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Abstract. Remote sensing is currently an indispensable tool for retrieving the leaf area index (LAI) of forests. However, the applicability of remote sensing in retrieving LAI of forests in urban areas has not been thoroughly investigated. The ability of spectral and spatial information from IKONOS-2 imagery to retrieve LAI of forests was studied through analyzing the correlations of four commonly used vegetation indices (VIs) and four texture measures (TEXs) with LAI measured at different types of plots in the urban area of Nanjing, China and comparing the ability of models based on these parameters to estimate LAI of forests. The results show that VIs and TEXs calculated from the high-resolution remote sensing data are both applicable in retrieving LAI of forests in urban areas. The relative advantages of VIs and TEXs are related to the density and spatial regularity of forests. TEX exceeds VI for regularly planted low broad-leaf forests with low density owing to the deterioration of the linkage of VIs with canopy LAI caused by strong soil noise. For forests with moderate and high density, VI exceeds TEX in the retrieval of LAI. As to natural broad-leaf forests with high density and spatial complexity, combining VI and TEX can improve the accuracy of the retrieved LAI by 8.9% to 27.0%. VIs and TEXs are exclusive in retrieving LAI due to the intrinsic linkages of these parameters. The atmospherically resistant vegetation index over-perform other VIs in retrieving LAI of forests owing to its ability to constrain atmospheric disturbance on remote sensing data, which is serious and exhibits great spatial variability in the study area. © *2012 Society of Photo-Optical Instrumentation Engineers (SPIE).* [DOI: 10.1117/1.JRS.6.063556]

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1 Introduction

The spatio-temporal distribution of vegetations is a key factor affecting the exchanges of mass and energy on earth's surface. Therefore, the quantitative description of vegetation distribution is an ineluctable step in surface modeling of hydrological process, ecological development, and global change,[1–3] and a key measure in monitoring urban environments and urban growth.[4] Defined as one half of the total green leaf area per unit ground surface area,[5] leaf area index (LAI) is one of the widely used parameters representing vegetation distribution. Accurate and sufficient information on LAI has become a growing concern for more and more scientists engaging in environmental studies.

Compared to traditional methods measuring LAI on the ground surface, the remote sensing technique has the advantages of objectiveness, large coverage, and quick revisit, and is suitable for retrieving LAI at regional and global scales. Ideal estimation of LAI with remote sensing imageries has been implemented through the inversion of physical models based on sun-object-sensor geometry and radiative transfer processes,[6,7] but the intrinsic complexity of the models and the possible non-astringency of the inversion have long baffled the application

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of those models. Accordingly, another method, which is based on LAI-spectrum relationships, has been universally experimented in LAI estimation over a long period of time.[8–11] In LAI-spectrum relationship researches, vegetation indices (VIs), such as the normalized difference vegetation index (NDVI),[12] were most widely used for estimating LAI. As mathematical operations of typical bands (e.g., red and near-infrared) related to vegetation features, VIs can strengthen vegetation information, and eliminate atmospheric effects to some degree, but they are essentially still discrete gray values. These gray values reflect spectral intensity of discrete ground surface which corresponds to pixels on the image, and are inescapably influenced by background information and vegetation structures. Such influences are hard to be indicated through spectral intensity and will result in saturation effects in applications.[13,14] Spatial structures of forests can not be effectively described by VIs, because VI derived from near-nadir viewing remote sensing imageries only presents the horizontal expression of a stand. Stands with varying vegetation composition and structures may have similar VI values.[15]

Spatial variations of the gray values among adjacent pixels might be used to describe various structures of forests. The universally used indices to indicate such spatial variations are texture measures. Texture is the spatial variability of image tones and describes the relationship between elements of surface cover.[15] There are two main classes of texture measures: the first order (occurrence), and the second-order (co-occurrence) statistics.[16] The first-order statistics are derived from the histogram of pixel intensities in a moving window, but ignore the spatial relationship of pixels. The second-order statistics are calculated from the gray level co-occurrence matrix (GLCM), which indicates the probability that each pair of pixel values co-occurs in a given direction and distance.[17,18] Other methods used to calculate image texture include semi-variograms, Fourier transform, and fractal dimensions.[16,19,20] The first and second texture measures are most commonly studied. Typical texture measures like dissimilarity, contrast, and correlation were experimented in the estimation of forest structures. The effects of window size, displacement, and direction chosen on estimated forest parameters were also investigated.[21,22] Literatures are increasing on the applications of texture measures in image classification and segmentation,[23–25] stand structures inversion,[26,27] landscape metrics prediction,[28] and bird habitats description.[29] Studies have also been conducted to map forest LAI using texture measures. Wulder et al.[15] reported that inclusion of additional texture into the empirical LAI estimation model based on NDVI will increases R^2 from 0.42 to 0.61 for hardwood forests, and from 0.19 to 0.93 for softwood stands. Similarly, Colombo et al.[21] demonstrated that NDVI alone can only explain 33% of LAI variations among all plots while NDVI and texture information together can increase this number into 62%. Furthermore, the relationships of both LAI-NDVI and LAI-(NDVI and Texture) vary with vegetation types. These researches are instructive for integrating vegetation index and texture measure in LAI estimation, but the estimation in urban areas with particular vegetations and environments are much less documented.

