Forest leaf area index determination: a multiyear satellite-independent method based on within-stand normalized difference vegetation index spatial variability

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[1] The Leaf Area Index (LAI) and its spatial distribution are key features to describe the forest ecophysiological processes. A stable and reproducible relationship is obtained between the LAI and the standard deviation of pixel-based satellite-derived normalized difference vegetation indices (NDVI) of forest stands. In situ measurements of LAI have been performed with the LAI-2000 Plant Canopy Analyser over 8 years in the managed Fontainebleau forest (France) on about 31 stands each year, including oak, beech, and mixed oak-beech stands. Simultaneous satellite images have been acquired, atmospherically and geometrically corrected, and included into a geographic information system to get the mean NDVI and the \( \sigma_{\text{NDVI}} \) for each stand. A total of six different satellites with a 20- to 30-m spatial resolution have been considered over the eight studied years: SPOT1, SPOT2, SPOT4, LANDSAT ETM+, IKONOS, and HYPERION. The mean LAI of a stand is linked to the \( \sigma_{\text{NDVI}} \) with a unique relationship that appears to be mostly year- and satellite-independent, because the \( \sigma_{\text{NDVI}} \) is nearly insensitive to additive or proportional shifts on NDVI. The theoretical bases of the \( \sigma_{\text{NDVI}} \)-LAI relationship are investigated. The results show the combined importance of the shape of the within-stand LAI distribution (following a Weibull probability density function) and the shape of the within-stand LAI-NDVI curves (showing a saturation). The root mean square error of the predicted LAI over the 259 samples is 1.14 m²/m² when all years and satellites are considered, using the following equation: LAI = \( -2.45 \ln(\sigma_{\text{NDVI}}) - 5.58 \) \((r^2 = 0.63)\).


1. Introduction

[2] Leaf area index (LAI), defined as the surface of tree leaves per ground surface area, is a key parameter implied in a variety of forest ecosystem processes, including light and rain interception, transpiration, photosynthesis, and soil heterotrophic respiration (through litter fall). Its precise estimation is crucial for ecosystem modeling at the landscape or regional scale with process-based models that quantify carbon, water, and energy fluxes.

[3] Local estimations of LAI are often performed through optical (LI-COR LAI-2000, hemispherical photographs), direct and semidirect methods (litter collection and allometric methods). Routine in situ measurements of LAI, however, are time-consuming and even unfeasible for large-scale studies. For that reason, numerous works attempt to characterize LAI through remotely sensed data [Rouse et al., 1973; Curran, 1980; Justice et al., 1998; North, 2002]. The data acquired by remote sensing over vegetation areas give the reflectance in different spectral bands and with a given spatial resolution. LAI is classically derived from a combination of well-chosen spectral band reflectances [Goel and Qin, 1994; Turner et al., 1999; Walthall et al., 2004].

[4] Particularly, empirical relationships between LAI and Spectral Vegetation Indices (SVI) such as the Normalized Difference Vegetation Indices (NDVI) are widely used in the remote sensing community [Chen et al., 1997; Turner et al., 1999]. However, these relationships between LAI and remote-sensing vegetation indices, especially the NDVI, have several recognized drawbacks [Qi et al., 2000]: (1) saturation of NDVI for LAI greater than 3.5 m²/m² [Lüdeke et al., 1991; Fassnacht et al., 1997; Birky, 2001; Anderson et al., 2004; Wang et al., 2005], (2) the fact that a relationship established between the LAI and the vegetation

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index for a particular satellite sensor is generally not applicable to other sensors [Teillet et al., 1997; Wang et al., 2005; Soudani et al., 2006], (3) the previous point is also true for relationships between years for the same sensor [Wang et al., 2005], and (4) the fact that this relationship appears to be greatly species- and site-dependent [Qi et al., 2000; Colombo et al., 2003].

[5] The methods for analyzing remotely sensed images are usually pixel based; that is, the LAI is calculated for each pixel independently of the surrounding ones and then averaged over the stands if necessary. The use of satellite data is particularly interesting in intensively managed ecosystems, where stand polygons may be referenced in Geographic Information System (GIS) software for management practical reasons. These polygons, generally obtained by interpretation of aerial photographs, contain uniform attributes of interest to the manager. In a managed forest, the attributes that differentiate one stand from another (i.e., the criterion for the polygon mapping) may be species, age for even-aged stands, and tree density. The polygon mapping can be used to calculate a statistic for each polygon using the within-polygon pixels of the remotely sensed image; the statistic can be, for instance, the mean NDVI of the stand. For a selected set of stands, these stand-scale statistics can then be linked through empirical equations to stand measured characteristics, as the stand mean LAI. These empirical equations can finally be applied to other polygons. This polygon approach is of great interest for modeling purposes where such polygons may be used as simulation units in regional studies with process-based ecosystem models [le Maire et al., 2005]. The polygon-based approach for analyzing remotely sensed data was also shown to be more accurate than the pixel-based approach by reducing local data noise and allowing the exclusion of pixels on the boundaries of two contrasting stands [Wulder, 1998; Wicks et al., 2002].

