LEAF AREA INDEX RETRIEVAL FROM REMOTELY SENSED DATA: SCALING EFFECT AND PROPAGATION MECHANISMS

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Leaf Area Index (LAI) defined as the single-side leaf area per unit ground horizontal surface area is a key parameter in many processes and used as an input for various land surface models including vegetation, biogeochemical or global circulation models to characterize detailed information about vegetation [1]. It can be spatially estimated from remotely sensed data by either from a radiative transfer model or from a semi-empirical relationship between LAI and Normalized Difference Vegetation Index (NDVI) [2, 3]. However, all these retrieval methods are usually proposed and validated at local scale (fine resolution), which implies that when they are applied to large scale (coarse resolution) the retrieval results may become unreliable [4]. Application of the retrieval model validated at local scale to the large scale data may induce a scaling effect on the LAI estimate if the retrieval model is non-linear and the input parameters within the large scale are heterogeneous [5]. The relative scaling effect of LAI may reach even up to 50% if it is not corrected for [2].

In order to full demonstrate the influence of spatial heterogeneity and the model non-linearity on the estimation of LAI and reveal the scaling propagation mechanisms, in this paper, the scale problems relevant to LAI product are theoretically and practically analyzed based on the simulated data. First, the biochemical and physical properties of vegetation are elaborately considered and selected. Then, the red and near infrared bidirectional reflectances of canopy are simulated by the combination of PROSPECT leaf optical properties model and SAIL canopy bidirectional reflectance model [3]. Here, the red and near infrared reflectances and the corresponding LAI and NDVI at local scale are considered as the ‘true value’. Consequently, the local scale simulated data are aggregated with different aggregation scales. The distributed LAI products derived from the retrieval function first and then aggregated and the lumped LAI products derived directly from the aggregated inputs are compared. The scaling effect of LAI caused by the non-linearity of retrieval function of either the red and near infrared reflectances (a bivariate retrieval function) or NDVI (a univariate retrieval function) is separately analyzed based on the Taylor series expansion approach [2, 6]. The magnitude of the both univariate and bivariate scaling effect can be expressed as a function of (1) the degree of non-linearity of the retrieval function quantified by its second derivative and (2) the spatial heterogeneity of input variables in the retrieval function quantified by wavelet variance [7]. The discrepancy between the univariate scaling effect and the bivariate one is discussed. Finally, the scaling effect caused by the non-linearity of the NDVI as a function of the red and near infrared reflectances and the non-linearity of the LAI as a function of NDVI are compensated in a well designed two-step process. How the scaling effect propagates through the composition of several non-linear functions is then illustrated in detail.

This work shows that either univariate or bivariate scaling of LAI based on Taylor series expansion approach can reach promising accuracy and resolve the LAI scaling problem. The RMSE (root mean square error) and RE (relative error) of LAI caused by scale can be corrected. They are less than 0.05 and 2% respectively, if the spatial heterogeneity is well known in advance (Fig.1).

The scaling propagation analysis reveals that the scaling effects caused by several non-linear components may add up or compensate for each other. The LAI retrieval process can be divided into two non-linear components. The first is to retrieve NDVI from red and near infrared. The other is to retrieve LAI from NDVI. Fig.2 demonstrates the case of compensation of scaling effect resulting from these two non-linear components. The scaling effect (RMSE) caused by the non-linear of NDVI as a function of red and near infrared is about 0.17 and the corresponding one caused by the non-linear of univariate LAI as a function of NDVI is about 0.12. Coincidentally, they are deviating in the opposite direction as shown in Figure 2. Consequently, they cancel each other out, which caused the RMSE using the approximated LAI^{app} estimated from the aggregated inputs before correction to reduce to about only 0.04. This point of view may clarify the scaling propagation mechanism, and would enhance our confidence in use of LAI product over heterogeneity areas.

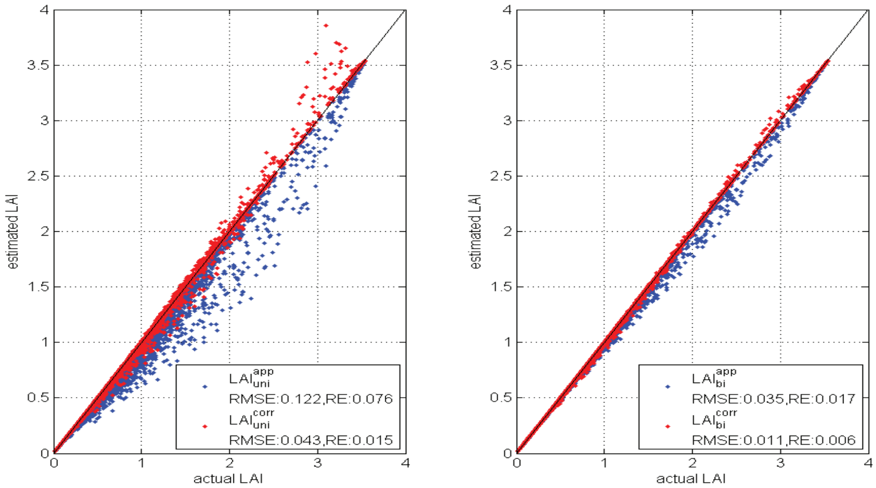

Figure 1 Scaling performance of LAI based on Taylor series expansion approach. LAI^{app} is the approximated LAI estimated from the aggregated inputs before correction; LAI^{corr} is the corrected LAI. (left) the univariate model, where the LAI is the function of NDVI and the scaling effect of NDVI is not considered; (right) the bivariate model, where the LAI is the function of the red and near infrared reflectances.

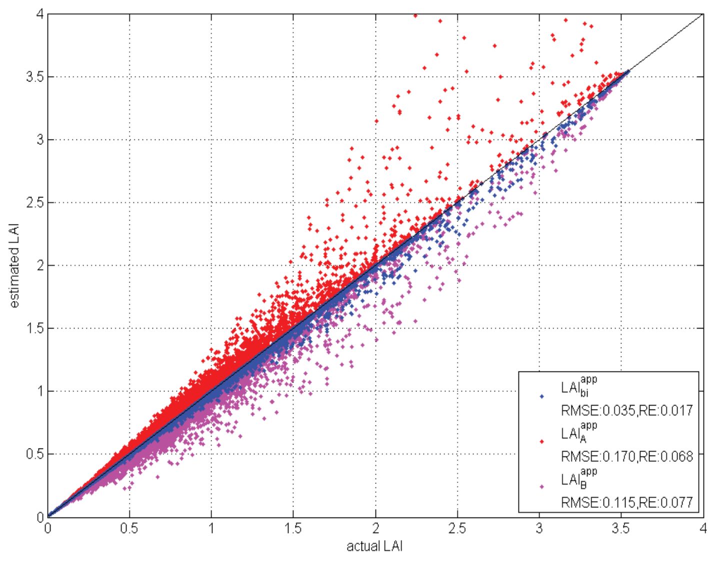

Figure 2 Scaling propagation analysis of LAI based on a well designed two-step process. LAI_A^{app} *is the approximated LAI where the scaling effect caused by the non-linear of univariate LAI is removed. While* LAI_B^{app} *is the approximated LAI where the scaling effect caused by the non-linear of NDVI is removed.*

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