Bidirectional texture function of high resolution optical images of tropical forest: An approach using LiDAR hillshade simulations

Nicolas Barbier a,b,⁎, Christophe Proisy a, Cédric Véga c, Daniel Sabatier a, Pierre Couteron a

Abstract

Quantifying and monitoring the structure and degradation of tropical forests over regional to global scales is gaining increasing scientific and societal importance. Reliable automated methods are only beginning to appear; for instance, through the recent development of textural approaches applied to high resolution optical imagery. In particular, the Fourier Transform Textural Ordination (FOTO) method shows some potential to provide non-saturating estimates of tropical forest structure, including for large scale applications. However, we need to understand more precisely how canopy structure interacts with physical signals (light) to produce a given texture, notably to assess the method’s sensitivity to varying sun-view acquisition conditions. In this study, we take advantage of the detailed description of canopy topography provided by airborne small footprint LiDAR data acquired over the Paracou forest experimental station in French Guiana. Using hillshade models and a range of sun-view angles identical to the actual parameter configurations, we introduce the bidirectional texture function, which summarizes these effects, and in particular the existence of a textural ‘hot spot’, similar to a well-known feature of bidirectional reflectance studies. For texture, this effect implies that coarseness decreases in configurations for which shadows are concealed to the observer. We also propose a method, termed partitioned standardization, that allows mitigating acquisition effects and discuss the potential for an operational use of VHR optical imagery and the FOTO method in the current context of international decisions to reduce CO2 emissions due to deforestation and forest degradation.

© 2010 Elsevier Inc. All rights reserved.

1. Introduction

Assessing the biophysical parameters of tropical forests is becoming an important economic and political endeavor, notably because of the role of these ecosystems in the carbon cycle (IPCC, 2007; Lewis et al., 2009; Malhi et al., 2008; Wright, 2005). Canopy structure, in particular, is an essential feature because it regulates the microclimate, e.g., light and moisture levels (Cochrane, 2003), within the forest as well as the interactions between the forest and the macroclimate through the exchange of energy, water vapor and other gases with the atmosphere (Bonan, 2008). The size distribution of tree crowns and the spacing between them is thought to be linked allometrically to a number of dynamical and structural forest parameters such as recruitment and mortality rates, trunk diameter distribution and biomass (Chave et al., 2005; Enquist et al., 2009). Canopy structure also reflects disturbance history and the level of forest degradation (Weishampel et al., 2007). Obtaining precise information about the structure of a forest’s ‘folded surface’ (Birnbaum, 2001) could help advance various activities spanning the quantification of forest degradation, carbon stocks and dynamics, the water cycle and forest resilience to natural hazards, such as fire and invasive species.

Remote sensing data and methods have been successfully used to characterize and monitor forest structure and biomass in temperate and boreal ecosystems. However, repetitively assessing high biomass levels and complex structures such as those found in tropical forests over significant extents remains problematic, due to signal saturation of both reflectance (Huete et al., 2002) and backscattering signatures (Le Toan et al., 2004), as demonstrated by radiative transfer modeling studies (Gastellu-Etchegorry et al., 1996; Proisy et al., 2000).

Alternatively and quite promisingly, the potential for high resolution images to be used for mapping forest structure is being explored through the development of crown detection algorithms (Asner et al., 2002; Gougeon & Leckie, 2006; Palace et al., 2008) and the analysis of canopy textural properties. For the latter, canopy surface properties are investigated using semivariograms (Bruniquel-Pinel & Gastellu-
et al., 2007). Indeed, the ‘green carpet’ (Asner et al., 2002) provided by medium resolution imagery then translates into a more informative image consisting of sunlit and shadowed canopy areas (Couteron et al., 2005). Designing and testing methods of textural characterization is therefore critical for processing such information on canopy conditions into meaningful information pertaining to forest structure.

Profiting from the Google Earth™ digital globe interface, Barbier et al. (2010) demonstrated that processing a large number of images (i.e., a set of 200 Quickbird™ high resolution images) is no longer a limit for such studies. It is indeed possible to automate the flow of computational operations needed to consistently map canopy texture and to develop approaches that are largely independent of the values of both the mean and variance of the images and therefore of problematic atmospheric corrections (Song & Woodcock, 2003).

Fourier-based textural ordination (FOTO) of high resolution images (Couteron et al., 2005; Proisy et al., 2007) was shown to meet these requirements. It aims to identify the main gradients of textural variation by coupling 2D Fourier spectra describing the spatial frequency distribution of image variance in canopy scenes with principal component analysis (PCA). The resulting indices (i.e., scores for the main PCA axes) allow canopy structure to be described in terms of mean apparent crown size or canopy heterogeneity (Barbier et al., 2010). Indeed textural index values obtained from real-world Quickbird images proved to be consistent with those obtained from simulated images (applying the DART radiative transfer model of Gastellu-Etchegorry (2008) to simple templates of forest structure), thereby validating the model inversion (Barbier et al., 2010).

