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Research paper

A robust leaf area index algorithm accounting for the expected errors in gap fraction observations

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ABSTRACT

The leaf area index, LAI, representing the physiological and structural functions of vegetation canopies, can be estimated from gap fraction measurements obtained at different zenith angles. Earlier works have provided practical and convenient theoretical solution to retrieve LAI based on the integration of contact numbers (a projected area of leaves on a plane perpendicular to the view or solar zenith angle) over zenith angles as obtained by a linear regression, i.e., LAI = $2(A + B)$, where A and B are the coefficients of the regression of contact numbers against zenith angles. This graphical procedure is equivalent to the more accurate method of LAI retrieval by integrating gap fraction measurements from nadir through horizon angles. However, using an ordinary least-squares regression on inherently unsteady relationship between contact numbers and zenith angles limited the use of a simple graphical procedure for LAI estimation. In this study, we introduce the use of robust procedure to retrieve regression coefficients (i.e., A and B), and assess the performance of the new procedure using numerically derived hypothetical data, computer simulated and real measurements of hemispherical photographs. Our results indicated, the new procedure not only outperformed the ordinary least-squares solution for graphical procedure, but also outperformed all existing LAI methods We conclude from analyses using numerically derived hypothetical data, computer simulated and real measurements of hemispherical photographs that estimating A and B (where LAI = $2(A + B)$) using a robust procedure is a convenient and sufficiently accurate method for estimating LAI from field measurements of gap fractions at different zenith angles.

1. Introduction

Leaf area index (LAI, one-half the total leaf surface area per unit of horizontal ground surface area (Chen and Black, 1992)) is an important physiological and structural property of vegetated landscapes. A wide range of models used in agriculture, ecology, carbon cycle, climate and other related studies use LAI to estimate radiation, heat, momentum, water, and various gas exchanges. For example, LAI is one of the essential climate variables defined by the Global Climate Observing System (GCOS) that are important in improving the parameterization of the land surface-atmosphere interaction processes in a range of models (GCOS, 2011).

LAI can indirectly be estimated *in situ* from the observations of gap fraction or the fraction of light transmission under forest canopies (Breda, 2003; Jonckheere et al., 2004; Weiss et al., 2004). The mathematical analyses for retrieving LAI from both gap fractions and contact numbers (i.e., the logarithm of gap fraction) are very similar and have been presented in cascades of methods in the second half of the 20th century (Wilson, 1959, 1963; Miller, 1964, 1967; Nilson, 1971; Campbell, 1986; Lang, 1986; Lang and Xiang, 1986; Lang, 1987; Chen and Cihlar, 1995; Norman and Campbell, 1989; Ross, 1981). Briefly, the probability of gap fraction (P_0) for a given LAI can be described by Poisson distribution:

$$P_0(\theta) = e^{-\mathrm{LAI}\frac{G(\theta)}{\cos\theta}} \quad (1)$$

where P_0 is a gap fraction (a probability of non-interception of incident light) for a direction defined by zenith angle θ, and G is the mean projection of a unit leaf area in the direction of θ and onto a plane normal to θ. From Eq. (1), the following expression can be derived:

$$-\cos\theta \ln P_0(\theta) = \mathrm{LAI}\,G(\theta) = K(\theta) \quad (2)$$

where $K(\theta)$ is the mean contact number. The mean contact number is

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Table 1
Summary of sampling and optical errors on gap fraction (P_0) data especially near zenith ($\theta = 0°$) and horizon ($\theta = 90°$) angles.

Source of error	Cause, statistical nature of error	Location of P_0 data
Large weight of single gaps	Sampling, random depending on clumping	Especially important near zenith
Too few gap samples	Sampling, random especially at high LAI	Near the horizon
Interference of trunks	Sampling, systematic depending on trees	Especially near the horizon
Objects beyond plot limits	Sampling, more or less systematic	Especially near the horizon
Topography	Sampling, more or less systematic	Especially near the horizon
Light scattering	Optical, random depending on sun elevation	Potentially all angles
Unsharpness ("mixed pixels")	Optical, systematic depending on focus	Especially near the horizon
Motion blur (by wind)	Optical, random depending on speed	Especially near zenith
Lens vignetting	Optical, systematic depending on zenith angle	Near the horizon

