A MODELING STUDY ON THE USE OF PASSIVE MICROWAVE DATA FOR THE MONITORING OF SPARSELY VEGETATED LAND SURFACES

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Abstract

This paper presents some aspects of a scheme which uses remote sensing measurements to control the simulations of a coupled land surface process and passive microwave radiative transfer model. Based on an iterative minimization procedure, the scheme estimates model input parameters or initial conditions. The study focuses on the feasibility of the scheme and its sensitivity to errors. It is shown that important parameters can be retrieved with the scheme, and that the parameters to which the simulations are most sensitive, are also those which are more liable to be retrieved satisfactorily in the presense of noise.

Introduction

Satellite remote sensing is generally considered potentially useful for improving the estimation of important land surface processes (net primary productivity, heat and water fluxes, etc.) over large areas. As the link between the processes and the remotely sensed radiances is not direct, current efforts are mainly devoted to relate the latter, empirically or by the inversion of radiative transfer models, to surface variables (soil moisture, Leaf Area Index (LAI), surface temperature, etc.), which in turn are used to estimate the processes of interest. Our ongoing research is focused on exploring ways by which different remote sensing data can be incorporated in a land surface process model. The approach is an extension to natural vegetation, of methods developed by agricultural scientists, whose intent was to use remote sensing to complement the performance of crop growth models [1] [2]. In these methods, estimations of land surface processes arc to be provided by modeling, and the remote sensing data are used only to control the simulations of the model. The approach is based on the coupling of a land surface process model with radiative transfer models in the visible/near infrared, active and passive microwave domains. The control of the model simulations by remote sensing data is then realized by minimizing the difference between observed and simulated remote sensing measurements.

Many issues still remain to be addressed before the method can be implemented fully. In particular, the spatial scales at which the surface processes or characteristics arc modeled arc usually not compatible with the scales of the satellite data [3]. Often, the scales at which physical principles apply arc local rather than regional. The extrapolation of a locally validated process model to regional applications cannot be readily justified or verified, and is in that sense unsatisfactory. Another important issue is the propagation of errors in the coupled surface process and radiative transfer model when used in a retrieval scheme [3]. Both issues are currently under investigation; this paper presents some aspects of the retrieval scheme using a coupled process and passive microwave radiative transfer model, its feasibility and its sensitivity to errors. After a brief presentation of the models used, the retrieval scheme is outlined, The numerical experiment is then described and the results obtained are discussed.

Model description

The rationale for coupling a land surface process model with a radiative transfer model is to obtain simulations of remote sensing observations and of the relevant processes at the same time, establishing the link between the processes and remote sensing observables, implicitly by modeling. The coupling is primarily realized by ensuring that the land surface process also simulates surface variables or characteristics used as inputs in the radiative transfer model.

Land Surface Process Model

The ecosystem chosen to evaluate the methodology is a semi-arid grassland as typically found in the Sahel, The herbaceous layer is composed of annuals whose emergence is triggered by the first rains which normally occur in June. The rainy season itself lasts about 3 months, and within two months after the last rains, the herbaceous vegetation has dried out. The surface processes arc grouped into two submodels. The first one describes the water and energy budgets, and has a one hour time step. The other one groups the processes related to vegetation growth, and runs with a daily time step. The coupling of the two submodels is done by the exchange of variables like the daily average canopy temperature and water potential, Leaf Area Index and vegetation height (Fig.1). The energy partitioning in the sparse vegetation follows the formulation of [4]. The soil temperature and moisture time dependent equations follow those of [5]. The system is solved by writing an energy budget separately for the canopy and the soil, integration in time is carried out using the Crank-Nicholson method after linearization of non linear terms. The vegetation growth submodel is taken from [6]. Vegetation growth is obtained on a daily basis as the result of photosynthesis minus respiration and senescense, and particularly in these regions, is closely controlled by water availability.