[6] In the present study a stable and reproducible relationship is obtained between the LAI and the standard deviation of the NDVI of that stand. Standard deviation or variance measurements of reflectances are usually used to characterize the texture of an image, generally through a moving window [Lillesand and Kiefer, 2000]. The variation in texture, characterizing the relationship between neighboring pixels, has been related to spatial variation in vegetation distribution and mostly used for forest stand classification [St. Onge and Cavayas, 1995; Lark, 1996; Ryherd and Woodcock, 1996; Coburn and Roberts, 2004].

[7] Relatively few studies have focused on the use of texture properties to estimate the LAI. Wulder et al. [1996, 1998] show that the classical LAI-NDVI relationship on deciduous forests is improved if the texture (based on Grey-Level Co-occurrence Matrix, GLCM) is included as a second independent variable, compared to NDVI alone. Their interpretation is that the empirical relationship between LAI, NDVI, and texture is possible because of complementary information content: the texture variables are sensitive to stand structural characteristics while NDVI is sensitive to the vegetation content.

[8] Instead of considering separately NDVI and texture, Davi et al. [2006], using the variance of the NDVI as a texture measurement, have shown with SPOT images the existence of a linear relationship between LAI of forest stands and the logarithm of the variance of the NDVI. As noted by Coburn and Roberts [2004], the use of variance as a measure of texture instead of GLCM has not been extensively used yet in the remote sensing community. The relationship obtained by Davi et al. [2006] gave an RMSE of 1.13 m²/m² on the estimated LAI. The present study shows the existence of a single largely applicable relationship between the mean LAI of a stand (LAI, m²/m²) and the standard deviation of the within-stand NDVI pixels (σNDVI), with different satellites and years. The experimental data set consists of 8 years (between 1994 and 2004) of measurements on deciduous stands and six different satellites (SPOT1, SPOT2, SPOT4, LANDSAT ETM+, IKONOS, and HYPERION), which allow us to assess the generality of the relationship between LAI and σNDVI.

[9] The objectives of this article are (1) to investigate the theoretical bases of the LAI – σNDVI relationship using Weibull modeled LAI distribution fitted on real LAI distributions coupled with LAI – NDVI within-stand relationships; (2) to compare the strength and accuracy of the classical LAI versus mean stand NDVI (NDVI) approach to the new LAI-σNDVI approach on 8 years of data with six satellites (259 stands); (3) to test the sensitivity of the stand-scale LAI-NDVI and LAI-σNDVI relationships to variation of the pixel-based NDVI over the image (which may come from year to year atmospheric variations, changes in soil surface properties, and satellite sensor variations such as drifts or inappropriate calibrations); (4) to test the sensitivity of the LAI-σNDVI relationship to variations in the satellite image spatial resolution; and (5) to show on a given year and for all deciduous stands of a managed forest that the σNDVI is more reliable, i.e., constant, than the NDVI between different satellite images.

2. Material and Methods

2.1. Study Site

[10] The Fontainebleau forest, located in the southeast of Paris (48°25′N, 2°40′E, mean altitude 120 m) is a large forest extending over 17,000 ha in a region characterized by a temperate climate, with a mean annual temperature of 10.6°C and mean precipitation of 750 mm fairly well distributed throughout the year. This forest is actively managed by the French National Forest Office (”Office National des Forêts”, ONF), and divided into 2992 management units localized on a GIS database (with the software ArcGIS 8.1, Environmental Systems Research Institute Inc., Redlands, California). These management units, called “stands” in this study, are even-aged and homogeneous in species, stand structure, and tree density. The Fontainebleau forest is representative of an even-aged high forest, with the successive stage development describing the stand structure including: seedlings, thickets, sapling stands, pole stands, mature forest, and seed tree stands. These successive development stages are the result of regular forestry practices that strongly modify the stand structure and species composition of the forest.

[11] Thirty-one experimental stands were selected in flat areas. They include the two main deciduous species of the Fontainebleau forest: oak (Quercus robur L./Quercus petraea (Matt.) Liebl., 14 stands) and beech (Fagus sylvatica L., 13 stands), and mixed oak-beech (dominated
by oak, 4 stands). These stands are representative of the different stage developments and stand structure of deciduous stands found in the Fontainebleau forest. A detailed description of the Fontainebleau experimental stands in terms of stand structure, maximum height, diameter at breast height, density, age, and basal area is given by Le Dantec et al. [2000].

In this paper, these stands are defined as “homogeneous” since they are even-aged, with a given species composition, and without localized broad gaps or tree clumps. These stands, however, are not homogeneous regarding the LAI, which is spatially variable within the stands.

