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Corresponding Author: Prof Raffaele Casa, PhD

Corresponding Author's Institution: University of Tuscia

First Author: Raffaele Casa

Order of Authors: Raffaele Casa; Fréderic Baret; Samuel Buis; Raul Lopez-Lozano; Simone Pascucci; Angelo Palombo

Dipartimento di Produzione Vegetale
Via San Camillo de Lellis
01100 Viterbo
Tel. 0761357559
Fax 0761357558
e-mail rcasa@unitus.it

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Subject: submission of revised manuscript "Estimation of maize canopy properties from remote sensing by inversion of 1-D and 4-D models" to Precision Agriculture.

Dear Editor,
please find here enclosed the third revision of the paper "Estimation of maize canopy properties from remote sensing by inversion of 1-D and 4-D models", by R.Casa et al. modified according to the suggestions. We have incorporated all the editing suggestions and have remove citations from the Conclusions as requested. We have also deleted from the reference list the following references:

Bonhomme, R., Varlet-Grancher, C., & Chartier, P. (1974). The use of hemispherical photographs for determining the leaf area index of young crops. Photosynthetica, 8, 299-301.

Knyazikhin, Y., Martonchik, J. V., Diner, D. J., Myneni, R. B., Verstraete, M., Pinty, B., & Gobron, N. (1998). Estimation of vegetation leaf area index and fraction of absorbed photosynthetically active radiation from atmosphere-corrected MISR data. Journal of Geophysiscal Research, 103, 32239–32256.

Makowski, D., Hillier, J., Wallach, D., Andrieu, B., & Jeuffroy, H.M. (2006). Parameter estimation for crop models. In D. Wallach, D. Makowski& J. W. Jones (Eds.), *Working with dynamic crop models* (pp. 101-149). Amsterdam: Elsevier.

Myneni, R. B., Hoffman, S., Knyazikhin, Y., Privette, J. L., Glassy, J., & Tian, Y. (2002). Global products of vegetation leaf area and absorbed PAR from year one of MODIS data. *Remote Sensing of Environment*, *83*, 214–231.

Figures are now provided as separate files with higher resolution.
We would be grateful if you could consider this paper for potential publication in the journal Precision Agriculture.
Best regards

Prof. Raffaele Casa
corresponding author

Estimation of maize canopy properties from remote sensing by inversion of 1-D and 4-D models

Casa R. [1*], Baret F.[2], Buis S. [2], Lopez-Lozano R.[2], Pascucci S.[3], Palombo A. [3], Jones H.G.[4]

[*] corresponding author

[1]Dipartimento di Produzione Vegetale, Università degli Studi della Tuscia (DPV), Via San Camillo de Lellis, 01100 Viterbo, Italy, e-mail: rcasa@unitus.it , tel: +390761357559, fax: +390761357558.

[2]INRA-UMR EMMAH, Domaine Saint Paul - Site Agroparc, 84914 Avignon, France

[3]C.N.R. -LARA, Via del Fosso del Cavaliere, 100, 00133 Roma, Italy

[4]University of Dundee, Division of Plant Science, Invergowrie, Dundee DD2 5DA, United Kingdom

Abstract The inversion of canopy reflectance models is widely used for the retrieval of vegetation properties from remote sensing. However the accuracy of the estimates depends on a range of factors, most notably the realism with which the canopy is represented by the models and the possibility of introducing *a priori* knowledge on canopy characteristics to constrain the inversion procedure. The objective of the present work was to compare the performances and operational limitations of two contrasting types of radiative transfer models: a classical one-dimensional canopy reflectance model, PROSPECT+SAIL (PROSAIL), and a three-dimensional dynamic (4-D) maize model. The latter introduces greater realism into the description of the canopy structure and implicit *a priori* information on the crop. The assessment was carried out with multiple view angle data recorded from field experiments on maize at stages V5 to V8. The simplex numerical optimization algorithm was used to invert the two models, using spectral reflectance data for PROSAIL and gap fraction data for the 4-D maize model. Leaf area index (LAI) was estimated with a RMSE of 0.48 for PROSAIL and 0.35 for the 4-D model. Retrieval of average leaf inclination angle (ALA) was problematic with both models. The effect of the number and distribution of observation view angles was examined, and the results highlight the advantage of oblique angle measurements.

Keywords Multiple-look-angle · PROSPECT · SAIL · PROSAIL ·Leaf area index (LAI) · Leaf inclination distribution function (LIDF) · Average leaf inclination angle (ALA)

Introduction

Remote sensing at a range of spatial scales, from close range tractor-based sensors to those on satellite platforms allows non-intrusive and cost effective monitoring of crop status and of its spatial and temporal variation. Remote sensing observations should be capable of providing reliable and quantitative estimates of canopy biophysical properties, such as leaf area index (LAI), leaf angle distribution (LAD) and chlorophyll content (C_{ab}). Knowledge of these variables can be useful for several applications, including site-specific crop management in precision agriculture, leading to more efficient use of inputs together with reduced environmental impacts.

The performances of such approaches, for example for nitrogen fertilizer management (Baret et al. 2007; Houlès et al. 2007), depend on the strength of the link between the remote sensing signals and biophysical variables such as canopy structure and leaf optical properties. They depend on the type of measurements made, which is defined by the spatial, spectral and directional sampling and their measurement accuracy, and also and on the methods of interpretation used.

Inversion of radiative transfer models can potentially estimate biophysical variables from remote sensing efficiently (Jacquemoud et al. 2000; Weiss et al. 2000) because local calibration is not required unlike the empirically based methods that use vegetation indices. However, several difficulties in the model inversion process limit the accuracy with which canopy properties can be retrieved. For example, different combinations of model input variables may result in similar simulations of reflectance that correspond closely to actual remote sensing observations (Baret et al. 2007). This arises from the generally ill-posed nature, in mathematical terms, of the inverse problem in remote sensing (Combal et al. 2002). Radiometric information alone is usually not sufficient to identify a unique solution. Therefore, the inverse problem needs to be stabilized by exploiting additional information. Prior knowledge on the statistical distribution of input variables to the model (Weiss et al. 2000) or spatial (Atzberger 2004) and temporal constraints (Baret et al. 2007) can be introduced into the algorithm for this purpose.

In addition, the simplification included in the canopy radiative transfer model may induce large deviations from actual observations. During the last few decades, several advances in radiative transfer and canopy modelling have been made. A large number of models have been developed. These range from turbid medium to geometrical-optical models, which describe the vegetation in terms of simple geometrical objects such as cylinders, spheres, ellipsoids, for which surface properties are known. Finally models that account explicitly for the detailed 3-D canopy structure and compute radiative transfer by ray tracing (Disney et al. 2000) or radiosity (Borel et al. 1991) algorithms have been developed (e.g. Chelle et al. 1998; España 1998). These initial 3-D models were essentially static, whereas dynamic models have been developed recently some of which take into account interactions with environmental factors. They result in 4-D or functional-structural plant models (Godin and Sinoquet 2005). Progress in this field is driven by the availability of increasingly fast hardware, more efficient computer graphics algorithms and the rapidly-emerging field of 3-D canopy structure measurement (Godin et al. 1999).