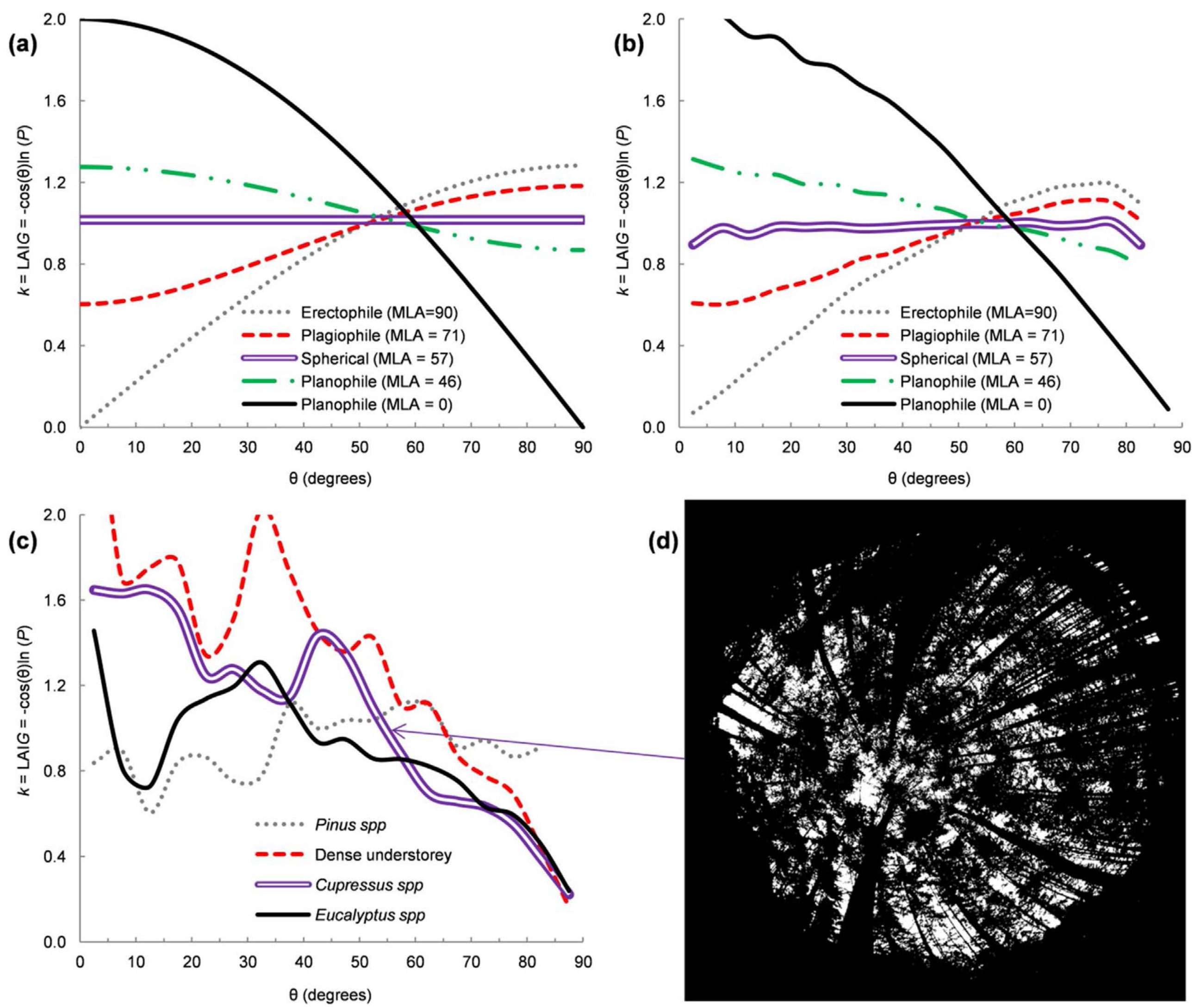

Fig. 1. Typical contact numbers, K, as functions of zenith angles (θ) and mean leaf angles (MLAs) of idealized canopies with leaf area index (LAI) value of 2 (a), K derived from computer simulated hemispherical photographs (Schleppi et al., 2007) for LAI value of 2 and various MLAs (b), K derived from true hemispherical photographs taken on various forest types (with various LAI therefore K does not converge at θ value of 57.3°) (c), and example hemispherical photograph plotted in (c) for *Cupressus* spp. Plantation, from Taita Hills, South-East Kenya (Gonsamo and Pellikka, 2008) (d). The five canopy MLAs considered in (a) and (b) are: erectophile (vertical leaves with MLA = 90°), plagiophile (predominantly inclined leaves with MLA = 71°), spherical (the relative frequency of leaf angle is the same as for surface elements of a sphere, with MLA = 57°) and two planophile (one with predominantly horizontal leaves with MLA = 46° and the other is horizontal leaves with MLA = 0°).

determined by the overlapping of projected areas of leaves on a plane perpendicular to the direction of the ray of light (i.e., θ), which penetrates the canopy along a given path length. Lang (1987) argued that $K(\theta)$ can be recovered from Eq. (2), using the relationship:

$$K(\theta) = A + B\theta \tag{3}$$

where A is the intercept and B is the slope of the regression of $K(\theta)$ (i.e.,$-\cos\theta \ln P_0(\theta)$) against θ in radians. Using the original Miller's integral (Miller, 1964, 1967) for flat leaves with symmetry about azimuth yields:

$$\mathrm{LAI} = 2 \int_{\theta=0}^{\theta=\pi/2} K(\theta) \sin\theta \, d\theta \tag{4}$$