In this study, LAI of forests with different structures were *in situ* measured in the urban area of Nanjing city, China, and then related to vegetation indices and texture measures. Single/multi-variable based linear regression models were established, to test the effectiveness of high spatial resolution images for estimating LAI of forests in urban areas, and whether texture measures can help improve the estimation of LAI.

2 Materials and Methods

2.1 *Study Area and Data Used*

The study was conducted at Purple Mountain and Qingliang Mountain in the urban area of Nanjing city, China (118° 38' E, 31° 56' N) (see Fig. 1). The north subtropical monsoon climate prevails here, with an annual mean temperature of 15.1°C, and annual mean precipitation of 1019 mm. Field LAI measurements were carried out at four forest sites in Purple Mountain (25 km^2) and two forest sites in Qingliang mountain (1 km^2). The sampling plots are all located at lower parts of the hills with a slope <15 deg. Forest plots were grouped into three types. They are planted low broad-leaf forest (PLB), planted mature forest (PMF), and natural broad-leaf forest (NBF), in the order of tree ages from several years to several decades, of tree heights

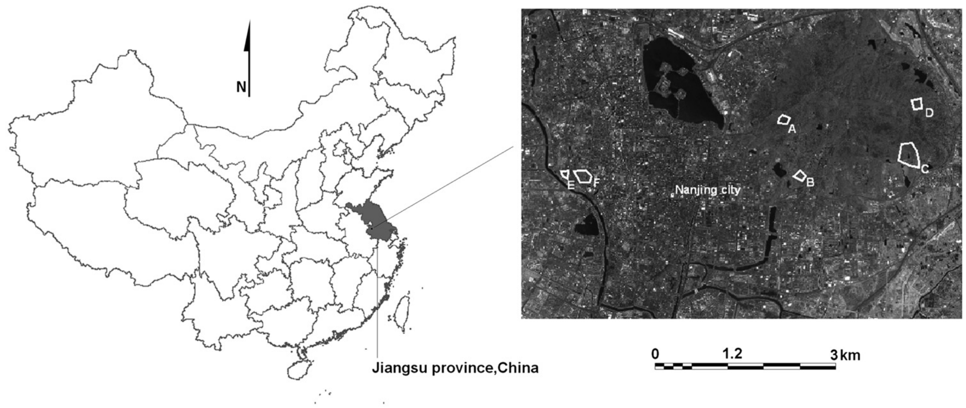

Fig. 1 Study area and sampling plot locations. A, B, C, D, E, and F are plots measured in this study. The background is a subset of panchromatic IKONOS-2 imagery acquired on June 18th, 2009.

from about 3 to 20 m, and of vegetation distribution regularities from high to low. Trees of PLB and PMF are located on sites B and C (see Fig. 1). They were planted four to eight years ago, and all trees on site C were planted in rows, nearly at the same height of about 3 m. Natural forests of NBF on sites A, D, E, and F have grown for about 40 years without significant disturbances. They have relatively complex vertical and horizontal structures, dominated by broad-leaf trees, together with various kinds of understory shrubs and grasses. The tree species in the planted forests are mainly *Acer palmatum* Thunb, *Photinia serrulata* Lindl, and *Liquidambar formosana*, in natural forests are mainly *Sophora japonica*, *Cinnamomum camphora*, *Pterocarya stenoptera*, and *Cyclobalanopsis glauca*, etc. The statistics of forests at different plots are summarized in Table 1.

An IKONOS imagery acquired on June 18, 2009 was used in this study, including one Panchromatic (1-m resolution) band and four multispectral (4-m resolution) bands. Overall cloudy coverage of this imagery is less than 10%. None of the sampling plots were affected by clouds. A 1:10 000 scale relief map was used as a benchmark to implement geometrical correction of the IKONOS imagery.[30]

2.2 *Field Measurement of LAI*

Sampling plots for measuring LAI were selected according to stand homogeneity, accessibility, and a cloud-free image.[22] One to twenty-three plots (15×15 m^2) were set in each site. There are in total 52 plots at which LAI was measured, with 18, 13, and 21 measurements taken for PLB, PMF, and NBF, respectively (see Fig. 1, Table 1). The precise locations of the plots were recorded using a Starlink Invicta 210 global positioning system (GPS) receiver (RAVEN Industries, INC).