Independent case studies using field datasets have also shown that FOTO canopy texture indices were correlated with several important parameters characterizing forest structure, such as mean trunk diameter (DBH), mean tree height, stand density, and even biomass (Couteron et al., 2005; Proisy et al., 2007).

From these promising results, the systematic use of the FOTO method at regional or continental scales requires a thorough examination of how and to what extent FOTO texture indices may be influenced by variation in acquisition parameters across scenes such as sun height and sensor viewing angles. Changes in these parameters may induce sensible textural variations, as tree crowns and associated shadows may seem bigger or smaller in different configurations. This may disrupt the consistency of any kind of texture measure based on a set of scenes acquired under heterogeneous lighting and viewing conditions. Such heterogeneities are unavoidable if the scene array is to cover extensive areas. Preliminary tests (Barbier et al., 2010) were performed on the basis of a correlation analysis of the textual properties of Quickbird images and their acquisition parameters, and also using the DART radiative transfer model (Gastellu-Etchegorry, 2008) applied on simple templates of 3D forest structure. In both approaches, the influence of acquisition parameters was shown to be small but significant. However, a correction method, based on a partitioned standardization of Fourier spectra according to bins of similar acquisition configurations, showed good potential to mitigate instrumental discrepancies.

The aim of the present study is to reach a broader level of understanding of the effects of acquisition parameters on FOTO-based texture quantification and to further test our mitigation method. We ground the methodological analysis in real-world patterns of forest canopy structure. We therefore produced a database of images of sampled structures acquired under different conditions of observation and illumination but not quantified using quantitative texture indices as proposed in the present study. To our knowledge, only a similar attempt in the context of remote sensing applications is a recent contribution (Goodin et al., 2004) that investigated the effects of solar and viewing angles on the observed spatial structure of a tallgrass prairie, quantified through variograms. However, the range of scales considered (1 m between sampling points) was not compatible with the scales at which individual grass stumps or leaves could have affected the observed structural patterns.

2. Data

2.1. Study site

The study was conducted over an area of 300 ha of lowland terra firme rain forest, located within and around the Paracou Experimental Station (5°18′ N, 52°23′ W) in French Guiana. The station was established in 1984 by the French Agricultural Research Centre for Development (CIRAD) for silvicultural research within natural forest stands (http://arlequin.cirad.fr/arlequin/english/index.php, last consulted: July 23, 2009). The total number of stems and associated basal area ranged from 575 to 665 stems per hectare and 29.3 to 33 m² per hectare, respectively. A set of 14 permanent plots of 9 ha each were managed with contrasted silvicultural treatments and a 25 ha reference plot was delimited to study the natural forest (Gourlet-Fleury & Houllier, 2000). Silvicultural treatments ranging from severe to highly selective logging regimes provided an important diversity of forest structure and consequently of canopy texture. A floristic survey revealed about 546 different plant species belonging to 57 families, with a dominance by Caesalpinioideae, Lecythidaceae, Chrysobalanaceae and Sapotaceae (Sabatier & Prévost, 1990).

The climate in the study area is equatorial, characterized by mean annual rainfall and temperature around 3040 mm and 26 °C, respectively. It is marked by a dry season from mid–August to mid–November and a shorter dry period in March (Gourlet-Fleury et al., 2004). The moderate undulating topography consists of a succession of small elliptical hills ranging from 100 to 300 m in diameter and 20 to 35 m in elevation above sea level. Slopes vary from 25 to 45%. Soils are mostly shallow ferralic, developed on schists and sandstones on the hills and bottomlands, respectively (Delcamp et al., 2008).

2.2. LiDAR data

The light detection and ranging (LiDAR, Lefsky et al., 2002) data were acquired over the study site using the ALTOA system (http://www.altoa.fr/) on October 20, 2004 as part of the CAREFOR research project. This system includes a portable Rieg V laser ranger finder (LM-5014Q401-60) mounted onboard a helicopter flying at a speed of 30 m s⁻¹ about 150 m
above the ground. The system emitted near-infrared (0.9 μm) laser pulses at 30 kHz, with a pulse density of up to 4 pts/m². Given a laser beam divergence of 3 mrad, the footprint was about 0.45 m wide on the ground. The scanning range was ±30°, producing a 173 m swath on the ground. The LiDAR dataset consisted of a cloud of laser echoes originating from terrain and vegetation. The discrete return ALTOA system, which was the only one available in French Guiana, allowed the recording of either the first return of each emitted laser pulse, the last return or the first and the last returns in alternation. Due to the low signal penetration rates in dense forests (Clark et al., 2004; Hirata et al., 2009), the acquisition was performed in the last return mode by the service provider as the best trade-off between collecting enough points at the ground level to create a digital terrain model, or DTM (Clark et al., 2004), while retaining most of the relevant information on the upper level of the canopy (see supplementary data, Figs. S1 and S2). The LiDAR xyz data were provided in WGS84, UTM zone 22 North. Additional information and another application of the ALTOA LiDAR data are provided in Proisy et al. (2009).

