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Remote sensing of surface reflective properties: Role of regularization and a priori knowledge

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ABSTRACT

Linear kernel-driven bidirectional reflectance distribution function (BRDF) models have been used for mapping albedo with single field-of-view satellite measurements such as Moderate Resolution Imaging Spectroradiometer (MODIS). Due to limited samplings and poor angular configurations available from these satellite remotely sensed data, BRDF models inversion is often plagued by numerical instability. In order to overcome the ill-posedness of the BRDF model inversion and robustly estimate terrestrial surface albedo, a regularization technique is employed for the cases where the number of observations is insufficient, or the angular distribution is poor. Emphasis is also placed on the combination of a priori knowledge with the regularized inversion. Numerical performances and case study results with ground measurements and MODIS observations suggest that the method is sound and robust for ill-posed BRDF inverse problems. The method presented in this study is promising for land surface reflective parameters retrieval even for regions where only sparse observations are available.

1. Introduction

Electromagnetic wave reflected from the Earth's surface at satellite sensors level records signals not only from the underlying surface but from the intervening atmosphere [1]. To better understand the interactions between the surface and the atmosphere, and its impacts on the climate due to land surface processes, it is of necessity to extract land surface reflective parameters from orbital observations. Methods for quantitative retrieval of information of interests from remote measurements in the reflected domain are a rapidly growing field and increasingly attract attention of remote sensing and climate communities. For instance, land surface BRDF can be estimated from satellite observations to capture the directional distribution of the reflected radiance field. Correspondingly, directional-hemispherical reflectance (which is also called black-sky albedo, BSA) and bi-hemispherical reflectance (which is also called white-sky albedo, WSA) can be obtained via performing integrals of BRDF in the viewing hemisphere and illumination hemisphere, respectively [2,3]. These two kinds of albedos are of great importance and constitute indispensable input quantities for climate models [4,5].

In quantitative remote sensing of terrestrial surface, the relationship between the state parameters x and collected observations y mixed with the noise component ε_y can be established by a forward model:

$$y = F(x) + \varepsilon_y \tag{1}$$

where F is referred to as analytic BRDF models for land surface parameters retrieval. Computing y given x is called forward problem while the mathematic process of inferring x from y is called inverse problem (Fig. 1).

However, in geophysics and remote sensing sciences, inversion problems are in nature ill-posed [6–10]. In fact, ill-posedness always arises out of the lack of information needed for solving inverse problems so that noises during the whole remote sensing processes (e.g., inherent instrument noise, misregistration, inconsistent atmospheric correction, etc.) will cause instability in the retrieval. To overcome this, a variety of studies that centered round exploitation of additional constraints were carried out over last decade. In order to obtain physically acceptable parameters, Li et al. [9] addressed the importance of implanting a priori knowledge into the BRDF model inversion. Practically, the a priori information can be constructed from the collected spaceborne or airborne remotely sensed data or in situ measurements. Incorporation of a priori

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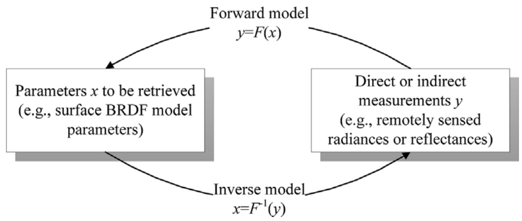

Fig. 1. Forward and inverse model in quantitative remote sensing of terrestrial surface.

information can increase numerical stability of the model inversion by making the original ill-posed inverse problem well-posed [9,11]. The multi-kernel least variance method (MKLV) developed by Gao et al. [12], selects least variance of albedo from various BRDF kernels as the best solutions and then combined these kernels as the most appropriate BRDF model. It is reported that the MKLV method is less sensitive to the sampling position and can operate well in small sample size. However, the MKLV method cannot deal with cases with less than three observations. Wang et al. [13,14] imposed a priori information from pure mathematical perspectives when performing regularized inversions. Quaife and Lewis [15] applied temporal smoothness constraints on BRDF model inversions using Lagrangian multipliers. Ways to obtain appropriate regularization parameters are not detailed in the literatures. However, crude selection of regularization parameters would limit the algorithm's efficiency and its applications. Cui et al. [16] improved the method for choosing regularization parameters and modified the algebra spectrum of the BRDF kernel matrix (i.e., replace tiny singular values with positive values after performing singular value decomposition (SVD) of the BRDF kernel matrix) to stable the BRDF model parameters estimates using the spectrum cut-off technique. Actually, the difference between these various approaches relies on how rigorously additional information is mathematically processed, and in particular, the uncertainties associated to this additional information.

In this study, we investigate the role of regularization in retrieving land surface reflective properties. In this paper, we first give a brief review of the selected BRDF model and a regularized inversion strategy established in our previous work. Then we extend the algorithm presented by integrating some additional constraints on the regularized BRDF inversion. Finally, selected case studies of BRDF model parameters inversion and albedo retrieval are presented to demonstrate the capability of our algorithm.

