are most grateful to Gilbert Saint for having provided the opportunity and initial stimulus to conduct this investigation. They also thank Pasquale Nardone, Soroosh Sorooshian, Dean Graetz, and Alan Strahler for their encouragements and constructive comments on earlier drafts of this article. The remarks of an anonymous reviewer and of Marvin Bauer were instrumental in making this article less abstract and more readable. R. B. M. acknowledges the financial support from NASA Grant NAG5-2370.

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