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Inversion problems for passive microwave measurements

The problems of restoring the values of the physical parameters of a natural medium from the data of remote sensing instruments are most important and complicated throughout the remote sensing information circuit. The features of interaction of electromagnetic waves of the microwave band have essentially extended the limits of traditional optical and IR observations and introduced completely new aspects into the issues of so-called inversion problems. The purpose of this chapter is to consider and analyse some basic elements of the problem of inversion of the physical parameters of a natural medium for microwave remote sensing which are now being actively developed by the researchers of various science teams.

13.1 FEATURES OF MICROWAVE MEASUREMENTS

As we have noted above (Chapters 1, 7 and 9), microwave measurements have a number of distinctive properties. First, the relationship between the intensity measured by remote sensing instruments and the thermodynamic characteristics of media under study is linear (the Rayleigh–Jeans approximation). Hence, it follows that microwave measurements can be used to obtain simple direct estimates of meteoparameters (such as the precipitable-water and liquid-water content of clouds). The earliest semi-empirical regression models for satellite and airborne observations with a monoconfiguration sensor (i.e., one polarization/frequency channel and the nadir view angle) were very simple. However, they made it possible to obtain fundamental results (as an example) on the global spatial distribution of water vapour and cloud liquid-water in the terrestrial atmosphere (Akvilonova *et al.*, 1971; Basharinov *et al.*, 1974; Vetlov and Veltishev, 1982).

Second, the fundamental distinctions of microwave bands from IR and visible bands consist in penetration and diffraction of interacting microwaves with media under study. This provides support for a wide spectrum of complicated (forward) models including thermal states of volumes and surfaces of media under observation (Wilheit and Chang, 1980; Sasaki *et al.*, 1987; Novak *et al.*, 1983; Mitnik, 1986). The latest forward models involve diffraction effects under the interaction of electromagnetic microwaves with the elements of the surface and in volumes, such as gravity waves, various types of vegetation crops, forests (Shin and Kong, 1982; Ulaby *et al.*, 1986; Irisov *et al.*, 1987; Ferrazzoli and Guerriero, 1996; Wigneron *et al.*, 2003; Trokhimovski *et al.*, 2000). On the basis of integrated (including diffraction effects) forward models, advanced integrated inversion procedures are now being actively developed. The physical parameters that may be recovered with microwave measurements are as follows: moisture (underground); the soil temperature fields (under vegetation); the elements of a sea wave spectrum; the structure of vegetation; the physical-chemical composition of soil; sea foam structures; oil pollution; precipitation parameters; surface wind speed fields (Novak *et al.*, 1983; Calvet *et al.*, 1995, 1996; Ferrazzoli and Guerriero, 1996; ESA, 1996a,b,c; Trokhimovski, 1997).

13.2 BASIC CATEGORIES OF INVERSION PROCEDURES FOR MICROWAVE SENSING

The variety of scientific and economic problems facing remote sensing investigations generates a spectrum of diverse procedures for specific problems of recovering necessary physical parameters of the atmosphere and land surface. By virtue of the rather lengthy historical period of development of remote sensing in the optical band of electromagnetic waves, cadasters and the methodology of inversion problems have their own quite particular and completed systematization (Kondratyev and Timofeev, 1970; Malkevich, 1973; Stone, 1979; Avduevskii *et al.*, 1983; Asrar and Dokken, 1993; Attema, 1993; Kramer, 1996; Thomas and Stamnes, 1999; Schultz, 1988; Sharkov, 1998; Schultz and Engman, 2000).

The active development of microwave methods and means in the last 20–25 years has, in its turn, put on the agenda the possibility of the solution of significantly new classes of problems, both in scientific and in economic respects. First of all, we should mention here hydrological and soil problems (subsurface moisture and temperature regime of soils), agricultural problems (the degree of maturation of crops), oceanological problems (the state of the surface of ocean, the surface wind, the energy exchange, the evolution of the fields of salinity), glaciological problems (the state of glaciers, the state and evolution of drifting ice) and many other problems (Bespalova *et al.*, 1983; Schultz and Engman, 2000; Wigneron *et al.*, 2003; Paloscia and Pampaloni, 1988; Sharkov, 1998; Vinnikov *et al.*, 1999; Comiso and Stock, 2000; Boyarskii *et al.*, 1993; Belchansky and Alpatsky, 2000; Matzler, 2000; Derksen *et al.*, 200a,b). A great diversity of new problems has generated, naturally, many new techniques for the solution of inversion problems, since this circumstance has given rise to some new problems, such as, for example, the relation between the spatial resolution, required for the given problem, and the existing spatial resolution of microwave systems. Nevertheless, a particular systematization (categories) in the approach to the solution of inversion problems for microwave remote sensing is formed (Ingmann, 1991; Matzler, 2000; Wigneron *et al.*, 2003) we shall just briefly outline below.