LAI measurements were taken in early October, 2010 using the LAI-2000 instrument under diffuse radiation conditions. The 16-month lag of the ground measurement to the IKONOS

Table 1 Summary of sampling plots. PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest. A, B, C, D, E, and F denote sampling sites, and the numerical numbers beside them are the numbers of plots in which LAI was measured. LAI = leaf area index, TH = tree height, and STD = standard deviation.

Plot type	Sample site	Mean LAI	STD of LAI	Mean TH (m)	STD of TH (m)
PLB	B4, C14	2.57	0.95	3.1	0.4
PMF	B4, C9	4.45	1.08	8.3	3.7
NBF	A3, D5, E4, F9	5.60	1.32	17.8	7.5

imagery acquirement was mainly due to the availability of the IKONOS imagery in the study area. In order to constrain the effect of such time lag on the estimation of LAI, plots were carefully selected with a criterion that without significant changes of forests occurred during this time. In the study area, forests start to grow in early April and the leaf fall starts in the middle of November. During the period from early middle May to early November, LAI of forests changes marginally. So, the effect of time difference between remote sensing acquisition and LAI measurement on the relationships of LAIs with VIs and texture measures might be assumed small and ignored. In the measurement of LAI, two LAI-2000 plant canopy analyzers (Li-COR, Lincoln, NE) were operated in remote data acquisition mode. One LAI analyzer was positioned in an open site close to the sampling sites, to collect reference-sky readings, while the other was carried into each plot to measure light transmission through the canopy. Both LAI analyzers were covered with a 270 deg view cap. About 5 to 8 below-canopy samples were taken at points distanced about 2 to 3 m along two parallel transects spaced by 10 m. The LAI value of a plot was calculated by averaging measurements at all spots inside it.

2.3 *Image Preprocessing and VI and Texture Calculations*

Geometrical correction was made with 22 ground control points acquired from a 1 : 10 000 scale relief map using a quadratic polynomial model. The corrected image was re-sampled using the nearest neighbor method. The overall root mean square error of the geometrical correction was constrained to be smaller than 1 pixel. Radiometric correction was conducted using the method described in Gu et al.[31] The digital number image was radiometrically calibrated to at-sensor radiance to eliminate errors caused by the sensor. Then the apparent reflectance was calculated using the absolute calibration gains and was calibrated to scaled surface reflectance using a dark object subtraction approach.[32] The near-infrared (N), red (R), and blue (B) band reflectance values of each plot was extracted from the surface reflectance images for calculating different vegetation indices. To constrain the influences of inherent geometric correction errors, a 10-m buffer around each plot center was made, and the individual band values corresponding to each plot were acquired by averaging the values of all pixels in the buffer. Four VIs which are universally used were selected to analyze the relationships with LAI (see Table 2). They are normalized difference vegetation index (NDVI),[12] ratio vegetation index (RVI),[33] soil adjusted vegetation index (SAVI),[34] and atmospherically resistant vegetation index (ARVI).[35]

To study the spatial variations of the pixel gray values and their correlations with stand LAIs, two 1st and two 2nd order texture measures were derived from the panchromatic band of the image. The 1st order texture measures are range (A) and entropy (E). The 2nd order ones are variance (V) and angular second moment (S). The formulae of these measures are listed in Table 3, and detailed introduction can be found on the website (http://fp.ucalgary.ca/mhallbey). The gray level was set at 64, the displacement at 1, and the direction at 0, 45, 90, and 135 deg and then the results in four directions were averaged for further analysis. Window size was set as 13×13, about 10×10 m, similar to the 10-m buffer in which VIs were derived. The image processing was implemented on the platform of ENVI version 4.5 (Research Systems, Inc.).

Table 2 Spectral vegetation indices used in LAI estimation. N, R, and B represent the reflectance of near-infrared, red, and blue bands of the IKONOS data. Parameters a, c, L, and γ regard, respectively, the gain and the offset of the soil line, the SAVI term (set equal to 0.5), and the ARVI term (set equal to 1).

Vegetation index	Algorithm	Reference number
Normalized difference vegetation index (NDVI)	$\mathrm{NDVI} = \frac{N-R}{N+R}$	12
Ratio vegetation index (RVI)	$\mathrm{RVI} = \frac{N}{R}$	33
Soil adjusted vegetation index (SAVI)	$\mathrm{SAVI} = \frac{N-aR-c}{N+R+L}(1+L)$	34
Atmospherically resistant vegetation index (ARVI)	$\mathrm{ARVI} = \frac{N-rb}{N+rb}$; $rb = R - \gamma(B-R)$	35

Table 3 Image texture description and formula.