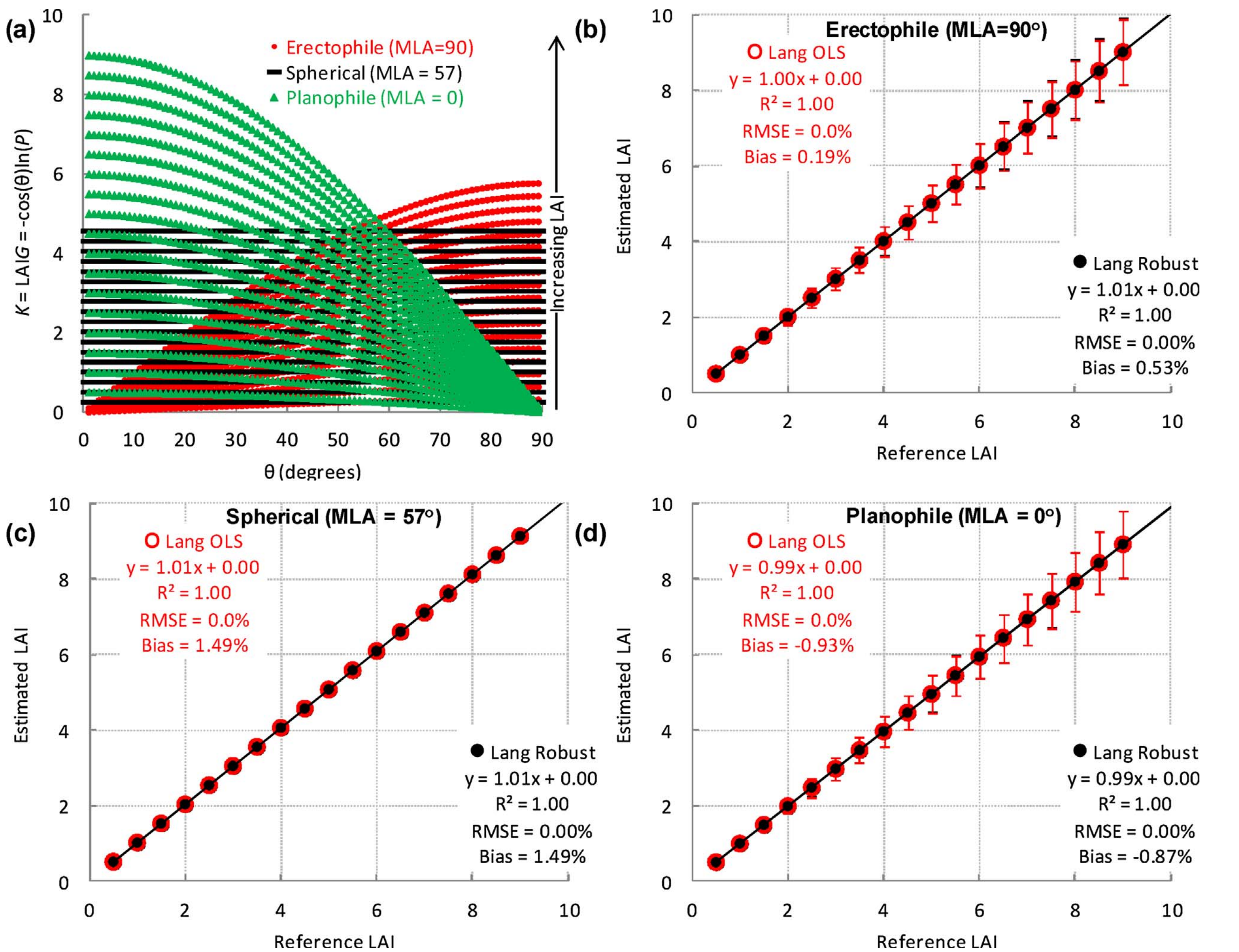

Fig. 2. (a) Comparisons of the reference leaf area index (LAI) with estimated values from Lang's ordinary least-squares OLS (Lang, 1987), and Lang's Robust (this study) algorithms for numerically derived contact numbers, K (a) as functions of zenith angles (θ) for three mean leaf angles (MLA), i.e., erectophile (b), spherical (c), and planophile (d). The numerically derived LAI ranged from 0.5 to 9 at interval of 0.5, each calculated for $\theta = 1^\circ$ to $\theta = 89^\circ$, at 1° interval. The numerical relationships among LAI, K and G (the mean projection of a unit leaf area in the direction of θ and onto a plane normal to the θ) can be found in De Wit, 1965; Stenberg, 2006; Gonsamo et al., 2010; Ross, 1981. For both Lang OLS and Lang Robust, the K vs. θ relationships (see Eq. (3)) were computed for each LAI class separately. The error bars represent a RMSE of the OLS and Robust fitting procedures in LAI units.

By substituting Eq. (3) into (4) and integrating:

$$\mathrm{LAI} = 2(A + B) \tag{5}$$

Eq. (5) is the exact solution to Miller's integral. This is equivalent to interpolating a value of K for θ equalling 57.3°, the angle where all types of G curves more or less come together: Stenberg, 2006; Gonsamo et al., 2010; Ross, 1981, and taking G at this point to be 0.5. This simple equation yields LAI and an estimate of mean leaf angle (MLA) can be calculated from B, the slope of the regression of $K(\theta)$ against θ using a sixth order polynomial (Lang, 1986). A great advantage of this method, compared to other methods (e.g., Campbell (1986) and Miller (1967)), is the possibility to estimate the statistical reliability of LAI and MLA, derived from the goodness-of-fit of the regression.

However, applying an ordinary least-squares regression as suggested by Lang (1987) on inherently unsteady relationship between K and θ, largely due to errors on gap fractions observations and optical and sampling limitations of optical instruments (Table 1), limited the use of Eq. (5) for LAI estimation. Therefore, in this study, we introduce the use of robust procedure to retrieve regression coefficients for Eq. (5) and eventually estimate LAI with a procedure resistant to the expected errors in gap fraction observations.

2. Theory and rationale

The form of K is the same as that of G, it converges at θ value of 57.3° where all types of curves of various MLAs more or less come together for a given LAI (Fig. 1). Fig. 1 shows, K as a function of θ derived from numerical solution of idealized canopies (De Wit, 1965; Gonsamo et al., 2010) (Fig. 1a), K derived from computer simulated hemispherical photographs (Schleppi et al., 2007) for LAI value of 2 and various MLAs (Fig. 1b), and K derived from true hemispherical photographs taken on various forest types in Taita Hills, South-East Kenya (Gonsamo and Pellikka, 2008) (Fig. 1c and d). From Fig. 1a, approximation of the K vs θ curves for different MLA by straight lines seems appropriate because the curves are reasonably linear, particularly around θ value of 57.3°. The key merit is that the straight line approximation works very well if the fitting is conducted for $\theta = 0^\circ$ to $\theta = 90^\circ$ (see integral of Eqs. (4) and (5)), or with spread of multiple zenith angles around 57.3° as long as the weighted integral of the multiple zenith angles is close to 57.3° (see Eq. (11) in Gonsamo et al. (2010)). This is because the impacts of different MLAs on K vs θ curve sum of intercept and slope on one side of $\theta = 57.3^\circ$ is cancelled out by nearly equal but opposing impact on the other side of $\theta = 57.3^\circ$, if the area weighted multiple zenith angles are centred around 57.3° (Fig. 1). However, when one moves from K vs θ relation derived from numerical