Most radiative transfer models currently used to retrieve canopy characteristics are turbid medium models, which represent canopy structure in a very simple way (Jacquemoud et al. 2000; Verhoef and Bach 2007). Vegetation elements are treated as infinitely small radiation scatterers that are randomly distributed within the canopy. Such models are computationally fast and require few input variables, which make them suitable for non-linear iterative numerical inversion schemes. This approach minimizes a cost function that quantifies the difference between simulated and measured reflectance. Although these models played a key role in describing generalized behaviour and mimicking canopy reflectance reasonably well in many cases, their application is ultimately limited to the simulation of relatively homogeneous canopies. This can leads to significant errors and biases, for example when applied to row crops at the early growth stages.

Recent developments in the use of look-up-table (LUT) and neural network (NNT) methods reduce the computing constraint for calculating canopy reflectance because they are based on pre-computed data bases (Knyazikhin et al. 1998). This opens the way for the inversion of more detailed 3-D models (Casa and Jones 2005; Disney et al. 2000).

Several 3-D or 4-D models have been developed for specific plant species, such as maize (España 1998; Fournier and Andrieu 1999), sorghum (Kaitaniemi et al. 1999), barley (Buck-Sorlin et al. 2005) rice (Watanabe et al. 2005), wheat (Evers et al. 2007) and cotton (Hanan and Hearn 2003). These models implicitly include a large amount of prior information on canopy properties for the given species.

In precision farming applications, considerable prior information is available about the crop type, the cultivar and cultural practices such as sowing time or row spacing. By exploiting this information and by improving the realism of the models used for the inversion with remotely sensed data, more accurate estimates of crop biophysical variables should be obtained in principle. However, these models should be evaluated in depth in terms of a more accurate description of the corresponding radiometric signal, to assess their usefulness in the context of retrieving canopy properties from model inversion.

The use of inversion techniques based on look-up-tables or neural networks (Baret and Buis 2007) allows very complex models to be used for estimating crop characteristics from remotely sensed observations. However, there must be a compromise between the realism of the 3-D canopy description and its parsimonious nature in terms of the number of parameters and computing time.

The objective of the present work was to compare the performances and operational limitations of the inversion of two contrasting type of models to retrieve leaf are index (LAI) and average leaf inclination angle (ALA). The models compared were the classical one-dimensional turbid medium canopy reflectance model PROSAIL (PROSPECT+SAIL) (Jacquemoud et al. 2009; Verhoef and Bach 2007) and a simple three-dimensional dynamic (4-D) maize model (Lopez-Lozano et al. 2007). The assessment was based on a set of multiangular field data recorded from maize canopies in Italy in 2007 and 2008 for this purpose. The data were representative of maize at the early growth stages, which we considered more interesting than a fully developed canopy for two reasons: 1) monitoring of an early stage crop seems more appropriate in the context of precision agriculture applications (e.g. fertilizer application) because management decisions based on a fully developed crop are likely to be too late to be effective, and 2) it is at early stages that row crops differ dramatically from the assumption of randomly distributed leaves present in 1-D models with an obvious clumping of foliage, whereas at later stages with full cover and more homogeneous canopy these assumptions pose fewer problems (Jacquemoud et al. 2000).

Materials and methods

Field data

Measurements were made on field grown maize crops at different growth stages in 2007 and 2008. In July 2007 the measurements were made in the Sele Plain at the Improsta Experimental Farm (Naples, Italy) on the 18th July, at a maize growth stage V6 (Iowa State University, 1993). In 2008 the data were collected from the Maccarese Farm (Fiumicino, Rome, Italy) for maize growth stages V5 on the 15th of May and growth stage V8 on the 28th of May. The interrow spacing of the maize crop was 0.75 m.

Ground based multiple-look-angle remote sensing data were acquired from a height of 3 m (at nadir) over the canopy with a field sensor positioning system, based on an extending bipod arm with levelling head hinged on a goniometer to measure angles to the vertical (view zenith angles) (Casa et al. 2009). The positioning system held 2 sensors: a spectroradiometer and a red-infrared camera. The Analytical Spectral Devices (ASD) Field Spec Fr Pro spectroradiometer measured radiance in the 350-2500 nm spectral range. Reflectance was then computed using a calibrated Spectralon panel. The field of view of the ASD spectroradiometer was 25° corresponding to a circular footprint at nadir of about 1.3 m in diameter. The red-NIR Dycam ADC camera (Dycam Inc., Chatsthereworth, CA, USA) was aligned with the spectroradiometer and provided images of the canopy with 496 × 365 pixels using an 8.5-mm f4.5 lens. Tests were carried out in the laboratory to assess the alignment between the spectroradiometer and the ADC camera, and a mask image was produced corresponding to the spectroradiometer footprint over the ADC image area. The mask was applied to all ADC images before further processing so that data were from exactly the same target area for both instruments.

In 2007 data were acquired at 9 view zenith angles (VZA) for each set of measurements, ranging from -40° to +40° with a step of 10°; this was increased to 13 VZAs (from -60° to + 60°) in 2008. Most data were recorded with the sun close to the principal plane, i.e. with view zenith angles equal to sun azimuth angles irrespective of row orientation. Therefore, angles between row and view direction varied between different data sets; in a few initial sets (in 2007) the measurement directions were parallel and perpendicular to row directions. Measurements were made at 4 different sites within a large field in 2007 and at 3 different sites for each date in 2008. For each site the measurements were replicated 2 to 4 times and all data from different view azimuth angles were pooled together.

Spectral reflectance data from sunlit soil were acquired separately at close range (nadir) for both fields at each site. Spectroradiometer data were smoothed using Savitzky-Golay filtering, with a polynomial of order 3 and frame size of 41 bands; this has been shown to remove noise without affecting spectral characteristics (Leone et al. 2007).

Dycam ADC images were classified (after applying the spectroradiometer footprint mask) with a supervised classification procedure using the minimum distance technique (Richards 1999) to obtain the ‘gap fraction’, i.e. the fraction of soil visible at different view angles. This was used subsequently for inversion of the 4-D maize model. In previous tests this procedure had an overall classification accuracy of 99.4% (Casa and Jones 2005).

Concurrently to acquisition of the remotely sensed data, biophysical characteristics of the maize plants were measured. Four plants per site (i.e. 16 in total) were characterized fully in the field in 2007: for each leaf insertion height, length and maximum width together with inclination angle of the midrib were measured with a rule and electronic clinometer. Stem diameters were also measured at each leaf insertion point. Each leaf was assumed to comprise segments of approximately constant inclination angle, and each segment length and width were measured together with the inclination angle. Leaf azimuth angles were measured with a compass. Plants were then taken to the laboratory where the area of each leaf was measured separately with a Li-Cor Li-3100 area meter.