2. Algorithm description

2.1. Forward model

The forward model F in Eq. (1), needed for land surface BRDF and albedo retrieval, has mathematically the following form:

$$r_\lambda(\vartheta_s,\vartheta_v,\varphi)=f_{iso,\lambda}K_{iso}+f_{geo,\lambda}K_{geo}(\vartheta_s,\vartheta_v,\varphi)+f_{vol,\lambda}K_{vol}(\vartheta_s,\vartheta_v,\varphi) \quad (2)$$

where ϑ_s, ϑ_v and φ are solar zenith angle (SZA), view zenith angle (VZA) and the relative azimuth angle (RAA), respectively. This semiempirical kernel-driven model describes the BRDF of a pixel, r_λ, as a linear superposition of three types of kernels: (1) isotropic scattering kernel K_{iso}, which denotes the Lambertian scattering contribution and always equals to the constant of unity; (2) geometric-optical surface scattering kernel K_{geo}, which is derived by Wanner et al. [17] from surface scattering and geometric shadow casting theory [18]; and (3) volumetric scattering kernel K_{vol}, which is derived by Roujean et al. [19] from a single-scattering approximation of radiative transfer theory [20]. The combination of these kernels constitutes one of the most effective models for accurate reconstruction of BRDF, and has been proved to be suitable for most of the land cover types [2,3,21]. f_{iso}, f_{geo} and f_{vol} are Lambertian coefficient, roughness coefficient, and volume scattering coefficient respectively to be retrieved. In this study, the Ross–Li–Maignan (RLM) BRDF model [21] is used to model spectral surface bidirectional reflectance.

2.2. Ill-posedness of the inversion problem

With multiple cloudless measurements accumulated, Eq. (2) can be expressed in matrix notation:

$$\hat{\mathbf{r}}_{m\times 1}=\mathbf{K}_{m\times n}\mathbf{f}_{n\times 1}+\varepsilon_{\hat{\mathbf{r}}} \quad (3)$$

Here, $\hat{\mathbf{r}}$ is the reflectance vector, $\mathbf{f}$ is the BRDF parameters vector, $\mathbf{K}$ is the kernel matrix, m denotes the number of observations and n denotes the number of kernels. Given measurements at known angles, it is possible to invert Eq. (3) to obtain the kernel coefficients. For the overdetermined case (i.e., $m>n$), the least squares estimation may be employed to minimized the impact of observations errors. Then the aforementioned inverse problems can be solved by

$$\hat{\mathbf{f}}=arg\min\left\{\frac{1}{2}||\mathbf{K}\mathbf{f}-\hat{\mathbf{r}}||_D^2\right\} \quad (4)$$

where $||\,||_D^2$ denotes the 2-norm of a vector in the measurements space D.

However, sampling geometry is a major source of uncertainty in determining the BRDF shape. Noises due to insufficient samplings or poor angular configuration will make the condition of the kernel matrix $\mathbf{K}$ very large, and the so-called ill-posedness arises. This means that the least squares solution (LSS) (4) is nonunique and unstable. This can be made clear with the SVD of the kernel matrix $\mathbf{K}$:

$$\mathbf{K}_{m\times n}=\mathbf{U}_{m\times n}\Sigma_{n\times n}\mathbf{V}_{n\times n}^T \quad (5)$$

where matrices $\mathbf{U}$ and $\mathbf{V}$ are respectively with orthonormal columns $[\mathbf{u}_1,\ldots,\mathbf{u}_n]$ and $[\mathbf{v}_1,\ldots,\mathbf{v}_n]$, forming bases for the measurement space and the solution space, respectively. $\mathbf{\Sigma}$ is a diagonal matrix containing nonnegative singular values $(\sigma_1,\ldots,\sigma_n)$ in decreasing order. Because $\mathbf{\Sigma}$ is a diagonal matrix, the choice of these bases yields a one-to-one correspondence between components of the BRDF kernel coefficients and those of the measurements.

Substitution of Eq. (5) in Eq. (3) yields

$$\hat{\mathbf{r}}=\sum_{i=1}^{n}\sigma_i\left(\mathbf{v}_i^T\mathbf{f}\right)\mathbf{u}_i+\varepsilon_{\hat{\mathbf{r}}} \quad (6)$$

and the LSS can be written as

$$\hat{\mathbf{f}}=\sum_{i=1}^{n}\frac{\left(\mathbf{u}_i^T\hat{\mathbf{r}}\right)}{\sigma_i^2}\mathbf{v}_i \quad (7)$$

For indices i larger than a certain index p in Eq. (6), the σ_i are so small that all the terms $i>p$ do not have an effect on the measurement within the measurement error $\varepsilon_{\hat{\mathbf{r}}}$. This means that the measurement $\hat{\mathbf{r}}$ is insensitive to components $\mathbf{v}_i^T\mathbf{f}$ of the parameters $\mathbf{f}$ along base vectors $\mathbf{v}_i$ for $i>p$. So, in LSS of Eq. (7), only the first p terms play a role in the minimization of the residual norm. When the number of observations is insufficient or the angular distribution is poor, noise components in $\hat{\mathbf{r}}$ are divided by small singular values, their contribution to the retrieved BRDF parameters is amplified [16]. Hence, the task of the retrieval algorithm is to filter out the noise-dominated components of the solution and thus to retrieve only that part of the BRDF parameters about which information is present in the measurements. This part of the BRDF