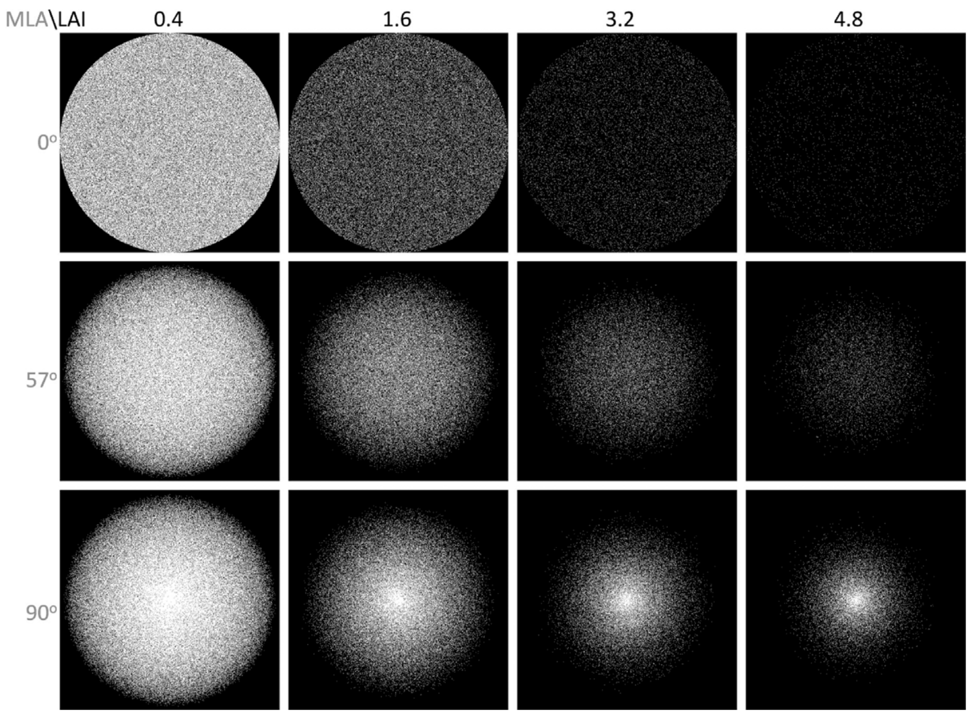

Fig. 3. Examples of simulated hemispherical photographs for leaf area index (LAI) values of 0.4, 1.6, 3.2 and 4.8, and mean leaf angle (MLA) values of 0°, 57° and 90°.

solution through computer simulations to actual measurements, the K vs θ relationship inherently becomes unsteady. Nevertheless, the scatter of observations of K as a function of θ for each MLA or vegetation type is small and unique compared to scatter of all MLA or vegetation types' K vs θ relationships (Fig. 1). Therefore, in this study we propose to derive regression coefficients (i.e., A and B in Eq. (3)) using a robust slope and intercept estimators which are less sensitive to extreme values, which could arise from poor spatial sampling of gap fraction, or optical limitations in zenith and horizon regions of optical instruments.

Table 1 presents the summary of the associated errors of hemispherical regions especially close to zenith ($\theta = 0°$) and horizon ($\theta = 90°$) angles for P_0 sampling for typical optical instruments such as hemispherical photography, LAI-2200C Plant Canopy Analyzer and Tracing Radiation and Architecture of Canopies (TRAC). One should note that the P_0 sampling errors are not proportional to that of P_0 itself at various θ. Various zenith regions are affected by different sources of errors (Table 1) therefore resulting in heteroscedastic errors on LAI estimation. Those errors particularly along the horizon angles are magnified on LAI since at this region, P_0 is usually small and the resulting logarithm for LAI estimation is very high. One instance in which LAD estimator should be considered is when there is a strong suspicion of heteroscedasticity, where the variance of the error term for Eq. (3) is not constant for all values of θ.

The robust procedure selected to estimate A and B in this study is that based on Least Absolute Deviations (LAD) median fit estimator (Press et al., 1987). LAD is selected among several other Robust solutions for linear regression because: (1) ease of implementation due to freely available libraries across different computer languages (see Press et al., 1987); (2) reliable estimate not only for slope (i.e., B) but also for intercept (i.e., A), and (3) LAD compared to others is both statistically efficient and robust to both response and explanatory variables. Although, LAD estimators have been around longer than the Ordinary Least-Squares (OLS) estimator, the algorithms for computing the LAD estimator are relatively slow and were used very little until recently. LAD gives equal emphasis to all observations, in contrast to OLS which, by squaring the residuals, gives more weight to large residuals, that is, outliers in which some of the K vs θ scatter points are far from the prevalent relationships. In this way, some of the anomalous K vs θ relationships caused predominately by optical and sampling limitations (Table 1) are suppressed and the prevalent relationships are better fitted. Thus A and B estimated from LAD differ somewhat from those estimated by OLS. The problem is precisely the robust version of the problem posed in Eq. (3) above, namely fit a straight line through K vs θ scatter points using LAD estimator. The merit function to be minimized for LAD is:

$$\sum_{i=1}^{n} \left| K_i - A - B\theta_i \right| \tag{6}$$

rather than minimizing the sum of squared residuals (i.e., $\sum_{i=1}^{n} (K_i - A - B\theta_i)^2$) as is the case for OLS, where n is the number of gap fraction measurements as a function of θ. It follows that for a fixed B, the value of A that minimizes Eq. (6) is

$$A = \mathrm{med}[K_i - B\theta_i] \tag{7}$$

where med[] represents the median operator applied to the set. Thus, equation for parameter B is

$$0 = \sum_{i=1}^{n} \theta_i \mathrm{sign}(K_i - A - B\theta_i) \tag{8}$$

where sign(0) is to be interpreted as zero. If A in Eq. (8) is replaced by the implied function $A(B)$ of Eq. (7), then we are left with an equation in a single variable which can be solved by bracketing and bisection, as described in Press et al. (1987). Unlike OLS, LAD regression does not have an analytical solving method. Therefore, an iterative method is required. The initial guesses for A and B are generated using OLS procedure. If outliers are so numerous, as often are the case for K observation using optical field instruments at different θ, the OLS generated using initial guesses of A and B are different from those estimated by LAD merit function, rendering the former of little use for estimating LAI. We have included the LAD estimator into CIMES software, a package of free programs for the analysis of hemispherical photographs (Gonsamo et al., 2011). In the following sections, we assess the performances OLS (hereafter, Lang OLS) and LAD (hereafter, Lang Robust) procedures to estimate effective LAI (hereafter named simply as LAI) using numerically derived hypothetical data, computer simulated and real measurements of hemispherical photographs.