Eight plants per site (a total of 48 plants for the 2 dates) were characterized similarly in 2008, except for the leaf inclination measurements which were replaced by digital photographs of plant silhouettes against a white background (Prevot et al. 1991). These images were then geometrically corrected and the coordinates of leaf midribs were obtained (Fig. 1). Relative leaf midrib coordinates were then used, together with all the other biometric data, for the 3-D reconstruction of each plant with the ADEL model (Evers et al. 2007; Fournier and Andrieu 1999;) in the OpenAlea (http://openalea.gforge.inria.fr) environment. For this purpose relative leaf width data were calculated with the model of Prevot et al. (1991) from measurements of leaf lengths and maximum leaf widths. The 3-D reconstruction of maize plants with the ADEL model resulted in visually similar plants to those measured, although the model did not account for leaf undulation and curling (Fig. 1). A comparison of the measured area of each leaf with that reproduced by the ADEL model (each leaf was composed of 20-30 triangles) gave an RMSE of 32.4 cm^2, corresponding to an absolute LAI error of 0.02 (i.e. 1% for a LAI of 2). This indicated an acceptable approximation provided by the Prevot et al. (1991) leaf width model as well as by the level of triangulation chosen. Therefore, the leaf inclination distribution from the modelled 3-D reconstructions of the plant could represent that of actual plants. The virtual plants are defined by a triangular mesh, therefore, the area and inclination of all leaf triangles were used to calculate the leaf inclination distribution function (LIDF) and average leaf angle (ALA) from the fraction of leaf area within each inclination angle class of 5°. The processing of silhouette images and subsequent 3-D reconstruction of the plants (Fig. 1) provides a procedure that is much less time consuming than direct measurements with clinometers or 3-D digitizers in the field.

Models and inversion techniques

The PROSAIL model was chosen as it has been widely tested and validated in the last 16 years in a great number of studies both in the direct and inverse mode (Jaquemoud et al., 2009). The version used here included the treatment of the 'hotspot', i.e. the peak of reflectance when the sun and the viewing directions coincide. It assumed that the soil acted as a Lambertian diffuser, accepting measured soil spectra as input to the model and corresponds to the version SAILH (Verhoef and Bach 2007). Inversion of the model against measured multiangular reflectance spectra was done with an optimization algorithm based on the simplex search method (Lagarias et al. 1998). The version used made it possible to constrain the estimated parameters to realistic ranges by providing bounds. Iterative optimization algorithms are known to be sensitive to the initial set of parameter values, and might also converge to local minima of the cost function instead of converging to the global minimum. For these reasons, a procedure was used in which initial parameter values were drawn randomly from within the specified bounds and the algorithm was rerun 10 times (replicates) for each estimation. The estimated parameter values retained were those that minimized the cost function within the 10 initial replicates. The parameters LAI and ALA (average leaf angle) were estimated simultaneously. The other PROSAIL parameters were fixed at their nominal values (Table 1), except for the soil spectra that were measured at each site and for sun and view angles that corresponded to the measurement configurations.

The inversion was carried out for wavelengths 400-1350 nm in steps of 1 nm for the Maccarese data of 2008 to avoid the absorption bands at longer wavelengths. For the 2007 Sele data they were limited to the 400-900 nm range because the data were very noisy at the longer wavelengths.

The 4-D model chosen was the one developed by Lopez-Lozano et al. (2007). In this model, maize plants are represented by simple geometrical shapes: a quadrangular pyramid represents the stem and each leaf is represented by an isosceles triangle. Leaf number, position on the stem, area and inclination are defined on the basis of equations derived from measurements and from a previous model developed by España (1998) which is driven by thermal time (i.e. degree-days above a base temperature of 10°C). The model has few input parameters (Table 1), but despite the rather crude simplifications it provides a remarkably more realistic canopy description (Fig. 2) than the homogenous opaque 'green slab' of a turbid medium model.

This model was chosen because of its simplicity, small number of parameters and fast execution time, typically 1.4 s on a laptop with an Intel Core 2 Duo Processor 1.66 GHz CPU for the generation of a 3-D scene such as that in Fig. 2. The attributes make it amenable to inversion by numerical optimization techniques.

The inversion of the 3-D maize model was done with the same algorithm that was used for the PROSAIL inversion, i.e. the simplex search method with bounds and 10 replicate runs for each inversion. However, in this case the cost function expressed the difference between measured and modelled gap fractions for the view configurations used in the measurements. Measured gap fractions were obtained from the Dycam ADC image classification data.

Modelled gap fractions were calculated using the Z-buffer technique. This involves projecting the generated 3-D scene in a given direction onto a grid. The value of each grid point is then associated with the depth of the corresponding triangle. The gap fraction is finally computed as the ratio between the number of soil grid points (maximum depth) to the total number of grid points. To avoid border effects, the scene was replicated infinitely as described by Chelle et al. (1998). The parameters to be estimated were T and $\Delta\theta_{\text{leaf}}$ (Table 1). The LAI and ALA (model outputs) were calculated from model simulations using the estimated parameter values.

Results and discussion

Actual LAI values obtained from direct measurements vary between 0.58 and 2.56, representing situations ranging from incomplete canopy closure to 73% ground cover at nadir. The average leaf inclination angles obtained from the 3-D plant reconstruction for the 2008 data are consistent with the clinometer data of 2007; most values are around 63° for less developed plants (stage V5 and V6) and increase somewhat to 67-68° for the more advanced stage (V8).

Spectral reflectance measurements show strong anisotropy, which is usually observed in multiangular measurements over plant canopies (Chopping, 2007), with a peak at view zenith angles roughly corresponding to the sun zenith angle where the minimum fraction of shades is observed (Fig. 3a). Reflectance values, especially for NIR wavelengths (700-1300 nm), are smaller for angles close to nadir because a much larger fraction of the field of view of the sensor was occupied by the soil. This is also shown by gap fraction data derived by simultaneous image acquisition from the camera (Fig. 3b).

The spectral reflectance data were used in the inversion of the PROSAIL model, which was generally fast, taking typically less than 30 s for one optimization on a laptop computer (see above). The chosen constraint settings for the simplex method were: a maximum of 500 iterations and a maximum of 10 000 function evaluations, or a tolerance of 0.1 on the cost function or 0.01 on the parameter values. These settings applied to the 10 replicates ensured that the cost function reached a global minimum. This was evident, for example, by plotting the estimated parameter values against the starting values used to initialize the simplex procedure. To constrain the estimates to plausible values, the parameters were allowed to vary within specific ranges only: 0–5 for LAI and 0–90 for ALA.

Estimation of LAI from inversion of the PROSAIL model shows in general reasonable results with an overall RMSE of 0.48 and an R^2 of 0.85 (Fig. 4a). The results for the 2008 data have a RMSE of 0.24 and an R^2 of 0.91, whereas some points in the 2007 data are overestimated giving a RMSE of 0.74 and an R^2 of 0.86.