### 2.2. Ground-Based LAI Data Collection

The Plant Canopy Analyser (PCA) LAI-2000 (LI-COR Inc., Nebraska) was used for ground LAI measurements. A detailed description of this instrument is given by Cutini et al. [1998]. Calculations were carried out using three rings, which give an approximate value for the integration surface covered by the LAI-2000 of 300 m², depending on tree height. A detailed description and analysis of the LAI measurement method is given by Dufreña and Bréda [1995], Le Dantec et al. [2000] and Soudani et al. [2006]. LAI measurements were performed on the 31 experimental stands each year from 1994 to year 2004 in summer when LAI has reached a maximum (Table 1). Note that LAI is not measured every year for all stands; over the 8 years, a total of 197 forest-stand samples were available. Each stand, and according to its size, 40 to 150 LAI-2000 measurements were taken each year of measurements at intervals of 8 ± 2 m on several transects. The sampling covers between 5% and 68% of the stand area, depending on stand area and on tree height. LAI is calculated for each local measurement with the equations given by Miller [1967] and its distribution inside the stand is obtained. The sampling density allows us to get the mean LAI of the stand (LAI) as well as the LAI distribution inside the stand and its standard deviation σLAI.

### 2.3. Satellite Images Acquisition and Processing

Eleven images were acquired with six different sensors between 1994 and 2004 during the period of maximum LAI. Spatial resolution in multispectral mode and bandwidth of these sensors are given in Table 2, with the date and acquisition geometry. In order to compute surface reflectance, images were geometrically and atmo-

**Table 1.** Details of the in Situ Measurements: Number of Stands for Each Species and Period of LAI Measurement

<table>
<thead>
<tr>
<th>Satellites and Products</th>
<th>Acquisition Date Details</th>
<th>Nb of Measured Stands</th>
<th>LAI Measurement Date</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>Oak: 14, Beech: 12</td>
</tr>
<tr>
<td>SPOT1 - HRV1</td>
<td>13 Aug 1997</td>
<td>29</td>
<td>Oak: 13, Beech: 12</td>
</tr>
<tr>
<td>SPOT1 - HRV1</td>
<td>06 Aug 1998</td>
<td>29</td>
<td>Oak: 12, Beech: 13</td>
</tr>
<tr>
<td>SPOT4 - HRVIR</td>
<td>21 July 2000</td>
<td>23</td>
<td>Oak: 7, Beech: 12</td>
</tr>
<tr>
<td>EO1-HYPERION</td>
<td>04 Sep 2004</td>
<td>8</td>
<td>5</td>
</tr>
</tbody>
</table>

*The dates of the corresponding satellite images are also given.*

**Details of the In Situ Measurements: Number of Stands for Each Species and Period of LAI Measurement**

- **Satellites and Products:** SPOT2 - HRV2, SPOT2 - HRV2, SPOT1 - HRV1, SPOT1 - HRV1, SPOT4 - HRVIR, Landsat - ETM+, IKONOS, SPOT2 - HRV1, Landsat - ETM+.
- **Acquisition Date Details:** Various dates between 1994 and 2004.
- **Nb of Measured Stands:** Numbers vary from 22 to 8.

The same methodology of NDVI extraction is applied on year 2000 to the entire Fontainebleau forest.
Table 2. Characteristics of the Satellite Images Used in the Paper: Date and Time of Acquisition, Pixel Size, View and Sun Geometry (θ is the Zenithal Angle), and Spectral Bands

<table>
<thead>
<tr>
<th>Satellite - Instrument</th>
<th>Acquisition Date</th>
<th>Spatial Resolution</th>
<th>Time, UT</th>
<th>θ_{sun}, deg</th>
<th>θ_{view}, deg</th>
<th>Red Band, nm</th>
<th>NIR Band, nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPOT2 - HRV2</td>
<td>10 July 1994</td>
<td>20 m</td>
<td>1100</td>
<td>27.4</td>
<td>4.0</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>SPOT2 - HRV2</td>
<td>10 July 1995</td>
<td>20 m</td>
<td>1041</td>
<td>29.7</td>
<td>21.7</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>SPOT2 - HRV1</td>
<td>17 July 1996</td>
<td>20 m</td>
<td>1107</td>
<td>28.7</td>
<td>14.8</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>SPOT1 - HRV1</td>
<td>13 Aug 1997</td>
<td>20 m</td>
<td>1053</td>
<td>35.5</td>
<td>3.9</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>SPOT1 - HRV1</td>
<td>06 Aug 1998</td>
<td>20 m</td>
<td>1116</td>
<td>32.3</td>
<td>23.7</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>SPOT4 - HRVIR</td>
<td>21 July 2000</td>
<td>20 m</td>
<td>1109</td>
<td>29.4</td>
<td>12.0</td>
<td>610–680</td>
<td>780–890</td>
</tr>
<tr>
<td>Landsat - ETM+</td>
<td>24 Aug 2000</td>
<td>30 m</td>
<td>1031</td>
<td>41.4</td>
<td>0.0</td>
<td>630–690</td>
<td>760–900</td>
</tr>
<tr>
<td>IKONOS</td>
<td>16 Aug 2000</td>
<td>4 m → 20 m</td>
<td>1052</td>
<td>36.9</td>
<td>23.6</td>
<td>632–698</td>
<td>757–853</td>
</tr>
<tr>
<td>SPOT2 - HRV1</td>
<td>20 Jul 2002</td>
<td>20 m</td>
<td>1117</td>
<td>28.5</td>
<td>23.7</td>
<td>610–680</td>
<td>790–890</td>
</tr>
<tr>
<td>Landsat - ETM+</td>
<td>29 Jul 2002</td>
<td>30 m</td>
<td>1029</td>
<td>34.8</td>
<td>0.0</td>
<td>630–690</td>
<td>760–900</td>
</tr>
<tr>
<td>EO1 - HYPERION</td>
<td>04 Sept 2004</td>
<td>30 m</td>
<td>1030</td>
<td>46.4</td>
<td>4.0</td>
<td>630–690(^b)</td>
<td>760–900(^b)</td>
</tr>
</tbody>
</table>

\(^a\)The original 4-m IKONOS pixel size has been resampled to 20 m to get the same resolution as the other satellites.