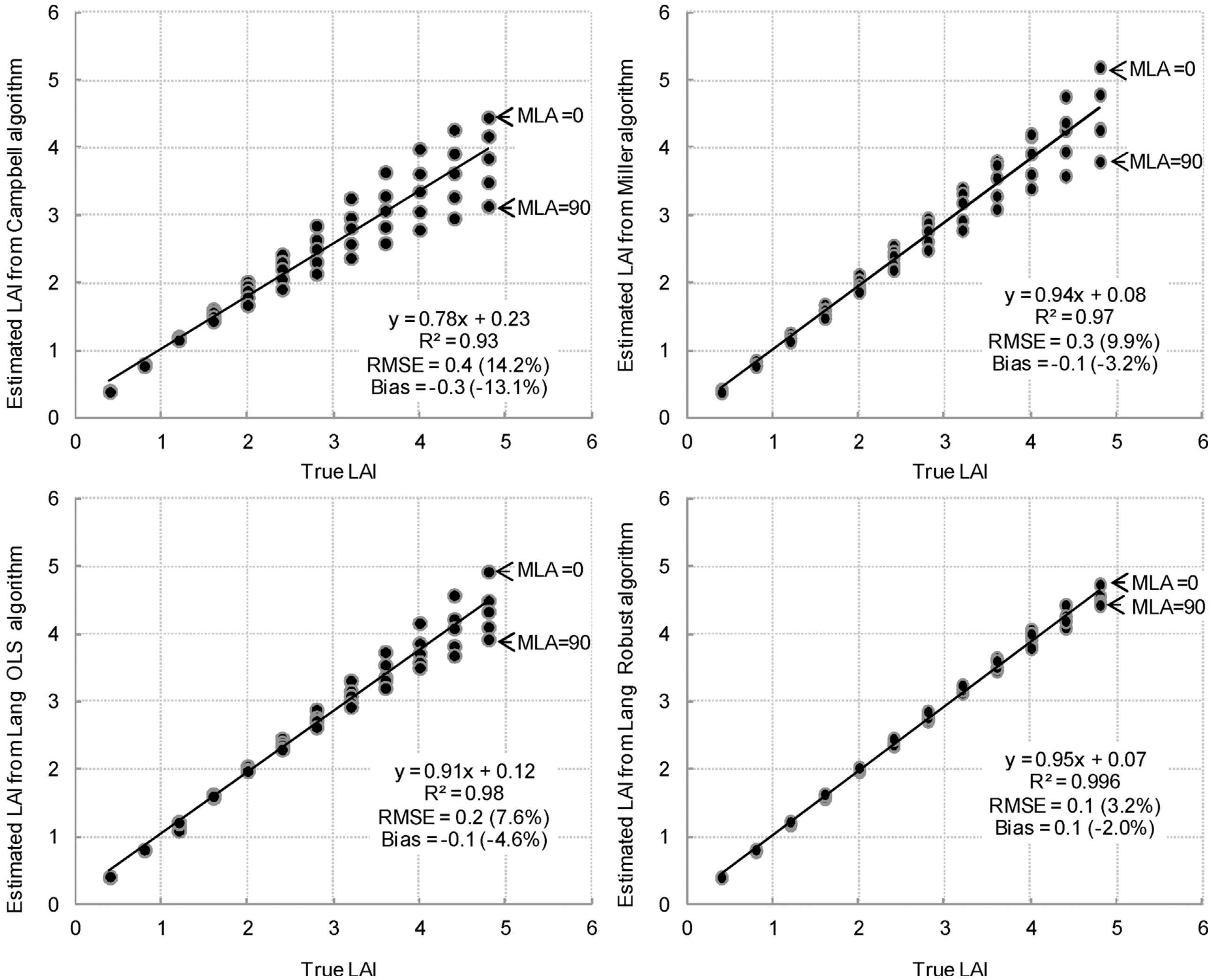

Fig. 4. Comparisons of the reference leaf area index (LAI) with estimated values from Campbell (Campbell, 1986), Miller (Miller, 1967), Lang's ordinary least-squares OLS (Lang, 1987), and Lang's Robust (this study) algorithms for 60 simulated hemispherical photographs.

3. Tests with numerically derived hypothetical data

Contact numbers, K, were generated for hypothetical canopies having LAI range from 0.5 to 9 at interval of 0.5, and three mean leaf angles (MLA, erectophile (MLA = 90°), spherical (MLA = 57°), and planophile (MLA = 0°)) (see for details of numerical relationships among LAI, K and MLA in De Wit, 1965; Stenberg, 2006; Gonsamo et al., 2010; Ross, 1981). Linear regressions were fitted to K as a function of θ, in radians for $\theta = 1°$ to $\theta = 89°$ at 1° interval, and LAI were calculated using Eq. (5). For both Lang OLS and Lang Robust regressions, straight lines to retrieve coefficients A and B in Eq. (5) were fitted to K as a function of θ for each LAI and MLA classes separately. Fig. 2a presents the entire numerically driven hypothetical data for each MLA, LAI, K and θ. Since the original Lang OLS method has not been widely used and validated, this test with error-free numerically driven hypothetical data is designed to evaluate how statistically stable both methods are using two extreme MLAs (i.e., erectophile (MLA = 90°) and planophile (MLA = 0°)) and a commonly used canopy MLA (i.e., spherical (MLA = 57°)).