From the point cloud dataset, maximum z-values selected within 2-m circular neighborhoods were interpolated (e.g., Chauve et al., 2009; Hyyppae et al., 2001) into a 1-m grid to produce a digital surface model (DSM). Using first and last return LiDAR data acquired as part of the DIME research project over 120 ha of the nearby Mt Serpents (52°22′ W, 4°44′ N) area, we demonstrated that this procedure produces a nearly unbiased DSM (see Appendix and supplementary data, Figs. S1 and S2). Indeed, although canopy height is significantly underestimated by 44 cm, this figure appears constant across all forest types (unit slope between first and last returns grids). Fig. 1 presents, for a sample forest area (125 m by 125 m) within the study site, a high resolution panchromatic optical image (Ikonos, Fig. 1a) and the LiDAR-derived altimetric description of the canopy surface (DSM, Fig. 1b). In the latter, the gray levels are proportional to height variations of the canopy surface, while in the former, the grey levels relate to the intensity of reflected sunlight assessed from the satellite viewpoint. The Ikonos image was acquired on the 12 October 2003, with the following sun-view acquisition parameters (see Hillshade models in Section 3.2 for parameter definitions): $\theta_V = 3.58°$ (view zenith angle); $\Phi_{S-V} = 20.47°$ (sun-sensor azimuth angle); and $\theta_S = 69.17°$ (sun height angle).

3. Methods

3.1. Processing steps

The four main steps of the workflow are summarized in Fig. 2.

- We partitioned the LiDAR DSM obtained in French Guiana over the Paracou experimental station into non-overlapping unit windows of 125 × 125 m. This size expresses a trade-off since windows must be large enough (compared to tree crowns) for texture characterization and, ideally, as homogenous as possible in terms of texture patterns (Fig. 2, data).

- Using this set of windows, hillshade images were simulated with a range of acquisition configurations for each unit window (Fig. 2, model).

- Textures were then quantified via the FOTO method for each simulated image, possibly using a correction algorithm (partitioned approach) aimed at mitigating the instrumental effects of acquisition configurations (Fig. 2, characterization).

- The textural indices then served to quantify the sensitivity of the texture quantification to directional features in acquisition parameters via the concept of the bidirectional texture function, or BTF (Fig. 2, analysis).

![Fig. 1. Data and models of the canopy surface from a 125 × 125 m area (1 m pixels) within the Paracou permanent station, French Guiana. Three parameters were used to characterize instrumental configurations, the sun–sensor azimuth angle, $\Phi_{S-V}$ (*), the sun height angle, $\theta_S$ (*), and the sensor vertical angle, $\theta_V$ (*). (a) Ikonos™ high resolution panchromatic optical image acquired on 2003-10-12. $\theta_V = 3.58°$; $\Phi_{S-V} = 20.47°$; $\theta_S = 69.17°$. (b) LiDAR digital surface model (DSM). Gray levels are proportional to surface elevation in the range 20–60 m a.s.l. for this extract. (c, d) hillshade models of the LiDAR DSM, $\theta_V$, $\Phi_{S-V}$ as in (a) and two highly contrasted sun height angles, i.e., (c) $\theta_S = 70°$. (d) $\theta_S = 30°$.](image)
3.2. Hillshade models

To model the interaction of the canopy with light and to reproduce equivalents of high resolution optical images, we applied a hillshade model to the DSM assuming Lambertian surface reflectance (Fig. 2, model). Fig. 1c,d shows hillshade images obtained using contrasting sun height conditions ($\theta_s = 70$ and $30^\circ$, respectively) on the LiDAR DSM. It is apparent that the position, shape and size of the shadows in the hillshade image of Fig. 1c look similar to what can be seen in the IKONOS optical image (Fig. 1a), acquired in a similar configuration. Indeed, the hillshade approximation appeared sufficient for the purposes of the present study, although modeling the canopy as an opaque surface is simplistic compared to turbid medium approximations (such as in the DART radiative transfer model (Castellu-Etchegorry et al., 2002)). Ongoing improvements will be discussed in Section 5 (see Discussion and conclusion).