\(^b\)Several hyperspectral bands have been averaged to obtain the indicated bandwidth.

(SPOT4, LANDSAT ETM+, and IKONOS images), using the GIS database created by the French National Forest Office (ONF) that contains the polygon delineation of the 2992 management units. The NDVI and \(\sigma_{NDVI}\) are calculated for every stand, respecting a buffer of 60 m as explained for the experimental stands. Only the oak and beech stands greater than 2 ha after buffer elimination are kept for the analysis. The 2-ha threshold corresponds to 22 pixels of 30 \(\times\) 30 m and is considered statistically sufficient for a standard deviation calculation. Stands with clouds were visually eliminated. The NDVI and \(\sigma_{NDVI}\) were finally calculated on the three satellite images of the year 2000 on 293 stands. Because the IKONOS image does not cover the whole forest, only 144 stands are used with this image.

3. Theoretical Basis of the LAI-\(\sigma_{NDVI}\) Relationship

[17] The theoretical basis of the observed LAI-\(\sigma_{NDVI}\) relationship [Davi et al., 2006] is studied here using a within-stand LAI distribution modeled with a Weibull Probability Density Function (PDF), previously calibrated on the experimental stands of the Fontainebleau forest (see Appendix A). This modeled LAI distribution is then transformed into a NDVI distribution using a within-stand LAI-NDVI relationship (see Appendix A). Then the LAI-\(\sigma_{NDVI}\) relationship is established and analyzed. This modeling approach allows us to study various factors that may affect the shape of the LAI-\(\sigma_{NDVI}\) relationship: (1) the shape of the within-stand LAI-NDVI relationship and (2) the shape of the distribution of the LAI within the stand. The aim of this chapter is to study the effect of these factors, and their relative importance on the final result.

[18] To study the first factor, four different arbitrarily chosen within-stand LAI-NDVI relationships were created; they go from a highly saturated one to a linear one (Figure 1). To study the second factor, the Weibull distribution of the LAI was changed into a Gaussian one with the mean equal to LAI and the standard deviation parameter fixed to a constant value (\(\sigma = 1.2\) m\(^2\)/m\(^2\), computed as the square root of the average LAI variances over the 197 forest-stand samples). In the case of the Gaussian distribution, the shape of the distribution is therefore identical whatever the LAI contrary to the case of the Weibull distribution where the shape depends on LAI (Appendix A).

[19] The two LAI distributions (Weibull and Gaussian) were tested together with the four LAI-NDVI relationships, leading to eight different cases. Figure 2 represents \(\sigma_{NDVI}\) versus LAI for these eight cases (note that case 2, medium saturation and Weibull distribution, is close to the real case).

3.1. Test of the First Factor: Shape of the Within-Stand LAI-NDVI Curve

[20] In the case of the Weibull LAI distribution model, when the LAI-NDVI relationship shows more saturation, the range of variation of the \(\sigma_{NDVI}\) increases. The maximum of the LAI-\(\sigma_{NDVI}\) curves shifts leftward, so that for the medium and high saturation cases the \(\sigma_{NDVI}\) monotonically decreases for LAI greater than 0.5 m\(^2\)/m\(^2\). For the most saturated LAI-NDVI relationship, however, (Figure 2a, case 1) the standard deviation becomes nearly constant for LAI greater than 3 or 4 m\(^2\)/m\(^2\) (this zone corresponds to the saturation plateau of the LAI-NDVI curve). For the medium saturation case, both the amplitude and the position of the maximum \(\sigma_{NDVI}\) allow the prediction of the LAI between approximately 0.5 and 6 m\(^2\)/m\(^2\). These results show that, considering a within-stand LAI Weibull distribution, a part of the link between the LAI and the \(\sigma_{NDVI}\) comes from the saturation of the LAI-NDVI curve, but that a too high saturation erases this signal for LAI greater than 5 or 6 m\(^2\)/m\(^2\).