Type of measures	Texture measure	Formula[15]
1st order measures	Range (A)	$A = \max\{X\}\text{-}\min\{X\}$ where $X = x_1, x_2, \ldots, x_k$, and k = number of gray tone values
	Entropy (E)	$E = -\sum_k x_k \ln(x_k)$
2nd order measures	Variance (V)	$V = \sum_{i,j=0}^{N-1} (i-\mu_i)^2 p(i,j)$ where, $\mu_i = \sum_i \sum_j ip(i,j)$, $p(i,j)$ is the $(i',j')^{\text{th}}$ entry of the normalized GLCM matrix $= p(i,j)/r$, where r is a normalizing constant, and N is the number of gray levels
	Angular second moment (S)	$S = \sum_{i,j=0}^{N-1} \{p(i,j)\}^2$

2.4 *Establishment and Validation of Models Estimating LAI*

Correlations of LAI with vegetation indices and with texture measures were analyzed for PLB, PMF, and NBF, respectively. Then single- and multi-variable based linear regression models were established with VIs or/and four texture measures (TEXs) as predictors. The performance of established models was assessed according to their determination coefficients. For LAI-VI single-variable models, each of the four vegetation indices was individually used as the predictor. For LAI-VI multi-variable models, all VIs were together used as candidate predictors. Similar procedures were carried out for the LAI-TEX models with four TEXs as potential predictors. All of four VIs and four TEXs were together used as the candidate predictors for establishing the LAI-(VI &TEX) multi-variable models. The stepwise regression method was used to select predictors for the multi-variable based models. The stepping method criteria was the probability of F value, namely, a variable is entered into the model if the significance level of its F value is less than the Entry value 0.05 and is removed if the significance level is greater than the Removal value 0.1.

To further validate the optimal models for each forest type with limited measured plots, the error of each linear regression model based on VIs or/and TEXs selected in the models was computed through a leave-one-out cross-validation method. In this method, the model i is established with all measured points except point i, which acts as a "true" value for the model validation, and the i alternate from 1 to n, the total number of the measured points. Leaving one plot in turn, the linear regression models of LAI with VI or/and TEX selected in the optimal models were established for each plot. The model error for each plot was then computed by relative error (RE) using Eq. (1):

$$\text{RE} = Abs(E_i - M_i) \times 100\%/M_i, \tag{1}$$

where E_i and M_i are estimated LAI and measured LAI of plot i. The statistical analyses were mainly performed using SPSS, version 17.0 (SPSS Inc., USA).

3 Results

3.1 *Correlations of LAI with VIs and TEXs*

LAIs of all plots were positively related to VIs [see Fig. 2(a)]. The correlation coefficient (r) between PMF LAI and ARVI is the highest one ($r = 0.935$, $p < 0.001$) among all correlation coefficients between LAI and VIs while the r between NBF LAI and RVI is the lowest one ($r = 0.556$, $p < 0.01$). The correlation coefficients between LAIs of planted forests (PLB and PMF, especially PMF) and VIs are all higher than those of natural forests (NBF). For each forest type, there are VIs like ARVI and NDVI correlated well with LAI, indicating the possibilities of using VIs to estimate LAI for these forest types.

LAI was found to correlate with texture measures, positively or negatively. Only the absolute values of correlation coefficients were described for short [see Fig. 2(b)]. LAI-TEX correlation

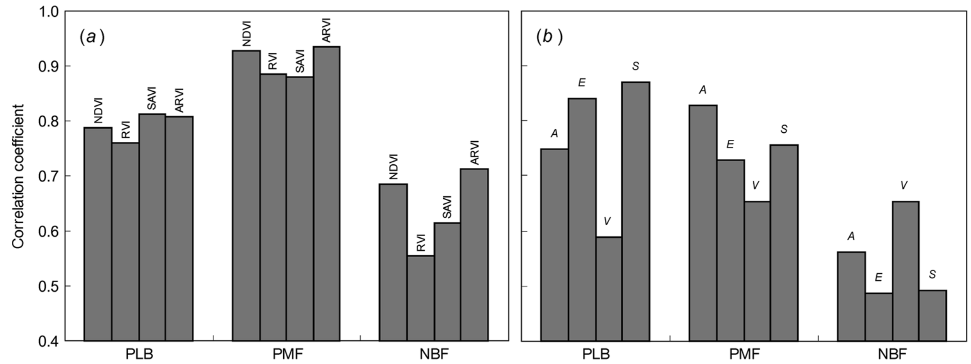

Fig. 2 Correlation coefficients of LAI with (a) vegetation index, and (b) texture measure. The formulae for vegetation indices and texture measures are given in Tables 2 and 3, respectively. The correlation coefficients between LAI and *S* are negative and their absolute values are shown here. Forest types: PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest.

coefficients vary from 0.491 ($p < 0.05$) between NBF LAI and E to 0.87 ($p < 0.001$) between PLB LAI and S. The correlation coefficients between LAIs of planted forests and TEXs are all above 0.7 except for the 2nd texture variance V, which correlates, however, higher with NBF LAI ($r = 0.654$, $p < 0.01$) than other TEXs, indicating the potentials of TEXs in LAI estimation for both planted and natural forests.