The different approaches used to account for the effects, caused by microwave interactions with terrestrial surfaces, may be subdivided into three main categories: statistical techniques, forward model inversion, and explicit inversion. Other techniques, such as data assimilation (Kalman filter optimal estimation and variational data assimilation), have also been used.

13.2.1 Statistical techniques

In general, these techniques are based on regression analysis. For each pattern on images or on a group of pixels for airborne and spaceborne observations, linear relationships between the measured brightness temperature and physical parameters are established. The slope and intercept of the regression line are then analysed in terms of physical parameters and variables which can be estimated from ancillary data.

A large number of algorithms are used to retrieve information on land surfaces and terrestrial atmosphere from remote sensing data by direct manipulation of the measured signals through empirical relationships of the type:

$$x_j = F_j(T_{B1}, T_{B2}, \dots, T_{Bn}), \tag{13.1}$$

where T_{Bn} corresponds to measurements made for various configurations of the sensor, in terms of incidence angle θ, polarization, or frequency; and x_j is a relevant physical parameter. For example, for passive microwave measurements over land, two different statistical approaches may be distinguished (Wigneron *et al.*, 2003), namely:

- classification based on dual- or multi-configuration observations. For instance, based on observations of the Special Sensor Microwave/lmager (SSM/I) data and of brightness temperature thresholds, various classification rules have been developed to distinguish among dense vegetation, forest, standing water, agricultural fields, dry and moist bare soil, etc. However, until now no study is known to have directly addressed the problem of classifying soils with different water contents, although many studies have reported spatial relationships between brightness temperature or emissivity and surface moisture;
- surface soil moisture is statistically related to a combination of microwave emissivities and vegetation microwave indices, which are used to correct for soil roughness and vegetation effects.

13.2.2 Forward model inversion

In this approach, a model is used to simulate remotely sensed signatures (output) on the basis of land surface parameters (input). The inversion methods are developed to produce an 'inverse model', in which the outputs are represented by the relevant land surface variables. The inversion methods are usually based on an iterative minimization routine of the root-mean-square error (RMSE) between the forward model simulations and observations.

The problem of forward model inversion to retrieve land surface variables can be defined as follows: the radiative transfer model Φ is used to simulate the microwave radiometric measurements $(T_B)_i$ $(i = l, \ldots, q)$ corresponding to measurements made for various sensor configurations in terms of incidence angle, polarization, or frequency), as a function of the physical parameters $x_j(j = 1, \ldots, p)$ (the so-called 'state variables'):

$$(T_B)_i = \Phi_i(x_1, x_2, \ldots, x_p; s_{1i}, s_{2i}, \ldots, s_{ri}) + \varepsilon_i \tag{13.2}$$

for $i = 1, \ldots, q$ and where $s_{ki}(k = 1, \ldots, r; i = 1, \ldots, q)$ stands for the configuration parameters which determine the observation conditions, and ε_i is the residual error between the simulated and measured brightness temperature values. Inverting the model consists of finding the set of variables under study $x_j(j = 1, \ldots, p)$ that provides the minimum value of the residual errors ε_i. Therefore, the retrieval methodology based on forward model inversion requires two main steps: (1) the selection of a forward model (Φ), and (2) the selection of a method for inversion by minimizing the residual error ε_i.

Both steps are specific for any particular retrieval problem and have been analysed in several publications (Ulaby *et al.*, 1981, 1982, 1986; Ingmann, 1991; Wigneron *et al.*, 2003).

Forward models may be classified into three main categories: (1) nonparametric data-driven models; (2) parametric data-driven models, where the model parameters are adjusted by comparison with observations; and (3) physical models, which include a physical description of the radiative transfer processes and where the model parameters can be directly related to the land surface and atmosphere characteristics. The majority of studies, which use nonparametric data-driven models (approach (1)), are based on the statistical regression analysis or on the neural network models. The models used in approach (2) require *a priori* knowledge of the functional form of the process that is being modelled. The model parameters are generally the 'best-fit' parameters computed by minimizing the squared error between the observations and the outputs of the model. The physical complex models (approach (3)) account for the multiple scattering effects that become important when the frequency exceeds a few gigahertz. In these approaches, a number of surface surfaces can be modelled as a continuous medium (Chapter 7) and the atmospheric systems as a discrete medium containing randomly distributed discrete scatterers characterized in terms of size, shape, density, and distribution of orientation (Chapter 10). However, these models require many input parameters and cannot be used easily to implement the retrievals of surface and atmospheric characteristics.