Figure 1. Four LAI-NDVI relationships created to test the theoretical basis of the LAI-\(\sigma_{NDVI}\) relationship using modeling. They go from a highly saturated one to a linear one.
3.2. Test of the Second Factor: Shape of the Within-Stand LAI Distribution

The distribution of the within-stand LAI is modeled by a Weibull function whose parameters (shape and scale) depend on LAI (Appendix A). The nonsaturating (linear) LAI-NDVI curve shows the direct effect of the LAI distribution on the LAI-NDVI relationship: The NDVI increases for LAI going from 0 to 4 m^2/m^2 and then, as observed above, decreases (Figure 2a, case 4). On the contrary, for a Gaussian distribution and for the same linear LAI-NDVI relationship, the signal disappears: The NDVI remains constant (Figure 2b, case 8). This shows that a part of the link between the NDVI and the LAI comes from the distribution of the LAI within the stand. Note that the observed insensitivity of the NDVI in the case of the Gaussian distribution does not occur for low LAI since the distributions are left truncated to prevent negative LAIs. For medium saturation LAI-NDVI curve (Figure 2, cases 2 and 6), the effect of the LAI distribution is more reduced, but still important since the Weibull LAI distribution reduces the flattening of the LAI-NDVI for high LAIs.

The combination of a saturating LAI-NDVI curve and a Weibull distribution (that takes into account the real distribution of LAI) leads to a decreasing standard deviation of the NDVI for LAI greater than approximately 0.5 m^2/m^2 (Figure 2a, case 2). The logarithmic transformation of this signal leads to a linear r-square (coefficient of determination) greater than 0.9, suggesting that the standard deviation of the NDVI follows an exponential decay with LAI. These results show the combined importance of the LAI distribution and the shape of the LAI-NDVI curves on the observed LAI-NDVI relationship, with a greater effect of the LAI-NDVI relationship shape.

4. Experimental Results

4.1. LAI Within-Stand Variability

Since the within-stand LAI distribution partly explains the LAI-NDVI relationship, measured LAI variations with LAI (Fontainebleau forest data) are given in Figure 3 to illustrate distinctive characteristics of real LAI distribution in managed forests: σ_LAI is small for low and high LAI, and is higher for intermediate values. This pattern shows the specific stand structure variations with LAI that are generated by the sylvicultural practices. In open and closed canopies, most measurements are performed in places with similar LAI values (low LAIs or high LAIs); this leads to low LAI standard deviation. In canopies with intermediate LAI, measurements are performed in more contrasting places mainly because of the discontinuous spatial distribution of trees; this leads to higher LAI standard deviation. This observed pattern is also obtained with the Weibull modeling (solid line on Figure 3), and, as developed above, mostly explains the LAI-σNDVI relationship.

4.2. Comparison of the Methods for Predicting LAI Based on NDVI or σNDVI

Figures 4a and 4b represent the average stand LAI (LAI) versus NDVI (Figure 4a) and versus σNDVI (Figure 4b). To fit these data, several regression models have been tested. The simple regression models that best fit the data are

\[
\text{LAI} = \frac{a}{\ln(NDVI)} + b \quad (1)
\]

\[
\text{LAI} = a \times \ln(\sigma_{NDVI}) + b, \quad (2)
\]

where ln is the Napierian logarithm and \(a\) and \(b\) are regression parameters. The \((-1/\ln(x))\) and \((-\ln(x))\) equations were applied to NDVI and σNDVI to get linear plots that are more explanatory (Figures 4c and 4d); \(a\) and \(b\) parameters are obtained with linear regressions on these transformed data, and these regression lines are reported on the scatterplot. The r-square and root mean square errors (RMSE) of these regressions are given in Table 3. Finally, a global regression was calculated on all-year and all-
satellites data (Figures 4e and 4f), and the results are reported in Table 3.

[25] For a given image, results show that the two models gave nearly equal r-squares (0.68 for NDVI and 0.71 for $\sigma_{\text{NDVI}}$ in average) and RMSE (0.99 m$^2$/m$^2$ for NDVI and 0.96 m$^2$/m$^2$ for $\sigma_{\text{NDVI}}$ in average). This means that when a single year and sensor is considered, both models are a priori equivalent. Considering the LAI-NDVI relationship, the regression lines are very different from a satellite image to another in terms of slope and intercept. Soudani et al. [2006] have shown that the great difference between IKONOS NDVI and other satellites NDVI comes from the radiance spectral responses of the sensor on the red band that goes until 698 nm for IKONOS, whereas other sensors generally stop before 690 nm (see Table 2) which leads to higher $R_{\text{RED}}$ values. Other possible differences between satellite images that causes the large NDVI scatter seen on Figures 4c and 4e may come from temporal variations in view and illumination conditions, in atmospheric effects and in biophysical and biochemical characteristics of the leaves of the forest canopy. These results show that the global LAI-NDVI relationship is poor (Figure 4e, $r^2 = 0.35$ and RMSE = 1.52 m$^2$/m$^2$), and that such a relationship should be calibrated for each sensor and for each year, as reported by Wang et al. [2005].

[26] This is not the case for the LAI-$\sigma_{\text{NDVI}}$ relationships, whose regressions stay within a close range, whatever the sensor and the date (Figure 4d). The multiyear multisatellite regression for the prediction of the mean LAI of a stand as a function of the standard deviation of the within-stand pixels NDVI is given by (see Figure 4f)

$$\overline{\text{LAI}} = -2.45 \times \ln(\sigma_{\text{NDVI}}) - 5.58 \quad (259 \text{ points, } r^2 = 0.63).$$

The root mean square error (RMSE) of this relationship is 1.14 m$^2$/m$^2$ for all 259 forest-stand samples (24% of the mean). The use of such a general relationship gives fairly precise results, and above all it can be used for different satellites and different years without systematically having to calibrate it with ground measurements. Nevertheless, a calibration will provide better results as may be seen in Figure 4d and Table 3. Note that all the relationships described in this section are applicable for both beech and oak stands.