Estimation of average leaf inclination angle (ALA) is rather poor by contrast (Fig. 4b) for both the 2008 data (RMSE 15.98, R^2 0.56) and especially for the 2007 data (RMSE 25.04, R^2 0.24), some of which fall on one of the bounds that were set for this parameter. It should be noted that in 2007 the data had been recorded along or across maize rows irrespective of sun azimuth angle, whereas in 2008 most data sets were acquired as far as possible along the sun's principal plane (i.e. with view azimuth coinciding with sun azimuth). The latter approach provided a better sampling of the typical bidirectional reflectance distribution function (BRDF) features such as the 'hotspot'. In addition, observations in 2007 were acquired at 9 VZAs (-40° to +40°) compared to 13 VZAs for 2008 (-60° to +60°). For the inversion of the PROSAIL model, *a priori* information was not taken into account in the formulation of the cost function, but it is now advised to do so (Baret and Buis 2007). Furthermore, the turbid medium models provide an estimate of the 'effective LAI' (Chen and Black 1992) because clumping is not taken into account and it is not possible to exclude the influence of stems, whereas actual LAI measurements include only leaves.

Inversion of the 3-D maize model was much slower than for PROSAIL, typically it took about 20 minutes for each optimization to run (i.e. 10 replicates) on a laptop (see above). The same simplex stopping criteria were used as for PROSAIL inversion. The parameters T and $\theta_{\max}$ were constrained by the bounds 50–2500 degree-days and 0–90 degrees, respectively. Other measured parameter values (Table 1) were obtained from previous field trials in Spain (Lopez-Lozano 2007). Overall, accuracy of LAI estimation with the 3-D maize model (Fig. 5a) appears to be similar to that obtained with PROSAIL, with a RMSE of 0.25 and an R^2 of 0.83 for the 2008 data, and a slight underestimation for the 2007 data with RMSE 0.48 and and R^2 of 0.78. Estimation of the average leaf angle (Fig. 5b) shows a distinct group of points, including all 2007 data plus two 2008 data points, for which ALA is markedly underestimated. The overall RMSE is larger than that obtained from PROSAIL ALA estimation. The RMSE and R^2 were 26.48 and 0.02, respectively, for the 2008 data and 49.9 and 0.25, respectively, for 2007 data.

The results obtained from the inversion of the 4-D model on gap fraction data are similar to those obtained with the turbid medium models although this model should provide a more realistic description of a maize canopy. It should be noted that the 4-D model was developed on relationships describing maize leaf arrangement and size, which had been derived specifically from maize experimental data (España 1998). This means that much of the *a priori* information was included implicitly in the inversion process.

In the comparison between the two models it should be noted that exactly the same inversion technique was used for both, therefore differences in the estimation results could be attributed to two possible causes: 1) the use of different types of measurements, i.e. gap fraction or reflectance data, because gap fraction depends only on plant architecture whereas canopy reflectance data integrate soil and leaf biochemical information; 2) the different descriptions of the canopy included in the models, for example the implicit assumption of leaf clumping in the 4-D maize model which is absent in the turbid medium formalism.

To clarify the relative importance of each of these two effects additional tests were carried out by inverting a simple Poisson model (Nilson 1971), on which the turbid medium approach is based, using the measured gap fraction data. The model was

$$Po(\theta_v) = \exp^{[-k\,LAI]} \;, \qquad (1)$$

where *Po* is the gap fraction at view zenith angle θ_v and k is the extinction coefficient, i.e. the average projection of leaves on to a horizontal surface, which was calculated as a function of the view zenith angle θ_v and the leaf angle distribution parameter χ of Campbell's ellipsoidal leaf angle distribution (Campbell 1986). The model was inverted using the simplex method with the same settings as those used for the PROSAIL and 4-D maize models, and the parameters *LAI* and χ were retrieved simultaneously, with bounds of 0.1–10 for χ and 0–10 for *LAI*. The average leaf angle (ALA) was then calculated from χ with Campbell's (1990) equation.

Although the Poisson model treated canopy structure in a similar way to PROSAIL, there are some small differences in the estimates of LAI (Fig. 6a). Estimates of the 2007 data are slightly better (RMSE 0.57, R^2 0.50) and those of the 2008 data are marginally worse (RMSE 0.30, R^2 0.86). The ALA is estimated considerably better than it was by both PROSAIL and the 4-D model; the RMSE is about 6.51° and R^2 is 0.05 for the 2008 data and 9.62 and 0.14 for the 2007 data (Fig. 6b).

However, none of the models seems to perform satisfactorily in the estimation of ALA. It should be noted that accurate direct measurement of leaf angle distribution is very difficult and time consuming, and so assessments of retrieval accuracy from radiometric observations are very in literature (e.g. Shibayama 2006). In maize the typical undulation and curling of leaf blades make it almost impossible to measure correctly the fraction of leaf area that is actually oriented in each direction. Thus many workers have resorted to measuring inclination angles of leaf midribs (e.g. Ford et al. 2008; Prevot et al. 1991). In such an approach it is assumed that leaf blades are flat, which introduces an error in the LIDF that is difficult to estimate, but that seems to have little effect on the gap fraction (España 1998).

From the estimates of LAI, the sampling of view zenith angles along the sun's principal plane seems to be particularly important because it exploits the maximum angular variation of canopy reflectance as shown by the results obtained with PROSAIL in 2007 and 2008 (Fig. 4). These results were obtained using data with fairly wide directional sampling. In practice, measurements with such directional coverage would be unlikely and one would be limited to data at far fewer view zenith angles. The difference between the gap fraction calculated by turbid medium models and models that account implicitly for leaf clumping, such as the 4-D model, depends largely on the viewing direction chosen (e.g. Lopez-Lozano et al. 2007); the larger discrepancies are for angles close to nadir.

The impact of the number and configuration of the view zenith angles chosen, therefore, was investigated by inverting different models using the same procedure as described above, but excluding progressively more view zenith angles from the data. The assessment was done for LAI only and only for the 2008 data because the 2007 data were not fully consistent with these, i.e. they had a different sun-view geometry and fewer VZAs. Two different strategies were used: in the first, data were gradually removed starting from the most extreme VZAs (more oblique) until only three VZAs close to nadir remained (0° and ±10°); in the second, the angles close to nadir were deleted until only the two most extreme angles remained (±60°).

The RMSEs from the LAI estimates of the three models show a difference between the two strategies (Fig. 7). The progressive elimination of the larger VZAs in the direction of nadir results in a gradual decrease in the accuracy of estimation, especially for the turbid medium models. When only the nadir and ±10° VZA were left, the PROSAIL model performs marginally better than the others. The results for the second strategy show a relative insensitivity to the number of VZAs in the accuracy of LAI estimates, which indicates that data obtained at just a few oblique view angles provide reasonable estimates of LAI. It should be noted that when only the most extreme VZAs remain (±60°), LAI estimation could be more robust because of the well known insensitivity of the leaf area projection function to leaf inclination distribution at 57.5° (Warren-Wilson 1963). Information embodied in the reflectance of a turbid medium target viewed from the nadir only is poor compared to that measured at an oblique angle (Jacquemoud et al. 2009); this is confirmed by the results of the tests shown in Fig. 7. Therefore, this consideration could also be extended to gap fraction data. Oblique view angle measurements, even if limited to few extreme angles, provide more accurate estimates of LAI.