Practically, the DSM of the study area was first divided into 125 m by 125 m square windows ($n = 188$). Each extract was then converted into hillshade models using the Matlab® (The MathWorks, Inc.) surf function, while viewing angles were modulated using the view function. These functions allow the production of 3D surface plots under varying lighting and viewing conditions. Three parameters were considered to characterize instrumental configurations, namely the sun–sensor azimuth angle, $\phi_{s-v}$ ($^\circ$), the sun height angle, $\theta_s$ ($^\circ$) and the sensor vertical angle, $\theta_v$ ($^\circ$). The parameterization of the hillshade models was chosen so as to cover 95% of the breadth of the actual parameter distribution (Fig. 3a–c) found for 200 scenes of a typical high resolution optical sensor (Quickbird) over the tropical forests of the Amazon Basin (Barbier et al., 2010). This pragmatic approach was preferred to using instrumental specifications of the sensor to derive possible configurations. We parameterized our hillshade models within those ranges of variation using discrete systematic sampling (Fig. 3d). The sun–sensor azimuth difference angles ($\phi_{s-v}$) ranged between 0 and $180^\circ$ in 20° steps, with the sensor azimuth angle fixed either to $180^\circ$ — South view, or to $270^\circ$ — West view, to test for the possible influence of systematic sources of anisotropy in the DSM. Sun height angles, $\theta_s$ ($^\circ$), defined in degrees from horizon, ranged between 47 and 71° in 3° increments. The sensor vertical angle, $\theta_v$ ($^\circ$) was defined in degrees from nadir to meet the usual conventions of Earth observation imagery providers and ranged between 3 and 21° in steps of 2°. In total, 630 different combinations of parameter values (or acquisition configurations) were used to mimic high resolution canopy images of the study area, totaling 118 440 images (188 DSM extracts times 630 configurations) (Fig. 2).

Geometrical deformations due to altitudinal variations in the DSM and to non-nadir viewing conditions were not corrected.

3.3. The FOTO method

Quantification of image textural properties (Fig. 2, characterisation) was performed via the Fourier Transform Textural Ordination (FOTO) method. This method has been extensively described elsewhere (Barbier et al., 2006, 2010; Couteron, 2002; Couteron et al., 2006, 2005; Proisy et al., 2007). We will therefore limit ourselves to a basic account of the main steps and principles. The processing of each 125 m by 125 m hillshade simulation starts with the computation of the 2D Fourier periodogram (power spectrum). Briefly, the periodogram is the partition of the gray level variability present in a grayscale image according to spatial frequencies. Periodogram computation implies the convolution of the image with periodic (sine and cosine) functions of varying frequencies (i.e., the Fourier transform). The result of these convolutions peaks for frequencies matching those of regularly-structured observable in the image. Differences of periodogram values across spatial (azimuthal) directions, i.e., reflecting anisotropic features, can possibly be studied but were averaged out in the present study via the computation of the so-called r-spectrum. The latter therefore expresses the amount of image variance that is accounted for by a discrete set of frequency bins (expressed here in cycles/km) across all directions.

The r-spectra of all hillshade textures were grouped, standardized and ordinated using PCA to identify the main axes of textural variation and derive indices of canopy texture. We only used the first principal axis, which generally expresses the gradient from coarse to fine textures, as it has been shown to account for most of the total PCA variance for terra firme forest canopy images (Couteron et al., 2005) and to be closely correlated with the apparent mean crown size of the upper forest strata (Barbier et al., 2010). Because of allometric constraints in trees and stands (Chave et al., 2005; Enquist et al., 2009), the first axis also correlates with a range of important forest structural parameters, such as stand density, biomass, mean diameter at breast height (Couteron et al., 2005) and even total aboveground biomass (Proisy et al., 2007).

To correct for possible bias due to varying acquisition conditions, we used a recently introduced “partitioned standardization” method (Barbier et al., 2010). The principle is to group canopy images into bins of similar acquisition configurations, and to standardize the r-spectra separately within each bin. With this method, each value of a given
3.4 Noise and bias characterization

To study the effects of instrumental noise and bias on texture estimation (Fig. 2, analysis), we considered pairs of acquisition configurations and performed correlation analyses between the corresponding two vectors of PCA1 scores, i.e., texture indices, obtained for the 188 hillshade models. We opted for Model II major axis linear regressions (Sokal & Rohlf, 1995), as similar amounts of error are expected on both axes of the regressions and because there is no a priori reason to chose one configuration or another as an independent predictor. Given a major axis of the form \( y = a + bx \), bias was quantified as: (i) the absolute deviation from the unit slope, \( |1 - b| \) and (ii) the absolute intercept value, \( |a| \). Both \( 1 - b \) and \( |a| \) contribute to the total bias. As each source could vary independently of the other, they were first considered separately, but eventually showed similar patterns of variation. Precision (i.e., \( 1 - \text{noise} \)), \( P \), was obtained as the ratio of the eigenvalue attached to the major axis on the sum of eigenvalues (total variance).

3.5 Bidirectional texture function

To analyze the bidirectional variation of texture (Fig. 2, analysis), or in other words its sensitivity to acquisition angles, we proceed in a way similar to the well-known BRDF approach (Gastellu-Etchegorry et al., 1999; Gerard & North, 1997; Kimes, 1983; Nicodemus, 1965), and we introduce the bidirectional texture function (BTF), which is so far new in the field of remote sensing and earth observation (but see Dana et al., 2007, 1999). For each one of the 630 configurations of the acquisition parameters (each dot in Fig. 3d), the whole array of DSM extracts (188 extracts) was translated into hillshade models, and their texture characterized using the FOTO method.