### 4.3. Sensitivity to Shifts of the NDVI

[27] The stability of the LAI-NDVI and LAI-$\sigma_{\text{NDVI}}$ relationship to shifts on the remotely sensed NDVI images have been tested. Shifts on the NDVI may come from incorrect atmospheric correction, leaf biochemical or biophysical change during the leafy season on the same stand, or other shifts from measurement instruments (sensor drift). To test the effect of such shifts, we have modified the NDVI pixels of the entire year 1995 SPOT2 image, either adding a systematical constant (NDVI modified = NDVI - $\alpha$) or applying a proportional bias (NDVI modified = NDVI * (1 - $\alpha$)). The same process of NDVI extraction of the images and calculations of the mean NDVI and $\sigma_{\text{NDVI}}$ as before has been used. Both LAI-NDVI and LAI-$\sigma_{\text{NDVI}}$ relationships have therefore been changed and their respective stability with respect to such biases have been compared. We used a value of $\alpha = 0.1$ for the calculations.

[28] Results are given in Figure 5. The LAI-$\sigma_{\text{NDVI}}$ is insensitive to a constant bias whereas the LAI-NDVI appears to greatly change, experiencing a direct translation. This result is rather trivial for the constant bias, the standard deviation remaining unchanged after the addition of a constant to the variable. For a proportional bias, once again the LAI-$\sigma_{\text{NDVI}}$ relationship is significantly more stable than the LAI-NDVI relationship. The proportional bias, indeed, is conserved both through the average calculation and through the standard deviation calculation: mean($\beta$X) = $\beta$mean(X) and std($\beta$X) = $\beta$std(X). The variation coefficient is of great importance in this case: The same proportional transformation on the output of a relationship (here NDVI and $\sigma_{\text{NDVI}}$) will have very different consequences on the final relationship appearance, depending on the variation coefficient of that output. Here the $\sigma_{\text{NDVI}}$ signal shows high amplitude (variation coefficient of 77%) compared to the low amplitude of the NDVI signal (variation coefficient of 5%). Therefore the 0.9 factor has low consequences on the LAI-$\sigma_{\text{NDVI}}$ and greater consequences on the LAI-NDVI relationship (see Figure 5). The conclusions would be the same for linear transformations of the NDVI pixels.

[29] In conclusion, the LAI-$\sigma_{\text{NDVI}}$ relationship is relatively insensitive to proportional or additive shifts on the image NDVI, which can partly explain its conservation between years and sensors.

### 4.4. Sensitivity to the Image Spatial Resolution

[30] The effect of the pixel size on the LAI-$\sigma_{\text{NDVI}}$ relationship is tested by aggregating the IKONOS image (with an initial resolution of 4 m). The pixel size is increased from 4 m up to 40 m, with a 10-m step. For each new resolution, the $\sigma_{\text{NDVI}}$ of each experimental stand is calculated. Only 16 stands are used because the IKONOS
image does not cover the entire forest. For the 40-m resolution, two stands with fewer than 20 pixels are excluded. The r-square between LAI and the $-\ln(\text{NDVI})$ transformation is calculated for each resolution.

[31] A first result is that the LAI-NDVI relationship changes because $\sigma_{\text{NDVI}}$ decreases with increasing pixel size (Figure 6). This decrease is similar to the one simulated by Gastellu-Etchegorry et al. [1999]. This is not the case for the LAI-NDVI that is insensitive to the pixel resolution.

[32] The other result (not shown) is that we cannot conclude that there are significant differences between the r-square calculated at the different resolutions, from 4 to 40 m (comparison of correlation coefficient test, $\alpha = 0.01$). This means that the accuracy of the recalibrated LAI-NDVI relationships does not change with the resolution. This result is partly due to the small number of points of the relationship. All r-square are between 0.56 and 0.69, with an average value of 0.60 and RMSE are between 0.81 and 0.94 m$^2$/m$^2$ with an average of 0.89 m$^2$/m$^2$.