3.2 *Models Predicting LAI Based on VI*

For each forest type, the LAI-VI scatter plots and their single-variable linear regression models are shown in Fig. 3. The mean R^2 of four models for each forest type is in the rank of PMF(0.8225) > PLB(0.6267) > NBF(0.4133), showing the LAI-VI models are most reliable for forests with moderate densities (see Table 1). The standard deviations of R^2 are in the order of NBF(0.0865) > PMF(0.0514) > PLB(0.0366), indicating the sensitivity of estimated LAI of mature forests to VI choice due to their high density and complicated structure (see Table 1).

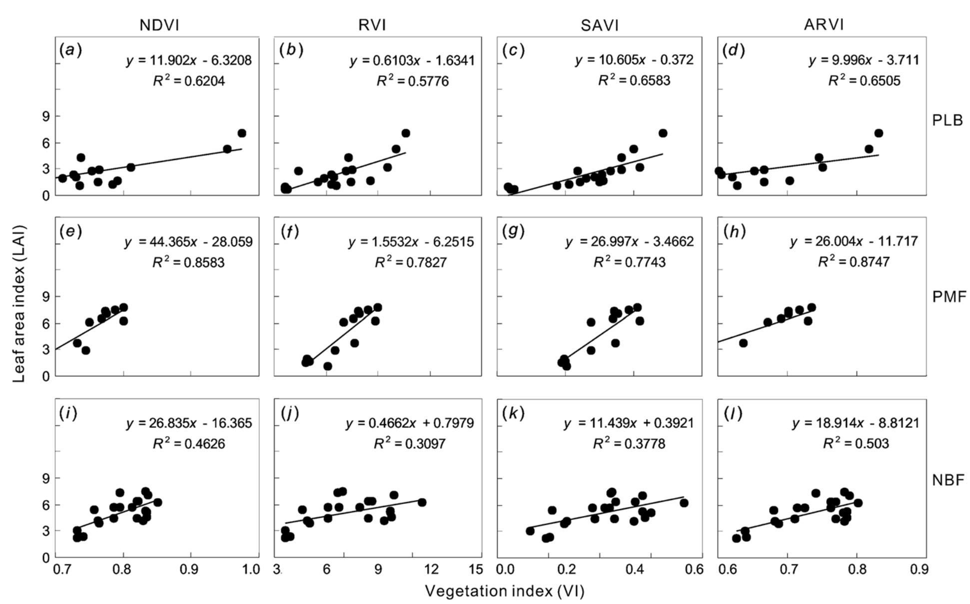

Fig. 3 Relationships between LAI and vegetation index. Plots on each column are based on the same vegetation index, and on each row are for the same forest type. The formulae for vegetation indices are given in Table 2. Forest types: PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest.

Table 4 The best models for estimating LAI based on single or multiple vegetation indices. The formulae for vegetation indices are given in Table 2. Forest types: PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest.

Model type	Plot type	Model	R^2	Sig.	Model No.
Single-variable	PLB	LAI = 10.605 (SAVI) – 0.372	0.658	0.001	1
	PMF	LAI = 26.004 (ARVI) – 11.717	0.875	0.001	2
	NBF	LAI = 18.914(ARVI) – 8.8121	0.503	0.01	3
Multiple-variable	PLB	Same as 1			
	PMF	Same as 2			
	NBF	LAI = 50.017 (ARVI) – 1.028 (RVI) – 22.22	0.608	0.01	4

In other words, cautions must be taken in selecting VIs to estimate LAI for natural forests with high vegetation density, while for planted forests with moderate or low vegetation density, the selection of VIs is not too critical.

Multi-variable based linear regression models were established using four VIs as candidate predictors for each forest type. As for PLB and PMF, the resultant models are the same as models with one VI as the candidate predictor: model 1 for PLB and model 2 for PMF, respectively (see Table 4), indicating the limited cooperation among VIs in LAI estimation for the planted forests. For NBF a new model was established [see model 4 in Table 4]. The addition of RVI as another predictor increases the R^2 value by 10% compared with model 3, the best single-variable model for this forest type.

3.3 *Models Predicting LAI Based on TEX*

The LAI-TEX plots and linear regression models for each forest type are similar to those of LAI-VI (see Fig. 4). PLB has the highest mean R^2 of four models using individual texture measure as the single predictor (0.5934), followed by PMF (0.5539) and NBF (0.3113), showing that