From there, there are two possible ways to characterize the bidirectional variation in texture. The first option is to study the bidirectional variation of instrumental bias (quantified by \( a \) and \( b \)) and noise \( (1 - P) \) to characterize their dependence on the values of

---

**Fig. 3.** Parameterization of hillshade models. (a–c) Histograms of acquisition parameters of a sample of 200 Quickbird™ images acquired over the Amazon basin (Barbier et al., 2010). (d) Discrete sampling of the parameter space used to parameterize the hillshade model and serving to build the bidirectional texture function (BTF). Each dot corresponds to a given configuration (among 630) of the three acquisition angles.
the acquisition parameters and on interactions between them. Strictly speaking, this analysis should be eight-dimensional, as it involves correlation analyses between pairs of PCA1 score vectors, each obtained using a four-dimensional instrumental configuration.

In the case of bias, a second option is to simplify the problem to three dimensions, $\Phi_{s-v}$, $\theta_s$, and $\theta_v$, and to study only the variation of the mean PCA1 value as a function of the acquisition parameters. This approach keeps the essential features of the BTF, as the pattern of variation is indeed very similar to that of both $|a|$ and $|1-b|$, but the function is simpler to derive and analyze as it neither requires performing numerous correlation analyses between pairs of acquisition configurations, nor handling a confusing number of parameters.

Note that, as already mentioned (Hillshade models section; Fig. 3), sun and sensor azimuths were combined in a single difference variable: $\Phi_{s-v}$ (°). Furthermore, $\Phi_{s-v}$ values were only studied in the range $[0, 180°]$, as it is reasonable to assume textures occasioned by fairly isotropic canopy patterns to be left–right symmetrical. This assumption is, however, to be treated with caution in the presence of possible anisotropic structures in real-world images, for instance induced by pronounced ground topography.

**Fig. 4.** Hillshade variants of a particular 125 m by 125 m extract of the LiDAR Digital Surface Model, simulated under extreme acquisition conditions as defined from the 200 Quickbird images sampled over Amazonia. (a, b) pair I: backward vs. forward azimuth configurations, with other parameters held at their median values; (c, d) pair II: low vs. high view zenith angle, with other parameters held at their median values; (e, f) pair III: low vs. high sun vertical angle, with other parameters held at the median values. The diagrams on the right side represent the configurations of acquisition parameters for each pair.
4. Results

4.1. Pairwise comparisons of example configurations

To begin to understand the effects induced by varying acquisition parameters on high resolution canopy texture, we first visualized, characterized and compared textures obtained using our hillshade model under 'extreme' configurations of the acquisition parameters, as defined from the 200 Quickbird images sampled over Amazonia. Fig. 4 shows several hillshade models obtained from a particular 125 m by 125 m extract of the DSM. In these pairs of examples (numbered pair I, pair II and pair III), we varied one parameter at a time while maintaining the other two at their medians. For instance, in pair I (Fig. 4a and b), $\Phi_{s-v}$ was set to 0° and 180°, while $\theta_v$ and $\theta_s$ were held at 9° and 59°, respectively. We observed that pairs I and III produced very different textures, in particular regarding the presence and size of visible shadows, while pair II did not.

To characterize these differences in a more objective way, we computed the mean of the r-spectra ($n=188$ extracts) obtained for the whole study area in each of the extreme configurations. In the raw spectra (Fig. 5a–c), we retrieved the direct translation in the Fourier space of the changes in texture we observed on the individual simulations of Fig. 4. First, we compared (Fig. 5a) the mean r-spectra for the backward and forward azimuthal configurations (pair I) and observed that the backward configuration induced a relative redistribution of the image variance (or power) towards higher frequencies. In other words, images presented a finer grain when the sun was located behind the sensor, as shadows were concealed to the observer (see Fig. 4a, b). We then compared (Fig. 5b) the spectra obtained for different view zenith angles (pair II). Not much change occurred between the two mean r-spectra, nor were there differences in the visual aspect of the hillshade images (Fig. 4c, d). In contrast, the last parameter, sun height, determined important differences between the spectra (Fig. 5c, pair III). We observed that high frequencies...
do take a lot more relative weight for higher sun angles due to the reduction of shadow sizes.

Fig. 5d–e illustrates the effect of the partitioned standardization approach on r-spectra and on the discrepancies created by contrasted acquisition configurations. This approach consists of binning spectra acquired under similar acquisition conditions and standardizing them within each bin. We used four bins for each of the acquisition parameters (thus a total of 64 bins). For the purpose of comparing (Fig. 5d–e) how much of the discrepancies induced by the acquisition parameters was reduced by the partitioned standardization method, raw (i.e., ‘non-standardized’) spectra were reconstructed from the corrected spectra using the global means and standard deviations.