Microwave Radiative Transfer Model

The passive microwave model used in this study is from [7]. It was originally developed to interpret spacecraft microwave data, and particularly to study the effects of surface temperature and atmospheric variability on the SMMR (Scanning Multichannel Microwave Radiometer) response to soil moisture and vegetation. The microwave brightness temperature measured by the radiometer is composed of (i) the upwelling atmospheric emission, (ii) the surface emission attenuated by the atmosphere, and (iii) the cosmic background emission and the downwelling atmospheric emission, reflected at the surface and attenuated by the atmosphere, The main surface or atmospheric variables which can significantly influence the brightness temperature arc : the surface reflectivity r_p, the single scattering albedo, (r), the opacity of the atmosphere τ_a, the canopy opacity τ_{cp}, the vegetation cover fraction C, the ground surface temperature Ts and the canopy temperature T_c. The subscript p stands for polarization H or V.

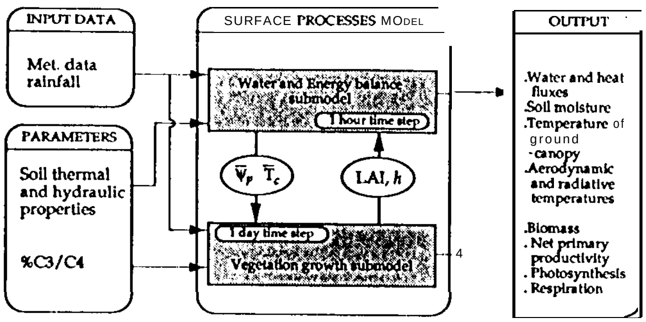

Figure 1: Diagram showing the two submodels which form the land surface processes model, their respective time steps, inputs, outputs and the variables through which they communicate.

Description and testing of retrieval scheme

The retrieval scheme relies on the assumption that both the land surface process model and tbc radiative transfer model arc formally correct, and that only some parameters or initial values of state variables arc not known. The scheme uscs an iterative procedure to estimate these unknowns by minimizing the difference between observed and simulated remote sensing measurements. One way of verifying whether the assumption holds, is to run the model on a test-sitc where a significant amount of data are available to describe the site, where meteorological data necessary to run the process model have been acquired continuously, and where a maximum number of biophysical variables and processes have been followed and measured throughout a growing season. Then, if the radiative transfer model, using a description of the surface given by the process mode], can correctly simulate the brightness temperatures actually observed, there is evidence that the retrieval scheme may be applicable to other less well-known sites to estimate similar processes. However, as stated earlier, scale issues render this verification difficult. Here, for the purpose of the study, synthetic data arc used instead of actual remote sensing measurements. The simulations of the process model carried out for the 1992 growing season in a grassland site inside the 1 ‘x 10 grid square of the Ilapcx-Sahel experiment [8] provide the microwave model with most of the inputs necessary to simulate temporal profiles of brightness temperatures. For example, soil moisture and temperature, vegetation cover fraction, and canopy temperature are directly simulated, whereas vegetation water content is estimated from the amount of green biomass. The synthetic data obtained correspond to an ideal case where the values of all the parameters used by the models to produce them arc regarded as the true values.

The scheme uses the Davidon-Fletcher-Powell minimization procedure as described in [9]. Starting from an initial guess of the parameters to be retrieved, the merit function ε^2 is minimized, calculated here using microwave brightness temperatures :

$$\varepsilon^2 = \sum_{i=1}^{n} (Tb_{obs} - Tb_{sim})^2 \qquad (1)$$

The procedure requires the evaluation of function derivatives and is normally more efficient in terms of the number of iterations needed, than other methods which do not use the gradient information, like the downhill Simplex or Powell [9]. Numerically, input parameters of both the radiative transfer model and the land surface process model can be retrieved at the same time, as shown in the following test. However, in a real application, once enough confidence is gained in the simulations of the radiative transfer model, it is preferable to apply the. scheme with process model parameters only, as the reliable simulations of the processes depend primarily on a correct estimation of these parameters. The first testing of the scheme is to verify whether certain model parameters arc retrievable. Two important parameters related to vegetation arc chosen: the percentage of C3 (and that of C4 by difference) vegetation present, a parameter of the vegetation growth submodel, and a coefficient A related to canopy structure, on which the canopy opacity used in the microwave mode] depends. In the table shown below, retrieved values arc compared to ‘real’ values when (1) %C3/C4 is retrieved alone, (2) A is retrieved alone and (3) the two parameters are retrieved together. Although the number of iterations increases significantly with the number of parameters retrieved, the accuracy of the retrieval is maintained.