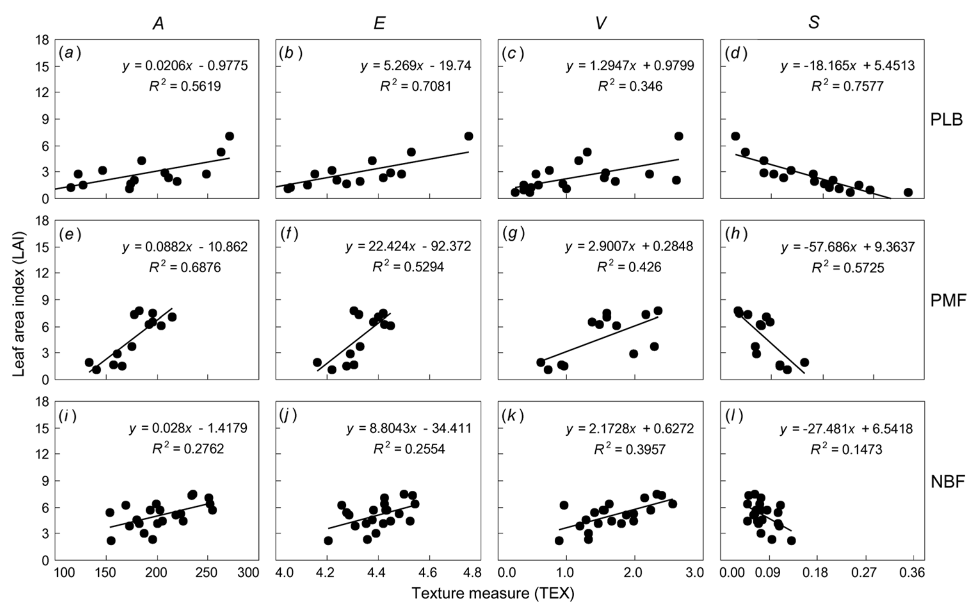

Fig. 4 Relationships between LAI and texture measure. Plots on each column are based on the same texture measure, and on each row for the same forest type. The formulae for texture measures are given in Table 3. Forest types: PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest.

Table 5 The best models for estimating LAI based on texture measures.*

Plot type	Model	R^2	Sig.	Model No.
PLB	$\mathrm{LAI} = -18.165\,S + 5.4513$	0.758	0.001	5
PMF	$\mathrm{LAI} = 0.0882\,A - 10.862$	0.688	0.001	6
NBF	$\mathrm{LAI} = 2.0652\,V + 1.5823$	0.428	0.05	7

*These models are established with individual texture measures as a single predictor. The models established with all texture measures together as candidate predictors are the same as the model listed in the above table for all types of forests. The formulae for texture measures are given in Table 3. Forest types: PLB = planted low broad–leaf forest, PMF = planted mature forest, and NBF = natural broad–leaf forest.

the applicability of TEXs in estimating LAI depends on the regularity of vegetation distribution. The standard deviations of R^2 are in the order of $\mathrm{PLB}(0.1847) > \mathrm{PMF}(0.1083) > \mathrm{NBF}(0.085)$, indicating the importance of properly selecting TEXs as the predictor of LAI for PLB which has high regularity of vegetation distribution. The single-variable models based on TEXs are listed in Table 5. The best predictor for PLB is the second order texture measure S. The R^2 value of this model based on this parameter is 0.758, higher than the value 0.658 of the best VI-based model. However, the R^2 values of the best TEX-based models are 0.688 and 0.428 for PMF and NBF, respectively, slightly lower than the corresponding values of the best VI-based models. Therefore, TEX-based models can be established for all types of forests, especially for forests with low density and regular spatial distribution.

When all TEXs were used as predictors of LAI to establish multi-variable models using the stepwise regression method, the resultant models are same as single- variable models for PLB, PMF, and NBF (see Table 5). This indicates that one TEX indicator can dominate others in predicting LAI for a specific type of forests. The TEX indicators should be carefully determined using field measurements of LAI if they are employed for mapping LAI of forests with different degrees of vegetation regularity.

3.4 *Models Predicting LAI Based on Both VI and TEX*

In order to investigate the potential of combining VIs with TEXs to improve the estimation of LAI, multi-variable regression models were established with all VIs and TEXs together as possible predictors. For PLB, the resultant model is same as model 5 in which the second order texture measure of variance S is the sole predictor, while the resultant model of PMF is same as model 2 using ARVI as the only predictor (see Tables 4 and 5). For NBF, a new model based on both VIs and TEXs was successfully established, indicating the effectiveness of combining VIs and TEXs in LAI estimation for such type of forests with high vegetation density and complicated vegetation structure. The model is Eq. (2) as shown below:

$$\mathrm{NBF{:}\ LAI} = 14.44(\mathrm{ARVI}) + 1.433V - 7.951 \qquad (\text{Adjusted } R^2 = 0.697,\ p < 0.01), \tag{2}$$

where ARVI means the atmospherically resistant vegetation index, and V is the 2nd texture measure of variance.

The performance of Eq. (2) exceeds that of model 4 based on ARVI and RVI and model 7 solely based on V. The (adjusted) R^2 of Eq. (2) is 9% and 27% higher than that of model 4 and model 7, respectively, indicating that the cooperation of VIs and TEXs can effectively improve the retrieval of LAI for this type of forests.