Our focal statistic for texture characterization is the FOTO index, which is the principal component(s) resulting from the ordination of the r-spectra. A perfect mitigation of instrumental discrepancies would result, for any pair of acquisition configurations, in a scattergram of PCA1 scores distributed along the 1:1 line with a minimum of scatter. To assess departures from such an ideal case, we computed the equation of the major axis, \( y = a + b x \) between PCA1 scores obtained for the study area (\( n = 188 \) extracts) for each of the three pairs of ‘extreme’ acquisition configurations. With the non-partitioned standardization (Fig. 6a–c), we observed (i) important deviations (bias) from the null intercept (\( a \neq 0 \)), (ii) important deviations (bias) from the 1:1 slope (\( b \neq 1 \)), but (iii) low levels of noise (good precision), as assessed by the proportion of variance explained by the major axis (\( P \)). In fact, the intercept bias can readily be interpreted in terms of our previous observations on the hillshade images (Fig. 4) and on the mean r-spectra (Fig. 5). For this, recall that higher values of PCA1 imply finer canopy textures (smaller apparent mean crown size and therefore higher contributions to high frequencies of the r-spectra). Therefore, for configuration pair I (numbered as in Figs. 4, 5 and 6), we obtained a negative intercept, \( a \), (Fig. 6a) when plotting the PCA1 scores obtained in backward configuration (x-axis) against those obtained in forward configuration (y-axis). PCA1 scores are thus on average lower (coarser

![Fig. 6. Correlation analysis (major axis) between the FOTO index values (PCA1 or principal axis resulting from the Fourier transform textural ordination) for the set of hillshade images simulated under the three pairs of configurations of acquisition parameters (see Fig. 4), for the two standardization approaches. (a, b, c) Non-partitioned standardization; (d, e, f) partitioned standardization using 4 bins for each parameter. Dashed lines indicate the (1,1) lines. (a) \( P = 0.81; y = -2.4 + 0.86 x \). (b) \( P = 0.96; y = 1.1 + 1.0 x \). (c) \( P = 0.90; y = 2.7 + 1.2 x \). (d) \( P = 0.82; y = 0.14 + 0.98 x \). (e) \( P = 0.96; y = -0.87 + 0.94 x \). (f) \( P = 0.90; y = 0.45 + 1.1 x \). For a major axis correlation model of the form \( y = a + b x \), with resulting precision \( P \) defined as the ratio of the first eigenvalue over the sum of the eigenvalues.](image-url)
textures) in the forward configuration. The near zero and positive intercepts obtained for the two other pairs (Fig. 6b,c) can be similarly interpreted in terms of mean variations of the PCA1 coarseness–fineness index. Interestingly, the partitioned approach (Fig. 6d–e) appears to notably reduce both intercept $[1−b]$ and slope ($b \approx 1$) bias. However, the type of standardization does not seem to affect precision ($P$), i.e., the scatter around the fitted major axis.

4.2. Systematic comparisons and binning configurations

To generalize the conclusion reached from the above three selected pairs of acquisition configurations, we considered the mean values of $a$, $[1−b]$ and $P$ obtained from the correlation analyses for a large number of random configuration pairs uniformly drawn within the ranges specified earlier (cf. Fig. 3). This was done with the aim to search for an objective way to design an appropriate binning scheme to be used in the partitioned standardization method. Thus we first set the total number of bins to 13 and investigated the effect of differently allocating the bin partitioned standardization method. Thus we first set the total number of bins to 13 and investigated the effect of differently allocating the bin numbers (#bins) between the acquisition parameters (Fig. 7). For each binning configuration, 500 correlation analyses were performed and the mean values of $a$, $b$ and $P$ were plotted. We see on Fig. 7a that mean $P$ turned out to be independent of the binning scheme, although it always remained very high (mean $P \approx 0.9$). In contrast, the mean bias for intercept, $a$, and slope, $b$, were effectively reduced as soon as two bins or more were taken for each parameter (Fig. 7b,c). A key question is of course how many bins are needed in total, as this will condition the number of images one needs to do the partitioned standardization. In fact, the lowest mean bias was obtained for the largest possible total number of bins.

The aforementioned results seem to suggest a correlation between both measures of bias ($a$ and $b$). Indeed, depending on the binning scheme used, the correlation between $a$ and $b$ can be very high ($R^2 > 0.8$), while correlation between bias and $P$ is generally non-significant.