The results comparing the estimated LAI using the Lang OLS and Lang Robust regressions against the reference LAI are given in Fig. 2b and c. The results indicate that both Lang OLS and Lang Robust procedures resulted in negligible bias and offset against the reference LAI (Fig. 2b and c). The closeness of LAI from both Lang OLS and Lang Robust procedures to reference value based on hypothetical data is pleasing and reflects that both methods are statistically stable to estimate LAI. Theoretical results indicate that the proposed method appears promising and warrants further tests on controlled experimental data and real measurements. In the following two sections, we further test the new Lang Robust procedure on simulated and real hemispherical photographs.

4. Tests with computer simulated hemispherical photographs

Artificial photographs were simulated based on an ellipsoidal leaf angle distribution as described in Campbell (1986) using CANOPIX software (Schleppi et al., 2007, http://www.schleppi.ch/canopix) with 1600 × 1600 pixels of 180° field of view. Five sets of hemispherical photographs were simulated each for erectophile (MLA = 90°), plagiophile (MLA = 44°), spherical (MLA = 57°), planophile (MLA = 19°), and planophile (MLA = 0°), for randomly distributed canopy elements for LAI values ranging from 0.4 to 4.8 at interval of 0.4. In total, 60 hemispherical photographs were simulated. Examples of the simulated hemispherical photographs are presented in Fig. 3 for selected MLA and LAI values. The gap fraction calculated by CANOPIX software determines the probability of any pixel to be white (gap) as a function of its θ, LAI and MLA. The colour (black or white) of each pixel is then set at random according to the calculated probability of gap fraction. Then LAI was estimated using Campbell (Campbell, 1986), Miller (Miller, 1967), Lang's OLS (Lang, 1987), and Lang's robust (this study)

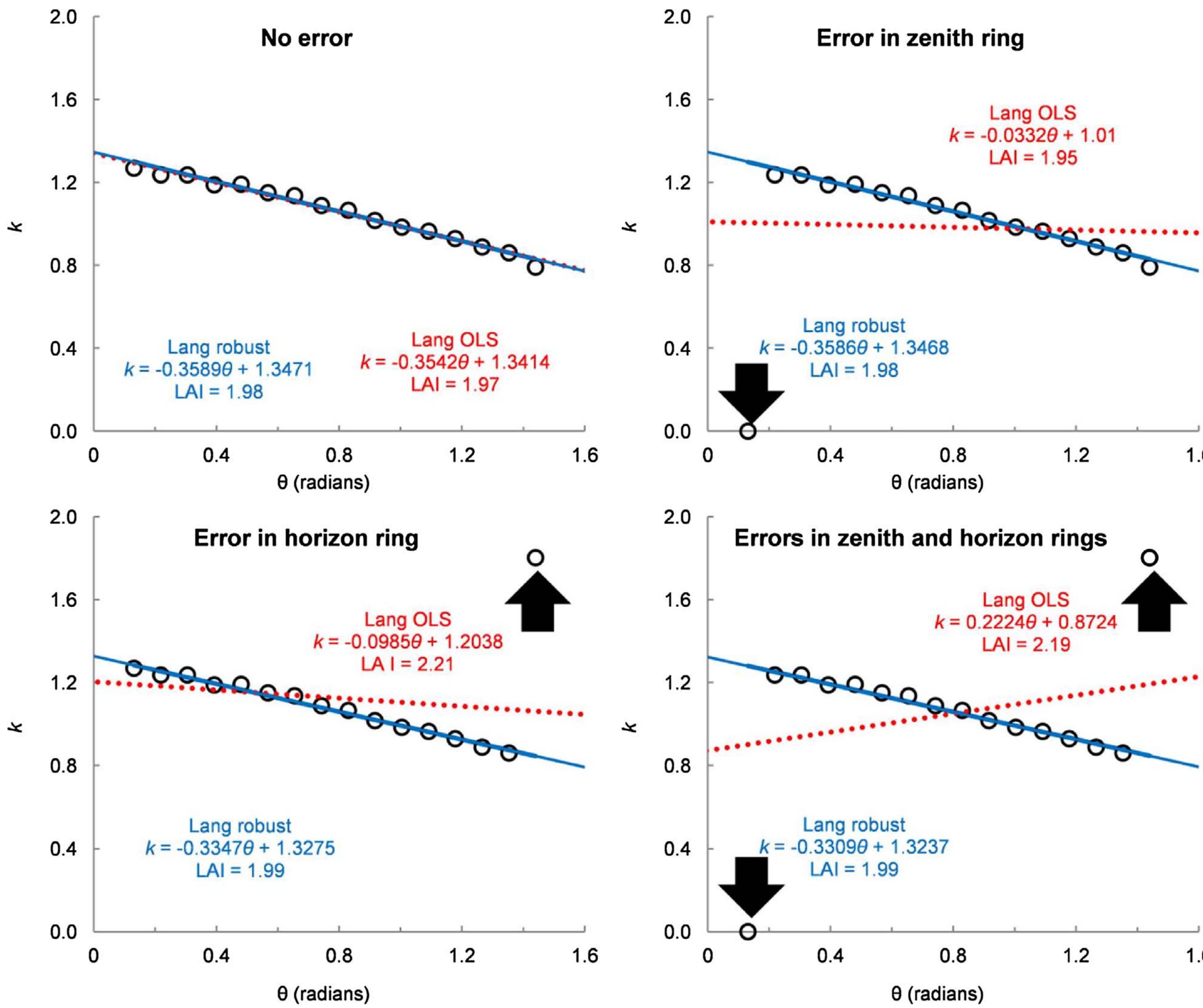

Fig. 5. Example illustration of the tolerance of Lang's ordinary least-squares OLS (Lang, 1987), and Lang's Robust (this study) algorithms for gap fraction errors in zenith (5°–10°), horizon (80°–85°), and both rings. The values of errors in contact numbers, *K*, are indicated with bold black arrow. This example demonstration is for simulated hemispherical photograph with reference leaf area index value of 2 and mean leaf angle of 46°. Errors are added arbitrarily by changing the actual gap fraction of zenith (5°–10°) ring into 0.99999 and horizon (80°–85°) ring into 0.0001 to demonstrate extreme cases of expected errors in hemispherical photograph based gap fraction observation at different regions of the hemisphere.

algorithms implemented into CIMES software over gap fraction data extracted from 5°–85° zenith angle ranges.