Conclusion

This work shows the feasibility of inverting a simple 4-D canopy model by using the same numerical optimization technique as generally used for 1-D models. The results of the estimation of LAI from inversion of the 4-D model are only marginally better than those obtained with the 1-D model, whereas average leaf inclination angle (ALA) is not estimated satisfactorily by any of the models. The use of gap fraction data, instead of spectral reflectance, is shown to be adequate for the situation in which observations from several view angles are available. A reduction in the number of view angles severely degrades the accuracy of estimation, especially when there are only near nadir observations. Conversely oblique view angle measurements are shown to allow more accurate LAI estimation.

Two problems inherent to the inversion procedure can be mentioned. The first concerns the arbitrary choice of values for the model parameters that are not estimated. The values chosen can have a remarkable influence on the results. The simplex algorithm is subject to the risk of converging to local minima of the cost function if the number of parameters to be estimated is increased. However, alternative techniques, such as those based on Bayesian methods could be more robust and allow the retrieval of several parameters at the same time. This alleviates the need to provide arbitrarily fixed parameter values. The second problem stems from the fact that variation in both LAI and average leaf inclination angle (ALA) can produce similar effects on canopy reflectance and gap fraction. This is highlighted by the difficulties of retrieving accurate LAI and ALA values simultaneously.

In conclusion, a more thorough comparison is needed to assess the capabilities of 1-D and 4-D models to retrieve canopy properties by exploring a much wider range of canopy types and observation configurations. For example, it would be useful to investigate the sensitivity in the inversion of different kinds of models to the well known saturation effect. The latter occurs with a dense canopy cover and reflectance becomes insensitive to changes in LAI because the lower layers of foliage are not visible. Comparisons of spectral reflectance from 1-D and 3-D or 4-D models could be improved if they were made under a range of situations, for example by using a ray-tracing or radiosity method to calculate reflectance from 3-D descriptions of the canopy.

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Tables

Table 1. List of the input parameters of the 1-D model PROSAIL and of the dynamic 4-D model of Lopez-Lozano et al. (2007) with the values used for their inversion.

Model	Parameter	Description	Unit	Used values*
PROSAIL	θ_S	Sun zenith angle	Radians	Measured
	θ_V	View zenith angle	Radians	Measured
	φ	Angle between sun and view azimuth	Radians	Measured
	Rs	Vector of soil reflectance	nm	Measured
	Cab	Leaf chlorophyll a+b content	µg cm^{-2}	40
	Cw	Leaf water content	g cm^{-2}	0.012
	Cdm	Leaf dry matter content	g cm^{-2}	0.005
	Cbp	Leaf brown pigment content	-	0
	N	Leaf mesophyll structure index	-	1.5
	Ang	Leaf surface roughness angle	Degrees	59
	LAI	Leaf area index		*Estimated*
	ALA	Average leaf angle	Degrees	*Estimated*
	Hot	Hotspot parameter	-	0.1
4-D maize	N_{max}	Maximum number of leaves per plant	N	18
	S_{max}	Maximum leaf area per plant	m^2	0.5
	DTc	Phyllochron	°C d^{-1}	50
	DTs	Leaf lifespan	°C d^{-1}	1200
	D	Plant density	plants m^{-2}	7
	Plasticity	Leaf azimuth adjustment parameter	-	0.2
	d_{rows}	Distance between rows	m	0.75
	H_{max}	Maximum plant height	m	2.5
	θ_{max}	Inclination of largest leaf	Degrees	*Estimated*
	$\Delta\theta_{leaf}$	Difference in inclination between the biggest and smallest leaf	Degrees	20
	T	Temperature sum	°C d^{-1}	*Estimated*

* values used were obtained from independent data sets obtained previously from maize plant canopies (Lopez-Lozano et al., 2007)

Figure captions

Fig. 1 **a** Example of the processing of a maize plant silhouette image, **b** acquisition of leaf midrib coordinates and **c** 3-D reconstruction of the plant using the ADEL model (Fournier and Andrieu 1999).

Fig. 2 A typical scene generated by the 4-D maize model of Lopez-Lozano et al. (2007).

Fig. 3 **a** Multiangular spectral reflectance data recorded from the maize canopy at a sun zenith angle of 43° using the ASD Fieldspec spectroradiometer and **b** the corresponding gap (soil) fraction obtained from the classification of collimated bispectral images acquired concurrently to the spectra.

Fig. 4 Results from the inversion of the PROSAIL model for the simultaneous estimation of: **a** LAI and **b** ALA on multiangular spectral reflectance data. The other model parameter values are those reported in Table 1. Filled triangles: measurements carried out at the Sele Plain in 2007; empty circles: measurements carried at Maccarese in 2008.

Fig. 5 Estimates of: **a** LAI and **b** ALA from inversion of the 4-D maize model of Lopez-Lozano et al. (2007) on multiangular gap fraction data. The other model parameter values are those reported in Table 1. Filled triangles: measurements carried out at the Sele Plain in 2007; empty circles: measurements carried at Maccarese in 2008.

Fig. 6 Results from the inversion of the Poisson model of Eq.1 for the simultaneous estimation of: **a** LAI and **b** ALA on multiangular gap fraction data. Filled triangles: measurements carried out at the Sele Plain in 2007; empty circles: measurements carried at Maccarese in 2008.

Fig. 7 Sensitivity of LAI retrieval accuracy to the number of observation view zenith angles (VZA): **a** gradual reduction in the more oblique VZAs in the direction of nadir and **b** gradual reduction in the less oblique VZAs in the direction of the more oblique angles (i.e. larger VZAs).

Figure1

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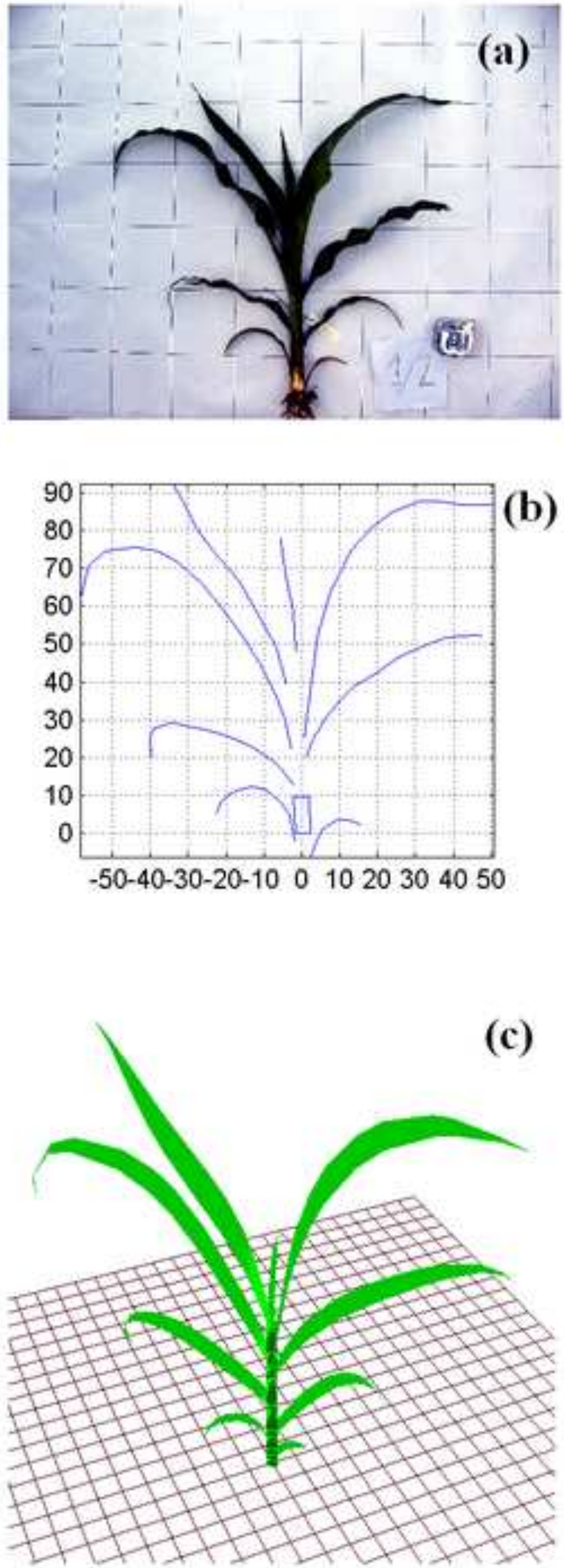