Once the forward modelling approach has been selected, the method for 'inverting' the model should be defined. A very common algorithm to invert a forward model is the statistical inversion approach. Its principle is to search for input parameters $(x_1, x_2, \ldots, x_p)$, consisting of the relevant geophysical parameters that minimize the squared error between the brightness temperature as measured from space $(T_B)_i$, and the actual outputs of the model $\Phi_i(x_1, x_2, \ldots, x_p)$. Thus, the inversion problem is

$$\operatorname{Min} G(x_1, x_2, \ldots, x_p) = \sum_{i=1}^{q} \frac{1}{2\sigma_i^2} [\Phi_1(x_1, x_2, \ldots, x_p; s_{1i}, s_{2i}, \ldots, s_{ri}) - (T_B)_i^2] + \sum_{j=1}^{p} \frac{1}{2\lambda_j^2} (x_j - x_j')^2, \tag{13.3}$$

where $G(x_1, x_2, \ldots, x_p)$ is the cost function; and (the *a priori* information) x_i' is the average value of the jth model parameter; λ_j is the standard deviation of the jth model parameter value; and σ_i is the standard deviation of measurement noise of the ith channel.

Many different iterative minimization algorithms (such as Tichonov's method, quasi-Newton, Simplex, etc.) are available to minimize the cost function $G(x_1, x_2, \ldots, x_p)$ (Tichonov and Arsenin, 1979; Press *et al.*, 1986).

13.2.3 Explicit inverse

The explicit inverse of the physical process can be built by transferring the input (remote sensing measurements) into the output (the land surface parameters). In the majority of studies, neural networks (NN) are used to produce this explicit inverse function. First, the appropriate set of input–output data is generated using the forward model Φ_i. Then a copy of the forward model (Φ_i) is made by training the NN on the set of data. Hence, the NN is able to capture very complex and nonlinear relationships within its self-organizing connections. The advantage of the NN technique is that, once the NN has been trained, the parameter inversion can be accomplished quickly. In the field of microwave radiometry, the NN has been applied to estimate snow characteristics (Davis *et al.*, 1993; Derksen and LeDrew, 2000; Derksen *et al.*, 2000a,b), surface wind speed over the ocean (Stogryn *et al.*, 1994), clouds and precipitation (Li *et al.*, 1997), and soil and forest parameters (Gopal and Woodcock, 1996; Paloscia *et al.*, 2000b; Chang and Islam, 2000; Kothari and Islam, 1999; Wigneron *et al.*, 2003). Another simple way to invert a forward model using NN is to train an inverse model by reversing the roles of the inputs and outputs: the measured brightness temperature becomes the input nodes of the NN, and the land surface parameters become the output nodes. This method, known as explicit inversion, is widely used in remote sensing (Li *et al.*, 1997; Jimenez *et al.*, 2000). However, the forward model is characterized by 'many-to-one mapping' (i.e. the set of measurements cannot be uniquely related to environment variables). Several studies expressed concerns about the fact that the explicit inversion approach may lead to wrong results when the inverse image of the forward model is not convex (Davis *et al.*, 1993; Li *et al.*, 1997), and that the iterative constrained inversion technique was found to be more appropriate, than the explicit inversion to deal with the many-to-one mapping.

13.2.4 Other techniques

Assimilation approaches (the Kalman filter optimal estimation and variational data assimilation) have been applied to the problem of retrieving the near-surface soil moisture and temperature profile from a time series of radiobrightness observations. Several studies have shown that the modelling of the heat and mass flow inside the sea surface–atmosphere and the soil can be used to derive information about the soil water content profile from the time series of microwave brightness temperatures. For instance, the feasibility of using the brightness temperature measurements (in the microwave and infrared channels) to solve the inverse problem, associated with soil moisture and heat profile, was proposed by Kondratyev and Shulgina (1971) (Chapter 8) and demonstrated by Liu and Minnis (2000) over bare soils. Burke and Simmonds (2001) have retrieved soil hydraulic properties from the time series of measured brightness temperatures over agricultural fields. Sequential and variational data assimilation approaches have been tested on experimental bare soil and vegetation (Calvet *et al.*, 1995, 1996; Macelloni *et al.*, 2001; Njoku and Li, 1999; Wigneron *et al.*, 1995, 2003) data sets and on a series of synthetic experiments based on the Southern Great Plains (SGP) 1997 Hydrology Experiment (Drusch *et al.*, 1999a,b; Liu and Minnis, 2000; Paloscia *et al.*, 1999). These studies have required continuous series of measurements, which were based on the coupling between soil–vegetation-atmosphere transfer models and radiative transfer models.

The detailed analysis of inversion problems for thermal atmospheric stratification and water vapour and cloud water stratification and spatial distributions with microwave measurements have been considered by Sharkov (1998).