	(1)	(2)	(3)	
	%C3/C4	A	%C3/C4	A
initial guess	50.00	0.1000	50.00	0.1000
true value	35.00	0.4270	35.00	0.4270
retrieved	35.01	0.4269	34.98	0.4271

Real observational data however, are acquired with an inevitable amount of noise, and it is important to assess how sensitive the retrieval is to the noise present. It would aiso be interesting to see how well a parameter is retrieved when the sensitivity of the simulations to that parameter is high or low. The second test is carried out with two parameters which arc used to calculate surface reflectivity for each frequency and polarization in the microwave model. The reflectivity is written as being linearly related to soil moisture, with parameter a as the offset and c the slope for H polari ration, and parameters b and d, the offset and slope for V polarization. Figure 2 shows the sensitivity of the simulated brightness temperatures at 37 GHz with respect to the four parameters.

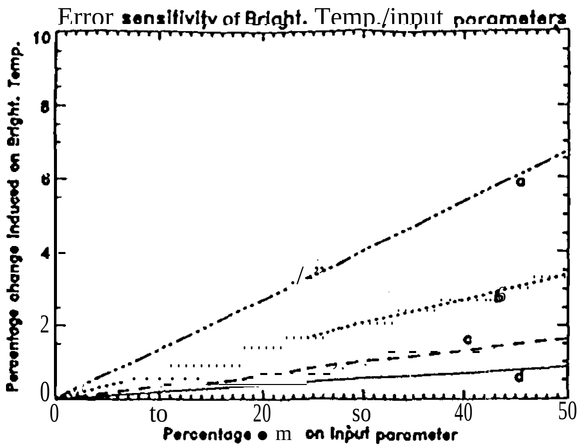

Figure 2: Sensitivity of the simulated microwave brightness temperatures at 37 GHz with respect to the parameters *a, b,* c, *d.* Note that *5%* of the brightness temperature corresponds to about 15 K and is therefore quite significant.

The figure clearly indicates that the simulations are more sensitive to the offsets in the linear relationship between surface reflectivity and soil moisture, than they are to. the slopes, and more so for horizontal than vertical polarization. In order to test the effect of noise on the retrieval of these parameters, the synthetic data are contaminated with normally distributed noise of zero mean and known standard deviations [10]. For each noise level defined with l%, 3% and *5%* standard deviations, forty noisy sets are generated and used to retrieve the four parameters, The sensitivities of the retrieved parameters to the different noise levels are defined as coefficients of variability (the standard deviation divided by the mean value), and are each calculated on a set of forty retrieved values.

Figure 3 shows the sensitivities of the retrieved parameters with respect to noisy data. The slope parameters c and *d are* found to be more sensitive to noise than the offset parameters *a* and b. This would imply that parameters which can significantly influence the simulation of brightness temperatures (which therefore need to be estimated more accurately) are more liable to be satisfactorily **retrieved in** spite of the presence of noise. However, this tendency has to be confirmed on real data in which the noise present maybe of a nature different from the one used in the study,

Conclusion

The theoretical feasibility of using remotely sensed data to control simulations of biophysical processes has been shown. The sensitivity and retrievability of key parameters of the coupled biophysical-radiative transfer scheme have been demonstrated. Techniques for temporal and spatial scaling between models and observations must be investigated further for practical implementation of the method.

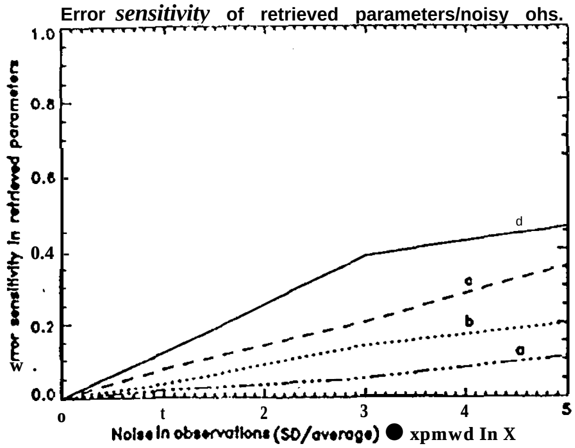

Figure 3: Sensitivity of the four retreived parameters to different levels of noise in the observational data,

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