### 4.5. Test of the Method Principle: Intersensor Stability of the $\sigma_{\text{NDVI}}$ Over the Whole Forest

[33] The generality of the stability of the $\sigma_{\text{NDVI}}$ between different sensors has been tested. Since we do not need LAI measurements for the inter-sensor comparison of NDVI and $\sigma_{\text{NDVI}}$ only, we have used a larger number of deciduous stands in the image, instead of the previous 31 stands (provided that the images are acquired the same year during the LAI plateau (July and August), so that the LAI does not vary between the images). For that purpose, we have extracted the NDVI and the $\sigma_{\text{NDVI}}$ of 293 deciduous stands of the Fontainebleau forest for a given year (2000) and for

![Figure 4](image-url)
Table 3. R-Square Coefficient and Root Mean Square Error of Linearized LAI-NDVI and LAI-$\sigma_{\text{NDVI}}$ Relationships Plotted in Figures 4c and 4d With the Regression Model Described by Equations (1) and (2)\(^a\)

<table>
<thead>
<tr>
<th>Number of Stands</th>
<th>LAI-NDVI</th>
<th>LAI-$\sigma_{\text{NDVI}}$</th>
<th>LAI-NDVI</th>
<th>LAI-$\sigma_{\text{NDVI}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPOT2 1994</td>
<td>22</td>
<td>0.84</td>
<td>0.87</td>
<td>0.86</td>
</tr>
<tr>
<td>SPOT2 1995</td>
<td>30</td>
<td>0.64</td>
<td>0.80</td>
<td>1.19</td>
</tr>
<tr>
<td>SPOT2 1996</td>
<td>31</td>
<td>0.81</td>
<td>0.69</td>
<td>0.95</td>
</tr>
<tr>
<td>SPOT1 1997</td>
<td>29</td>
<td>0.26</td>
<td>0.66</td>
<td>1.29</td>
</tr>
<tr>
<td>SPOT1 1998</td>
<td>29</td>
<td>0.79</td>
<td>0.68</td>
<td>0.87</td>
</tr>
<tr>
<td>SPOT4 2000</td>
<td>23</td>
<td>0.88</td>
<td>0.74</td>
<td>0.60</td>
</tr>
<tr>
<td>ETM+ 2000</td>
<td>21</td>
<td>0.83</td>
<td>0.84</td>
<td>0.72</td>
</tr>
<tr>
<td>IKONOS 2000</td>
<td>16</td>
<td>0.72</td>
<td>0.63</td>
<td>0.96</td>
</tr>
<tr>
<td>SPOT2 2002</td>
<td>25</td>
<td>0.60</td>
<td>0.52</td>
<td>1.09</td>
</tr>
<tr>
<td>ETM+ 2002</td>
<td>25</td>
<td>0.57</td>
<td>0.63</td>
<td>1.13</td>
</tr>
<tr>
<td>HYPERION 2004</td>
<td>8</td>
<td>0.56</td>
<td>0.78</td>
<td>1.19</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.68</td>
<td>0.71</td>
<td>0.99</td>
</tr>
<tr>
<td>All sensors together</td>
<td>259</td>
<td>0.35</td>
<td>0.63</td>
<td>1.52</td>
</tr>
</tbody>
</table>

\(^a\)The number of samples used in the regressions is given. The “all sensors together” line corresponds to a unique regression obtained on all the data set (Figures 4e and 4f).

Figure 5. Test of (left) LAI-NDVI and (right) LAI-$\sigma_{\text{NDVI}}$ relationships sensitivity to shifts of the image pixels NDVI with a constant bias (NDVI-0.1) or a proportional bias (NDVI * 0.9). Note that original NDVI and NDVI-0.1 plots are superimposed on the $\sigma_{\text{NDVI}}$ graph. Data are from SPOT2 image for the year 1995.
stand is defined here as a stand whose LAI distribution follows the Weibull model whose parameters are given by equations (A3) and (A4) in Appendix A (see also Figure A1 in Appendix A for the acceptable range around the nominal relationships).

The results have shown that both the local LAI-NDVI curve and the LAI distribution can explain the relationship between the mean LAI and the standard deviation of the NDVI of the stand. However, other unsuspected explanations may exist. The obtained relationship is modeled with strong conditions on the LAI distribution, fitted on measurements on managed forest stands that have a particular structure. For example, in this type of ecosystem, it is not possible to have high LAI and high standard deviation (i.e., high heterogeneity) of the LAI in a stand (Figure 3). This fact is mainly true in managed forest. For instance a maximum variation at medium values of LAI has also been observed in Norway spruce (Picea abies (L.) Karst.) managed forest [Schlerf et al., 2005]. This should be qualified, however, for other natural ecosystems.

Figure 6. Change of LAI-σNDVI relationship with increasing spatial resolution (from 4 to 40 m). Calculations are performed on the IKONOS image (initial resolution: 4 m).

Figure 7. Between sensors stand by stand comparison of NDVI and σNDVI in year 2000. 144 stands are plotted for the IKONOS images (top four graphs), and 293 stands (bottom two graphs). Here \( r^2 \) is the coefficient of determination. \( F \) is the Fisher statistic for paired measures: Low \( F \)-values indicate low sensitivity of the variable (NDVI or σNDVI) to the sensor.
The results obtained on the experimental stands and in the whole forest show that \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship is reliable: It is very stable between satellite images in comparison with the \( \text{LAI}-\text{NDVI} \) relationship. However, depending on the spatial resolution and on the stand area, the method may show some limitations related to the number of NDVI pixels in the stand: It is obvious that the number of pixels should be sufficient to get a good estimation of \( \sigma_{\text{NDVI}} \). Moreover, on small stands, \( \sigma_{\text{NDVI}} \) is more sensitive to image rectification and georeferencing errors than NDVI, especially when neighbor stands are contrasted. A large buffer width partly solves this problem. In this study, a buffer of 60 m (i.e., 2 pixels) was used to exclude overlapping pixels. The buffer can be reduced to one pixel width, depending on the spatial accuracy between polygons and image, and between different images if several images are used. In any case, \( \sigma_{\text{NDVI}} \) of stands with surface smaller than 2 ha (i.e., 22 pixels of 30 m) are less stable between sensors than NDVI.