3.5 *Validation of Optimal Models*

As shown in above analyses, model 5, model 2, and Eq. (2) are the best models in LAI estimation for the three forest types PLB, PMF, and NBF, respectively. To further analyze the reliability of the models, the relative error (RE) for each plot was computed with the VI or/and TEX selected in each of the three models, using the leave-one-out method described in Sec. 2.4. Results show

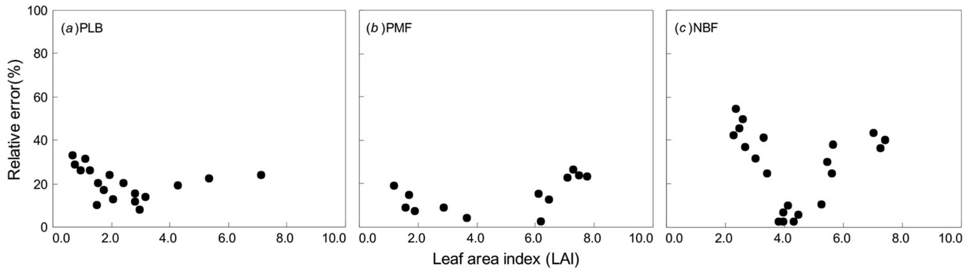

Fig. 5 Model relative error (RE) versus leaf area index (LAI). The RE was calculated using the leave-one-out method, with the vegetation indices or/and texture measures selected in model 5, model 2, and Eq. (2), the best models in LAI estimation for (a) PLB, (b) PMF,and (c) NBF, respectively. Forest types: PLB = planted low broad-leaf forest, PMF = planted mature forest, and NBF = natural broad-leaf forest.

that (see Fig. 5), REs corresponding to each forest type present a similar distribution trend: REs are all near the least when LAIs are close to 4, while for LAI < 4 and LAI > 4 REs decrease and increase, respectively, with increasing LAI, and REs for NBF change more quickly than the other two types. This indicates that either VI or TEX performs best in LAI estimation for forests with moderate LAI (= 4), moreover, the combination of the VI and TEX in LAI estimation for the natural forest type NBF leads to REs more quickly changed with increasing LAI when either LAI < 4 or LAI > 4. The average RE of PMF is 14.7%, lower than PLB (20.4%), and of NBF is the greatest (27.6%), showing that the accuracy of LAI estimation for planted forests with VI or TEX is higher than 80%, and for complex natural forest with the combination of VI and TEX the accuracy is higher than 70%.

4 Discussion

The above analysis indicates that it is practically feasible to estimate LAI in an urban area using VIs or/and TEXs calculated from high spatial resolution remote sensing data. The ability of VIs and TEXs to estimate LAI in the current study area is related to the density and spatial regularity of forests.

4.1 *Ability of Different Vegetation Indices to Retrieve LAI*

Vegetation indices represent mainly the spectral intensity, which is usually influenced by vegetation density and environmental noises. The correlations of LAI with VIs are more significant for PMF with moderate vegetation density than for PLB and NBF (see Table 1, Fig. 2). This is mainly due to the proper vegetation density of PMF, which can limit the influence of background noise and saturation problem of remote sensing signal in dense canopies. The vegetation density of PLB is low and remotely sensed signals are more seriously affected by background reflectance, which weakens the relationship of LAI with VIs. The dense canopies of NBF easily dampen the sensitivity of VIs to changes of LAI. The mean R^2 values of models for three different types of forests based on each VI are in the order of ARVI(0.676) > NDVI(0.647) > SAVI(0.603) > RVI(0.557), indicating that ARVI exceeds other VIs for estimating LAI in our urban study area, over which the atmosphere is more polluted and heterogeneous than that in rural areas. Atmospheric correction is of critical importance under this circumstance. For PLB, the performance of SAVI exceeds that of ARVI to some extent [see Fig. 3(c) and 3(d)] owing to the ability of SAVI to limit the disturbance of background noise, which is strong when canopy density of forests is low. The standard deviations of R^2 of models for three different types of forests based on each VI rank as RVI(0.237) > SAVI(0.204) > NDVI(0.199) > ARVI(0.187), indicating the stable ability of ARVI and NDVI to estimate LAI of different types of forests in the study area. Although the models based on RVI and SAVI has satisfied ability to estimate LAI for PLB and PMF, their performance is quite poor for NBF (see Fig. 2).