The Lang Robust procedure outperformed two other well established methods (Campbell and Miller), and the Lang OLS method, in that LAI from the Lang Robust procedure was more comparable to the reference LAI values (Fig. 4). LAI from Lang Robust procedure resulted in the smallest root mean square error (RMSE), bias and offset, and the regression slope was close to unity. Furthermore, varying MLA had the lowest effect on LAI estimated using the Lang Robust method compared to the other three methods (Fig. 4). We further tested the impacts of extreme outliers by arbitrarily changing the actual gap fraction of zenith (5°–10°) ring into 0.99999 and horizon (80°–85°) ring into 0.0001 to graphically illustrate the Lang Robust algorithm resistance to outliers. Fig. 5 demonstrates that the Lang Robust procedure is more tolerant to errors in zenith (5°–10°), horizon (80°–85°), and both rings than the Lang OLS method.

5. Tests with real hemispherical photographs

Real hemispherical photographs were collected in January 2010 from large range of contrasting forest fragments of Taita Hills, South-East Kenya (03°15′ to 3°30′ S, and 38°15′ to 38°30′ E) (Gonsamo and Pellikka, 2008). Due to lack of narrow view angle reference photometer, large range of canopy cover, and complex topography of the study areas, the photographs were taken 1–3 stops underexposed from the automatic exposure measured by the same lens as recommended by Zhang et al. (2005) and then visually selected for processing. The contrasting forest types include tropical cloud forest (open and closed canopies), riverine forest, plantation forest (*Cupressus*, *Eucalyptus* and *Pinus* spp.), and woodland (dense, sparse and evergreen). The raw photographs (n = 713) were collected using 12.3 megapixels Nikon D5000 SLR digital camera equipped with a Sigma 4.5 mm F2.8 fisheye lens adapter. To separate sky from foliage, an automated well-known global Ridler and Calvard's threshold was used. LAI was estimated the same way as for the simulate photographs, that is, using Campbell (Campbell, 1986), Miller (Miller, 1967), Lang's OLS (Lang, 1987), and Lang's Robust (this study) algorithms implemented into CIMES software over gap fraction data extracted from 5°–85° zenith angle ranges. We computed reference LAI using Miller's (Miller, 1967) algorithm for 55°–60° zenith angle ranges where the impact of different MLA on LAI estimation is minimal (see Gonsamo et al. (2010)).

Results of the performances of the four LAI estimation methods on real hemispherical photographs are presented in Fig. 6. Miller's method resulted in the best performance as compared to reference LAI