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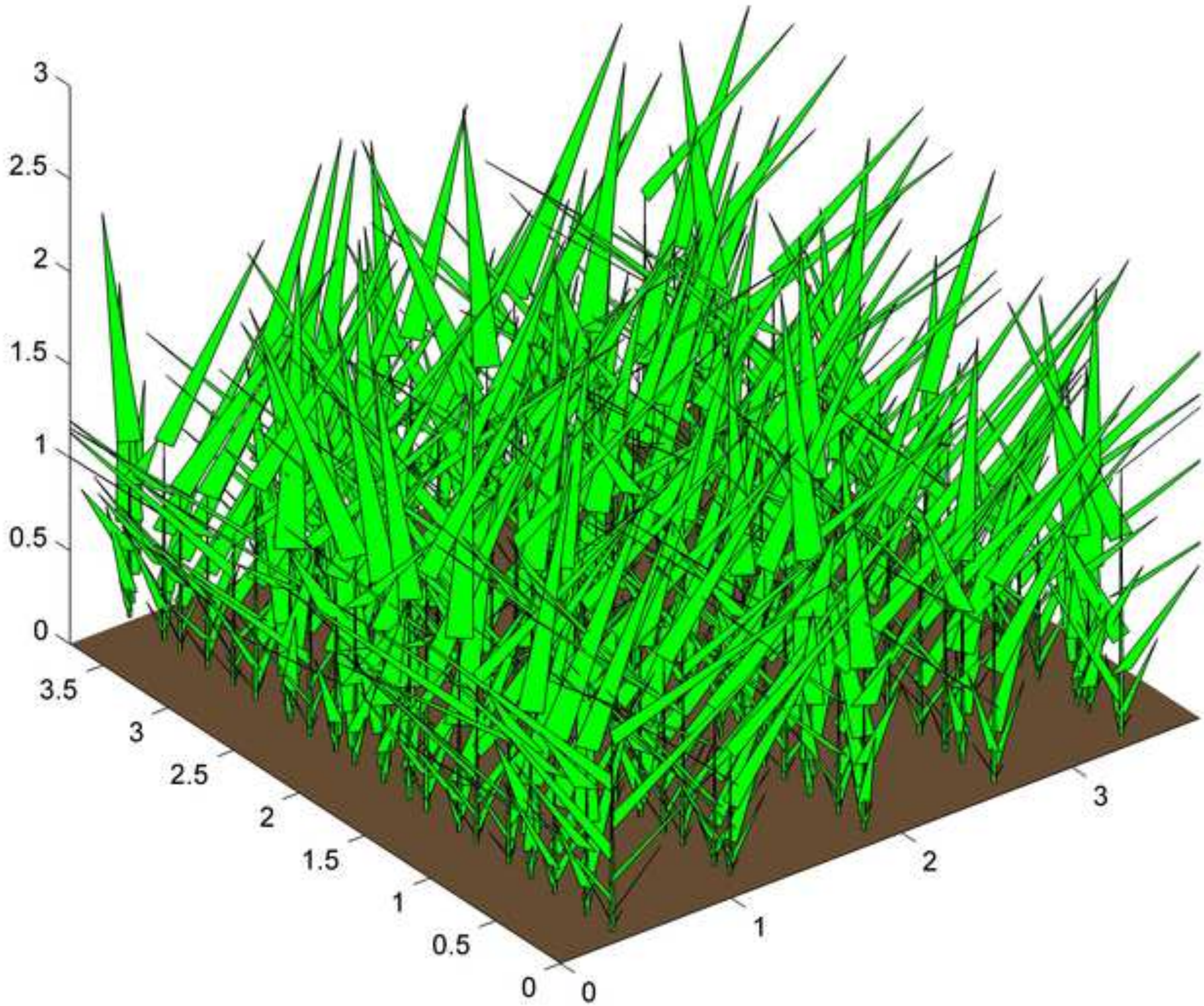

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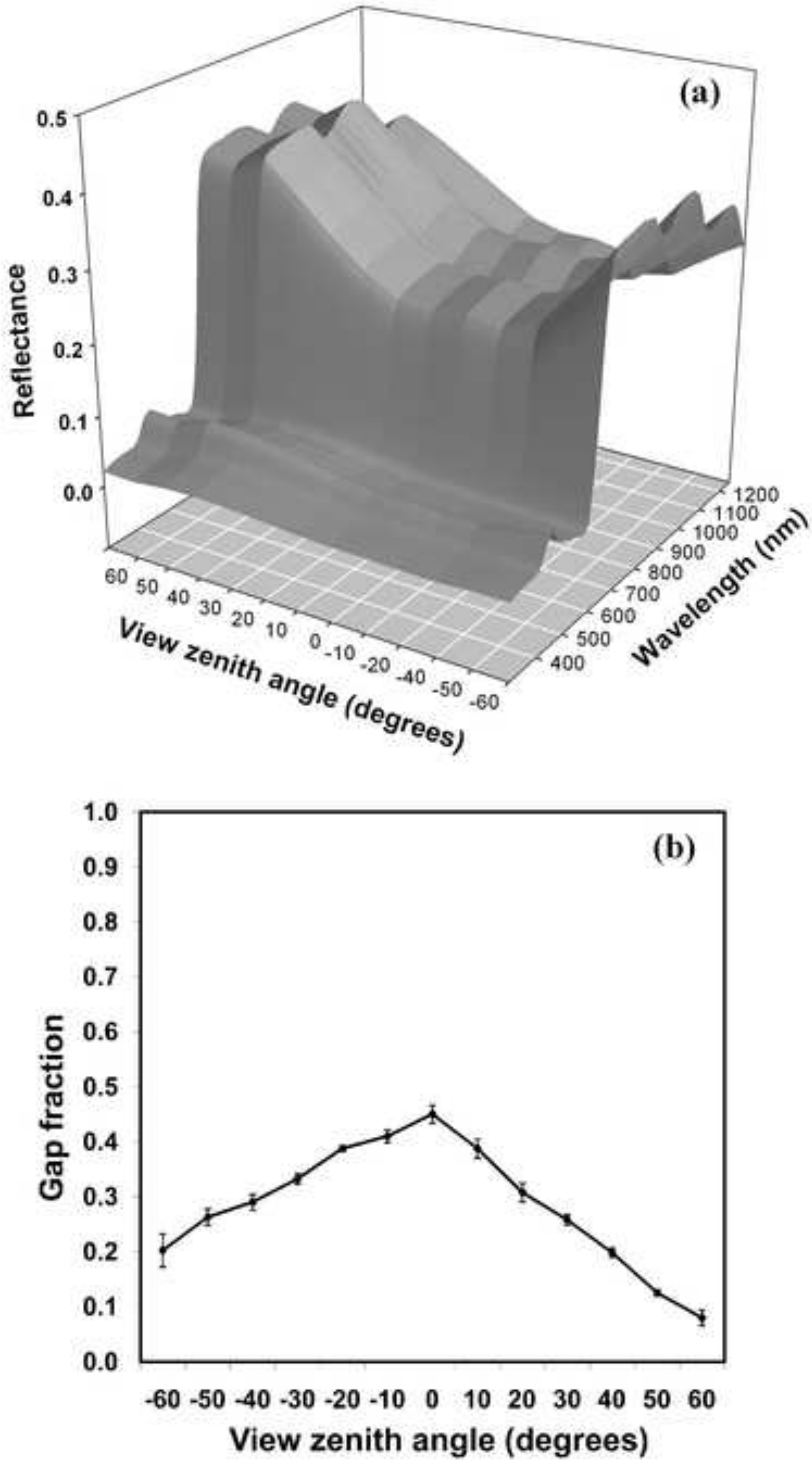