4.2 *Ability of Different Texture Measures to Retrieve LAI*

Texture measures indicate the spatial variations of the gray values among adjacent pixels, so they are closely related to vegetation spatial distributions. For planted forests regularly distributed like PLB and PMF, the texture measures *S*, *E*, and *A* perform well in LAI estimation [see Figs. 2(b) and 4]. For irregularly distributed NBF, the texture *V* performs obviously better than other measures [see Figs. 2(b) and 4(k)]. We argue that texture measures can be grouped into two types, regularity and irregularity indicators, and have different potentials for LAI estimation in planted and natural forests with different regularities. The R^2 values of the models for three types of forests based on *S* and *A* averaged for three forest types are 0.528 and 0.524, respectively, higher than the corresponding values of *E* (0.493) and *V* (0.4). The standard deviation of R^2 of the models for three forest types based on *S* is 0.254, followed by the values of models based on *E* (0.236), *A* (0.186), and *V* (0.047), indicating the ability of different texture measures to estimate LAI depends on forest types. *S* and *A* are the best predictors of LAI for PLB and PMF, respectively. *V* performs better in estimating LAI for NBF than other texture measures. However, it is the worst predictor of LAI for PLB and PMF. *E* is second only to *S* in estimating LAI for PLB and the worst predictor of LAI for NBF.

4.3 *Strategy for Selecting the Predicators of LAI*

VIs and TEXs correspond to the intensity and spectral variations of the spectrum, and can be used to represent density and spatial distribution characteristics of vegetations, respectively. The dominance of the two characteristics (density and spatial distribution) varies with forest types, resulting in different performances of VIs and TEXs in estimating LAI of different types of forests. Therefore, the effective spectral or texture parameters for LAI estimation should be carefully determined according to vegetation density and distribution. The appropriate predictor for estimating LAI of PLB is texture measure, such as *S* in this study [see model 5, Fig. 4(d)] owing to the obvious spatial regularity of this type of forest. The selected model based on vegetation index (model 1) is also acceptable. Nevertheless, the dominance of vegetation characteristics of this type of forests is the regular distribution. Consequently, TEXs can perform better than VIs. R^2 of the best model with a texture measure (*S*) as predictor (model 5) is 10% higher than that of the best model with a vegetation index (SAVI) as the predictor (model 1).

For PMF with moderate density and spatial regularity, the properties of both density and distribution facilitate LAI estimation. The R^2 values of the best models based on vegetation index (model 2) and texture measures (model 6) are both above 0.65. The R^2 value of model 2 is 19% higher than that of model 6, indicating VI is more suitable for estimating its LAI than TEX owing to the dominance of vegetation density over texture measure for this type of forests. For PLB and PMF, VIs and TEXs cannot be simultaneously selected as the predictors of LAI in a model.

For NBF with higher vegetation density and complicated vegetation distribution, VI and TEX are individually unable to estimate LAI accurately as for PLB and PMF [see Figs. 3 and 4]. The R^2 value of Eq. (2) based on both ARVI and *V* is 8.9% higher than the corresponding value of the best model based on VIs (model 4) and 27.0% higher than that of the best model based on TEXs (model 7), indicating the promise of combining the information on density and spatial distribution for mapping LAI of dense forests where vegetations are irregularly distributed.

5 Conclusions

In this study, the applicability of vegetation indices and texture measures calculated from high-resolution data in retrieving LAI of forests in an urban area was investigated. The following conclusions can be drawn:

(1) Both vegetation indices and texture measures can be used to retrieve LAI of forests in urban areas. Their ability to retrieve LAI is related to the density and spatial regularity of forests, good for moderate LAI (near 4), and poor under the condition of forests with high density and complex spatial structure.

(2) The relative advantages of vegetation indices and texture measures in retrieving LAI of forests also vary with the density and spatial regularity. Texture measures exceed the vegetation index in retrieving LAI of forests with low canopy density and regular spatial structure, in which soil background noise is strong and deteriorates the linkage of remote sensed signals with canopy LAI.

(3) Both vegetation indices and texture measures are strongly exclusive in retrieving LAI of forests, partially due to intrinsic correlations among different vegetation indices and among different texture measures. For PLB and PMF with low to moderate density and spatial complexity, only one vegetation index or one texture measure can be selected as the predictor of LAI, even all VIs and TEXs were separately and together used as candidate model predictors.

(4) In this study, LAI of forests were measured in two separate locations of the urban area of Nanjing city, China, in which atmospheric noise is serious and heterogeneous. ARVI performs better than other VIs in retrieving LAI, indicating the importance of proper atmospheric correction in mapping LAI of forests in urban areas.

The above conclusions are valuable for properly determining parameters calculated from high resolution remote sensing data for reliably mapping LAI of forests in a small region, which can be used as the benchmark for validating regional and global LAI products at moderate resolutions and to study the response of forests to global change and disturbances. However, it should be kept in mind that they are based on the LAI measurements and remote sensing data in a specific urban area. Their robustness needs further investigation.

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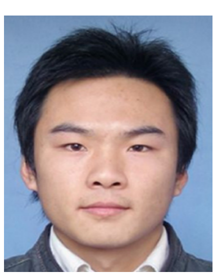

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