4.3. Bidirectional texture and noise functions

To characterize the dependence of instrumental bias (quantified by $a$ and $b$) on the value of the acquisition parameters and on interactions between them, we took a simplified (three-dimensional) approach and analyzed the bidirectional variation of the mean $PCA1$ score, which presents a pattern of variation very similar to that of both $a$ and $[1−b]$. Fig. 8a–c shows the BTF obtained after a non-partitioned standardization. We see that $PCA1$ scores (which are here proportional to the fineness of the texture) increase in backward configurations and for higher sun angles, confirming and generalizing the conclusions we reached from particular ‘extreme’ configurations (Fig. 4). However, this bidirectional texture function (BTF) summarizes the effect of acquisition parameters, and their interactions, in a more convenient and systematic way. The effect of $\theta_0$, for instance, clearly depends on both of the other parameters. It can be very mild for median $\varphi_{s-v}$ and $\theta_0$ values, as in the pair II example earlier, or quite strong for a high sun angle in a backward configuration (Fig. 8a–c). This result is reminiscent of the ‘hot spot’ situation usually observed in BRDF plots and has the same causes: textures appear finer when shadows are masked to the observer. The anisotropy of the BTF is therefore more intense when the sensor height ($90° − \theta_0$) is close to the sun height ($\theta_0$). Interestingly, the BTF of the other PCA axes (e.g., $PCA2$) did not present any consistent pattern of variation, indicating that all variability induced by acquisition parameters is taken up by the main textural gradient.

Using the partitioned standardization approach (Fig. 8d–f), the BTF loses most of its anisotropic structure and shows a much reduced variation around zero scores. This confirms the efficacy of the partitioned approach to alleviate intercept bias in all configurations of the acquisition parameters. This result was confirmed for both $a$ and $[1−b]$ by analyzing their complete eight-dimensional distribution functions (result not shown).

In the case of $P$, our measure of the precision ($1−noise$) of texture characterization under varying acquisition configurations, it was necessary to use a full (eight-dimensional) description, of which we present only a partial account of here (Fig. 9). To reduce dimensionality, we fixed one particular baseline configuration ($\theta_0=3°$, $\varphi_{s-v}=0°$ and $\theta_1=71°$) and varied only the second. We further fixed the azimuth of viewing angles (both sensors to the South) to reduce the problem to three dimensions ($\theta_0$, $\varphi_{s-v}$ and $\theta_1$) characterizing the configuration of the second sensor. Although these restrictions do not

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig7.png}
\caption{Mean noise and bias (absolute intercept and absolute deviation from the unit slope) obtained in the correlation analyses between FOTO texture values for different binning schemes used for the partitioned standardization approach (total number of bins = 13). The number of bins for $\theta_0$ can be obtained by subtracting the accumulated number of bins for the two other parameters from the total number of bins. The value plotted on the vertical axis in each binning configuration is assessed as the mean value for that parameter over 500 correlation (major axis) analyses between the $PCA1$ scores obtained for random pairs of acquisition configurations. (a) Mean $P$ of the regressions; (b) mean slope bias; (c) mean intercept bias.}
\end{figure}
allow an analysis of the interaction between texture and all acquisition configurations, they do allow for a sufficient preliminary approach. We thus systematically computed $P$ between the PCA1 scores obtained using 500 different configurations of the three parameters, taken at random with respect to a uniform distribution of probability, and the PCA1 scores obtained in the baseline configuration. As in the case of bias, the most striking feature of the resulting function is a ‘hot spot’ phenomenon (Fig. 9). In fact, the lowest precision ($P$) values, around 0.8, are obtained when the second configuration has a sun angle opposite to the baseline ($\theta_{S-V,2} \approx 180$), especially at low sun elevations ($\theta_S$).

As all the aforementioned results have been produced using a fixed sensor direction of 180° (South view), we performed further tests with a West view (sensor located at a 270° azimuth). Results were identical (not shown), confirming the absence of any systematic source of anisotropy in the LiDAR DSM we used or in the topography of our reference site.

5. Discussion and conclusion

The results presented here open numerous perspectives for the large scale characterization of tropical forests from high resolution optical remote sensing images. The first important point is the introduction in earth observation of the concept of the bidirectional texture function (BTF), which may prove as useful as the bidirectional reflectance distribution function (BRDF). The latter has indeed become essential in the pre-processing of medium resolution optical products (e.g. Huete et al., 2002). This work complements earlier research efforts by Barbier et al. (2010) and Bruniquel-Pinel and Gastellu-Etchegorry (1998) on how acquisition parameters influence textural properties of the forest canopy by proposing an original method of investigation. In particular, the BTF allowed analogies between the bidirectional variation of both texture and reflectance to be highlighted. Indeed, values of the texture index (PCA1 scores) show the same ‘hot spot’ increase in backward configurations, when the sensor height is similar to the sun height. In terms of texture, this “hot spot” effect consists of an increase in the relative amplitude (power) of the r-spectrum at higher frequencies, making texture look smoother. A contrario, textures appear coarser in other configurations, and in particular in a forward configuration (sun in front of the sensor) due to the influence of visible shadows. As an immediate follow-up to this study, topography-induced textural variations could also be accounted for within the BTF framework, for instance using...
SRTM (Shuttle Radar Topography Mission) or ASTER stereoscopic data that freely provide ‘top of the canopy’ (Carabajal & Harding, 2006) topography information at a resolution compatible with an application of the FOTO method over forested areas (since optimal sizes of the square windows is in the range of 75–125 m).