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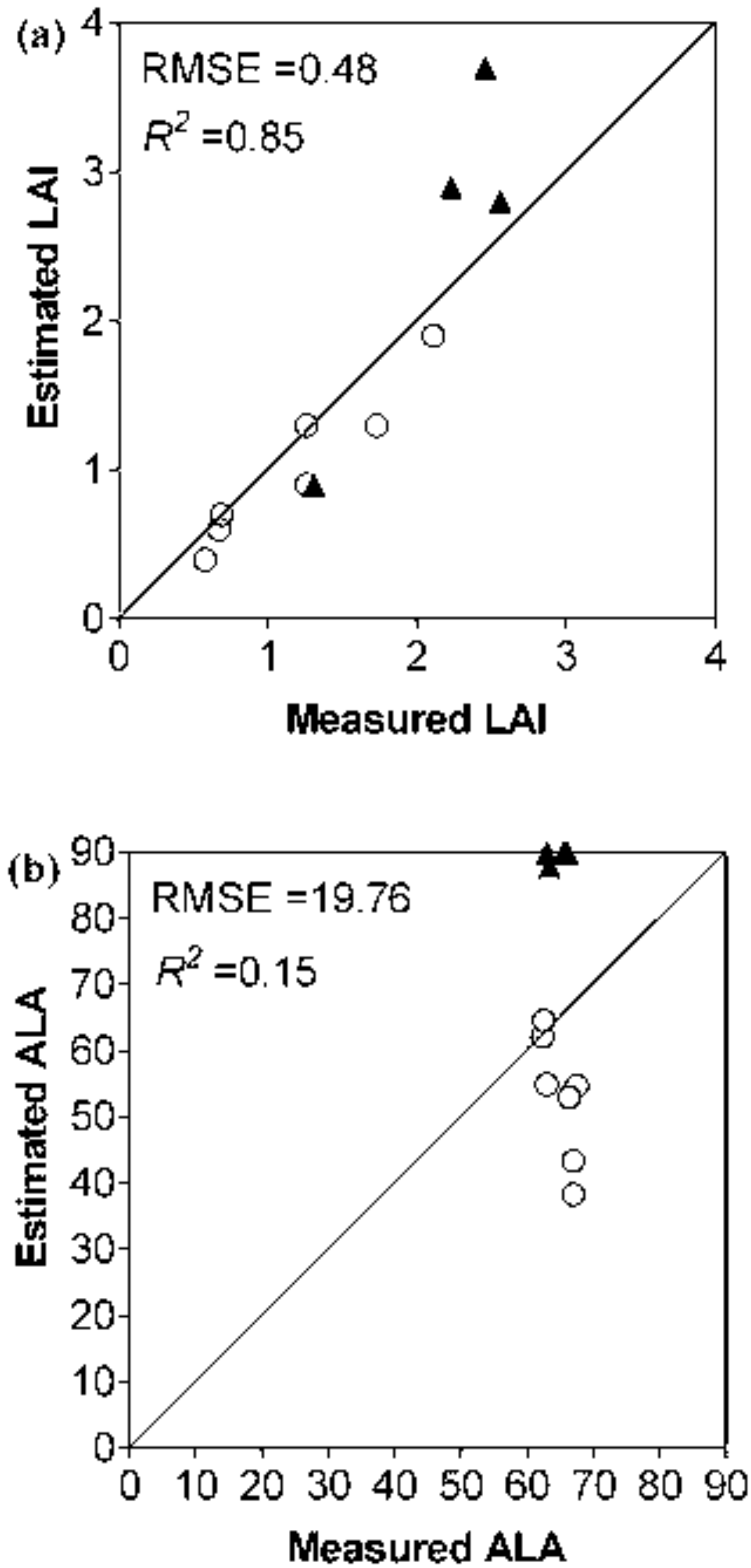