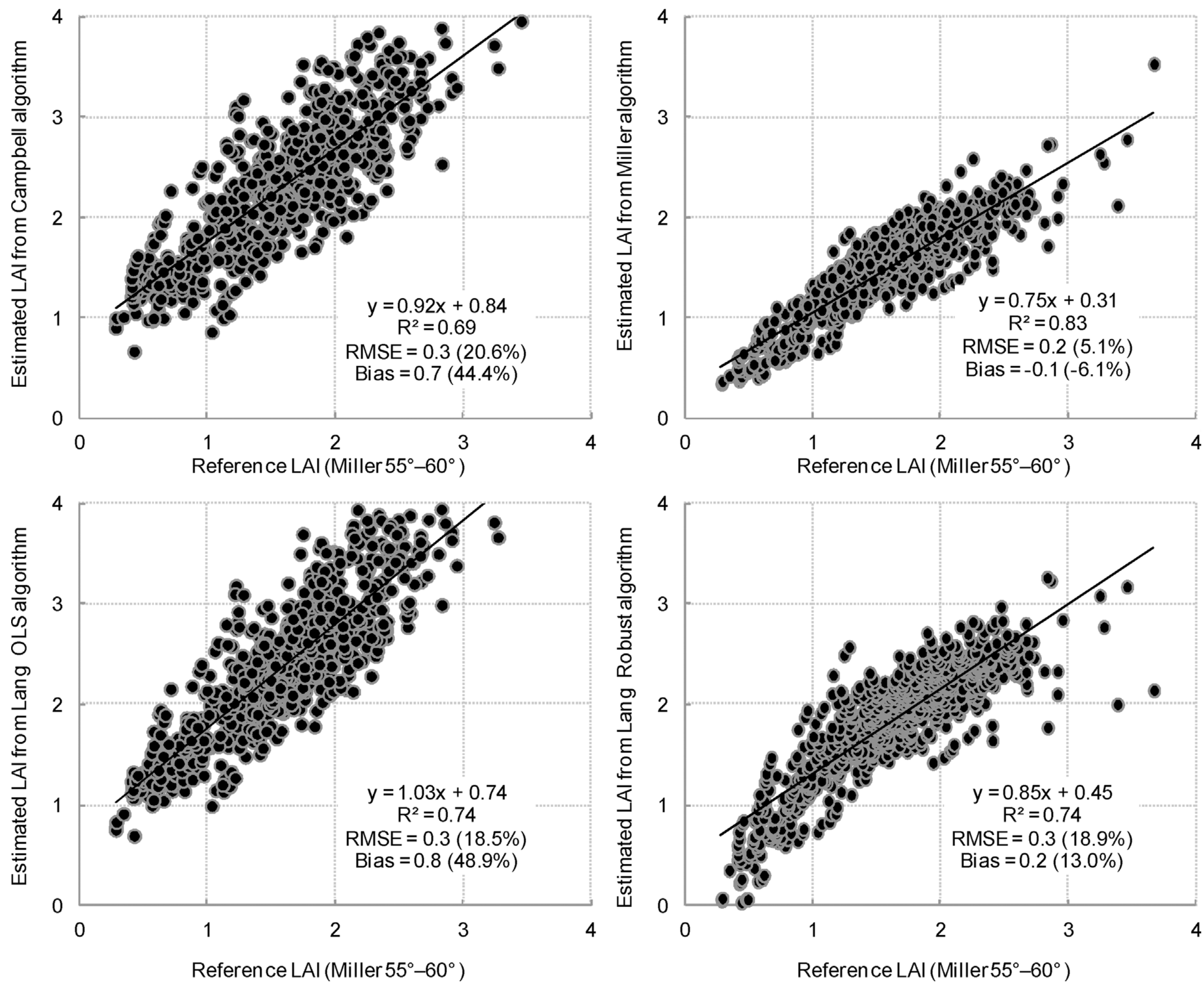

Fig. 6. Comparisons of the reference leaf area index (LAI: calculated using Miller algorithm for 55°–60°) with estimated values from Campbell (Campbell, 1986), Miller (Miller, 1967), Lang's ordinary least-squares OLS (Lang, 1987), and Lang's Robust (this study) algorithms for 713 real hemispherical photographs acquired from various forest types in Taita Hills, South-East Kenya (Gonsamo and Pellikka, 2008).

estimates. In the absence of independent measurements, it is important to note that Miller's algorithm for 55°–60° used as a reference is not statistically independent from Miller's algorithm for 5°–85° zenith angle range. Among the three remaining methods (i.e., Campbell, Lang OLS and Lang Robust), Lang Robust resulted in best performance given the other two produced biases above 40%. The Miller 55°–60° LAI offers reference measure because the relationship between LAI and gap fraction is independent of differences in MLAs. Nevertheless, the widespread scatter points between the reference and estimated LAI values in Fig. 6 are expected because of differences in spatial sampling from the limited field of view of 55°–60° and 5°–85° zenith angle range.

6. Discussion and conclusion

Responding to the need for new generation of robust LAI algorithms, we presented a practically convenient yet theoretically accurate method to retrieve LAI from gap fraction observations to an accuracy that is appropriate to the uncertainties in the collected data. Typical optical field instruments measure P_0 based on photographic information or radiation transmission through the canopy. The final true and "green" LAI measures from these instruments based on the P_0 are problematic due to the presence of non-photosynthetic canopy elements (including branches, stems, flowers and cones) and the complexity of canopy architecture in natural forest stands. The direct output of many optical field instruments is 'effective LAI' or 'effective plant area index' by assuming that foliage elements (including branches, stems, leaves, flowers and cones) are spatially randomly distributed. Therefore much effort and correction steps are needed to obtain the final true and green LAI. Both OLS and LAD regressions as applied to retrieve LAI are designed to estimate only effective LAI, and cannot be used to obtain canopy element clumping index nor to correct the contributions of non-photosynthetic canopy elements to LAI. Direct techniques through harvest and litter-collection result in true green LAI. On the other hand, effective LAI cannot be directly measured. Therefore, in this study, the performances of Lang OLS and Lang Robust regressions to estimate effective LAI were conducted using numerically derived hypothetical data and computer simulated hemispherical photographs for randomly distributed green leaves. Real measurements of hemispherical photographs were used to support performance evaluation of Lang Robust method relative to other well know methods (i.e., Campbell (1986), Miller (1967) and Lang (1987)).

Our approach is based upon a graphical procedure reminiscent of earlier works, i.e, LAI $= 2(A + B)$, where A and B are the coefficients of the regression of contact numbers against zenith angles. We have shown that deriving the coefficients (i.e., A and B) using a robust procedure is a better alternative than ordinarily least-squares regression to accurately estimate LAI. Since we have no direct measurements of LAI, we assessed the performance of the new robust procedure using numerically derived hypothetical data, computer simulated and real measurements of hemispherical photographs. We conclude from analyses using numerically derived hypothetical data, computer simulated and real measurements of hemispherical photographs that estimating A and B (where $\mathrm{LAI} = 2(A + B)$) using a robust procedure is a convenient and sufficiently accurate method for estimating LAI from field observations of gap fractions at different zenith angles.

The Lang Robust algorithm can be integrated into the existing software programs dedicated to each gap fraction measuring instruments such as, digital hemispherical photography, LAI-2200C Plant Canopy Analyzer, Tracing Radiation and Architecture of Canopies (TRAC), LIDAR, Inclined point quadrat, DEMON, and Ceptometer. Alternatively, the Lang Robust algorithm can be used once the gap fraction is compiled and the robust algorithm is implemented in any statistical software. For example, the Numerical Recipes for Least Absolute Deviations (LAD) estimator can be found in several computer languages under the routine name 'medfit' (Press et al., 1987). The Lang Robust LAI algorithm is included into HEMISFER (Schleppi et al., 2007; Thimonier et al., 2010) and CIMES software package of programs (Gonsamo et al., 2011) to analyse gap fraction data obtained from hemispherical photographs. Based on the robustness of LAD estimator shown in this study and together with the successful demonstration of a non-parametric (Theil–Sen) linear estimator for predicting biophysical parameters in the presence of measurement errors by Fernandes and Leblanc (2005), we recommend users of regression to test similar approaches in remote sensing and ecological studies. The Lang Robust method should be further investigated using realistic 3D simulated canopies and direct LAI reference measurements.

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