In this study, we used a LiDAR hillshade approach to mimic optical images from real-world patterns of canopy altimetry. This approach is an alternative to the simulation we previously made by applying the DART light transfer model (Gastellu-Etchegorry, 2008, 1996) to simple 3D templates of forest stands (Barbier et al., 2010). In fact, both methods have advantages and drawbacks for the study of the impact of acquisition parameters on the quantification of canopy texture. On the one hand, height variation in the canopy is directly measured in real natural forests thanks to the LiDAR instrument, and therefore realistically represented. On the other hand, the canopy surface is approximated as an opaque surface when the foliage could be more appropriately modeled as a turbid medium (as in DART). Consequently, acquisition parameters might have less impact on the FOTO index than depicted here, if the canopy surface were modeled more realistically as semi-opaque or turbid. The present results could therefore be considered as rather pessimistic. However, preliminary results using the DART radiative transfer model applied on 3D forest models using a turbid approximation of tree crowns and varying LAI (Leaf Area Index) values produced patterns of variation in BTF similar to those presented here (results not shown).

We proposed a method, the partitioned standardization, which satisfactorily mitigates artifactual BTF variations of the FOTO textual index. This mitigation is necessary for any large scale or multi-temporal operational implementation of texture as a tool to quantify and monitor forest structure and degradation. Coupled with other theoretical developments, such as the allometry theory of forest structure (West et al., 2009), this progress may prove useful for the future application of international decisions, such as REDD (reduction of carbon emissions due to deforestation and forest degradation) policies (UNFCC, 2007). Although the partitioned standardization method requires a large number of images to document variation in the BTF over a complete forest structural gradient, or more generally across the structural gradient of any phenomenon of interest, we think that the method could easily be implemented with the collaboration of imagery providers. In practice, the provider would only need to provide the end user with the textual characterization of a representative sample of the forests of interest covered for each category (bin) of acquisition configurations, in the form of a compact database of r-spectra or of empirical BTF models. Representativeness could for instance be achieved by stratified sampling along the coarseness-fineness gradient of the forest canopy, at a regional or continental scale.

Considering those prospects, an important result established in this paper is that instrumentally-induced variations of the texture index (bias) can be mitigated by partitioned standardization. Indeed, the correlation between FOTO scores obtained using any pair of parameter configurations is fairly tight and departures from the major axis can be seen as unbiased random noise with an average noise to signal ratio remaining below 10%. Of course, individual unit windows should not be compared to each other, since variation of texture for an individual window taken from different sensor positions or with different sun heights could be too large, especially if extreme configurations are chosen as shown through the directional description of noise we have presented (Fig. 9). It is perfectly feasible to carry out statistical comparisons of canopy structure at the scale of sufficiently large forest extents (e.g., more than 100 ha; i.e., about 75 to 125 unit windows) to detect variations (through space or time) of natural or human-induced origin.
Hence, the present results, along with previous publications, highlight the potential of textural approaches and the FOTO method in particular for the characterization and monitoring of (tropical) forest structure. This potential is further improved if considered in combination (fusion) with other space-borne sensors describing the vertical distribution of forest biomass, such as large footprint LiDAR (ICESat, Carabajal & Harding, 2006) or radar interferometry (Garestier et al., 2008). Altogether, the current methodological, theoretical and societal circumstances appear most favorable for rapid progress in knowledge regarding the functioning and structure of tropical forests.

Supplementary materials related to this article can be found online at doi:10.1016/j.rse.2010.08.015.

Acknowledgements

This research was supported by FRNS, INRA and Marie-Curie (IEF-FP7) post-doctoral grants. LiDAR data acquisition were carried out within the scope of the projects CAREFOR (2003–2007, Paracou site) and DIME (2003–2005, Mt Serpents site) funded by grants from the ‘Xénon Contrat de Plan Etat Région-Guyane’ (French Government and European Union) and from ‘programme Écosystèmes Tropicaux’ (French Ministry of Ecology and Sustainable Development, respectively).

References


Birnbaum, P. (2001). Canopy surface topology in a French Guiana forest and the role of forest structure in the vertical distribution of forest biomass, such as large footprint LiDAR (ICESat, Carabajal & Harding, 2006) or radar interferometry (Garestier et al., 2008). Altogether, the current methodological, theoretical and societal circumstances appear most favorable for rapid progress in knowledge regarding the functioning and structure of tropical forests.

Please note that the references list is not fully complete and may contain errors. The full list should be consulted for accuracy.