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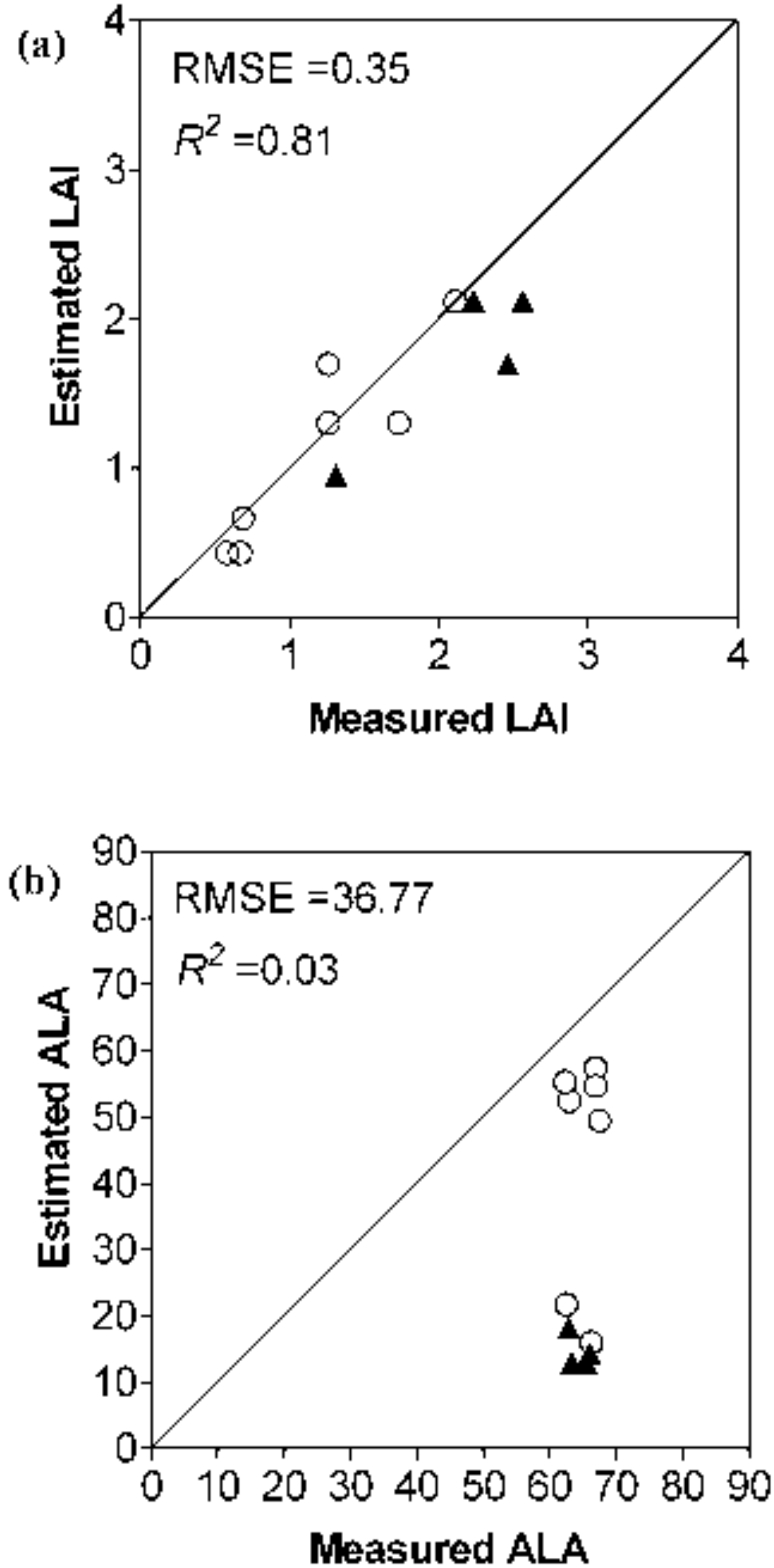

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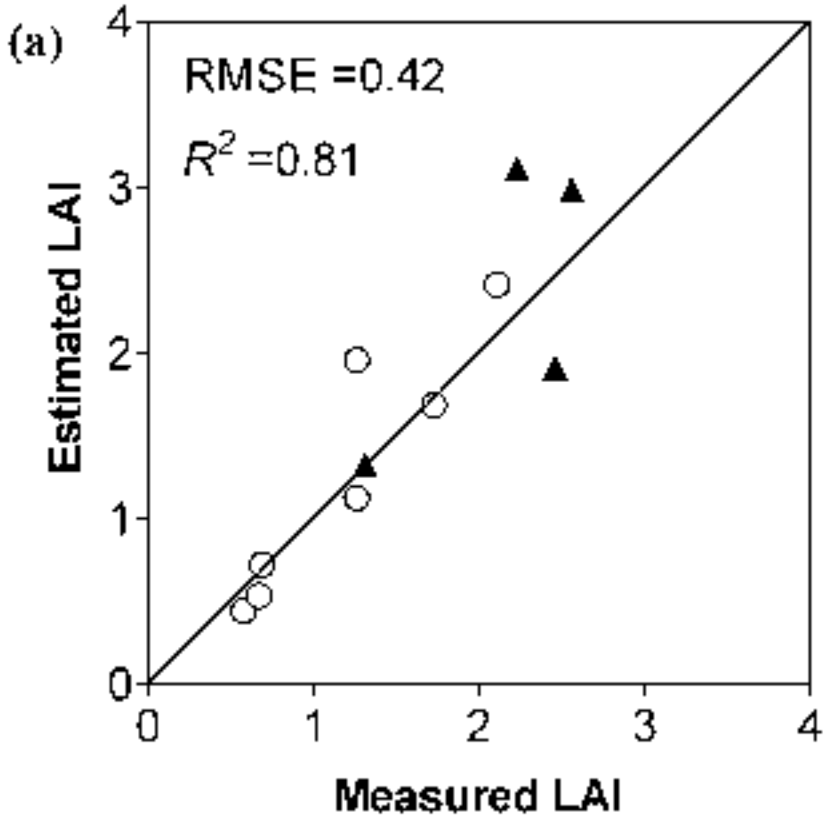

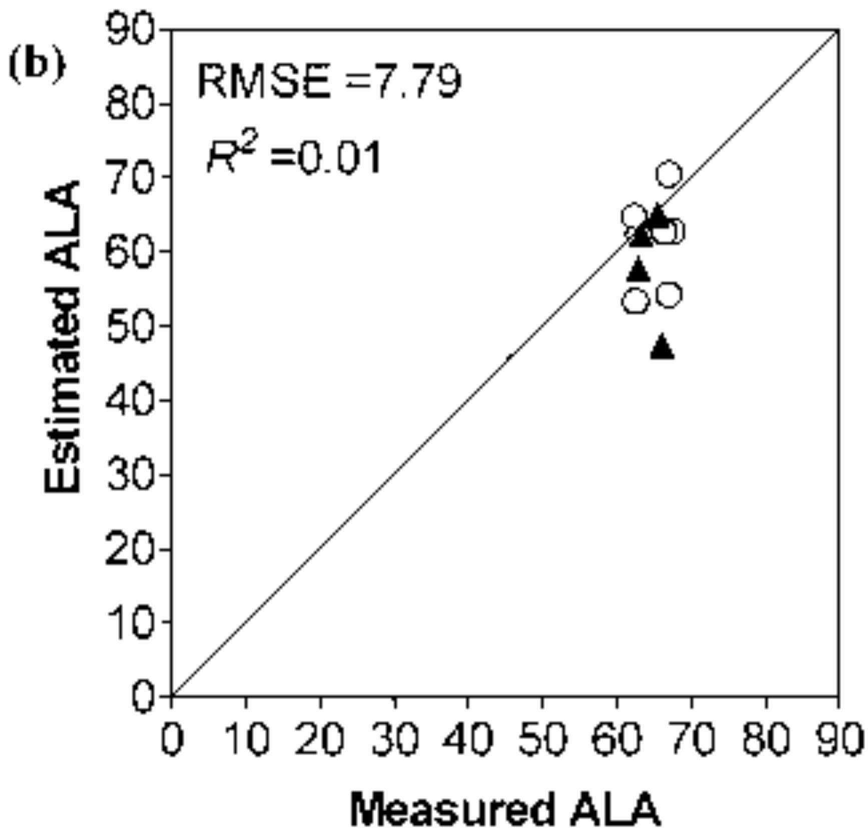

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