Another critical consideration is the size of the NDVI pixels, i.e., integration scale of NDVI. It is obvious that the larger the pixels are, the smaller the \( \sigma_{\text{NDVI}} \) is, because averaging the NDVIs reduces extreme values. A consequence is that \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship changes with the resolution. Despite this fact, we do not find any significant improvement or deterioration of these relationships in term of \( R^2 \)-square and RMSE for resolutions ranging from 4 m to 40 m. This means that \( \text{LAI} \) can be obtained from \( \sigma_{\text{NDVI}} \) in the 4- to 40-m range, but that a specific relationship has to be used for each resolution, or resolution range (satellites with resolutions between 20 m and 30 m may be considered a single group; see Figures 4 and 6). However, the question remains open because of the limited number of stands used for these calculations (16 stands).

The \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship given in this study (equation (3)) corresponds to sensors of 20- or 30-m pixel resolutions, and should only be used for satellites with these resolutions and on stands of at least 2 ha.

6. Conclusion

As a conclusion, we list the advantages and drawbacks of the \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship compared to the classical \( \text{LAI}-\text{NDVI} \) relationship. The advantages are as follows. (1) There is a unique multyear multisatellite relationship that gives fairly good accuracy on predicted mean stand LAI (RMSE of 1.14 m\(^2\)/m\(^2\)). (2) There is near-insensitivity to proportional and additive shifts on the NDVI that may occur (satellite drifts, view and illumination conditions, atmospheric corrections, variable sensor spectral responses, leaf biochemical or biophysical change during the leafy season, etc.). (3) The relationship is apparently fairly robust (multispecies (oak and beech), multisatellite) which allows its use in various situations. The drawbacks are as follows. (1) There is a necessity to have accurate delimitations of homogeneous forest stands included into a GIS. (2) Large enough stands are necessary to have valid \( \sigma_{\text{NDVI}} \) estimation. In this study, a minimum threshold of 2 ha (approximately 20 pixels) is used. Because of the 60-m buffer width, the original stand surface corresponding to that threshold is around 6 ha. However, the buffer width can be reduced as discussed before, or be specific to each image. (3) The \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship must be recalibrated before using it on images of different resolutions. However, as far as our study goes, the accuracy of recalibrated relationships does not change much with spatial resolution: Resolutions between 4 and 40 m have been tested on 16 stands resulting in RMSE comprised between 0.81 and 0.94 m\(^2\)/m\(^2\). The relationship stays nearly unchanged for resolutions between 20 and 30 m.

It must be stressed that this study was made on a particular forest and on two deciduous species (oak and beech). Preliminary results have shown that the \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship also applies to managed coniferous stands on the Fontainebleau forest (Pinus sylvestris L.). Further work on other managed forest or other ecosystems and species is needed to test the generality of these results.

The \( \text{LAI}-\sigma_{\text{NDVI}} \) relationship obtained in this study can be useful in biophysical models because it can be applied on remotely sensed images from different sensors and years, and therefore allows getting multiyear LAI data. Moreover, this relationship can be used without preliminary calibration, i.e., without LAI ground measurements. Finally, this method is fast and also quite simple to implement. It offers promising perspectives in applications requiring forest LAI series, especially in the climate change field and related continental biosphere studies.

Appendix A: Representation of Stand LAI Distributions With Weibull Functions

Our objective is to model the distribution of the LAI within a stand as a function of the mean LAI of the stand. The suitability of the Normal, Lognormal, Logistic or two-parameter Weibull Probability Density Function (PDF) to model the LAI distribution inside a stand is investigated. We use the Anderson-Darling test, which is an improved goodness-of-fit Kolmogorov-Smirnov test [Press et al., 1996]. For a given stand it tests whether there is a difference between observed and predicted distributions, with a level \( \alpha = 0.05 \) considered to be significant. The test is performed on each experimental stand and for each year when measurements are available (197 tests in total). Note that it is possible that two different distribution models (e.g., Logistic and Weibull) may represent well the same stand LAI distribution. The root mean square error (RMSE) of the fit of the models to the measured distribution is calculated, and an average value is given for each model.

The results are given in Table A1. Results are expressed in percent of success over all stands (same method as Nanang [1998]). There are 197 tests corresponding to 31 stands that are measured at different years. We can see that the Weibull function represents the best the distribution of LAI within a stand, with about 62% of success for the Anderson-Darling test. The mean RMSE, representing the accuracy of the fit, is also lower for the Weibull than the other PDF. The two-parameter Weibull function is therefore clearly the best model for the within-stand LAI distribution.

The Weibull function is widely used for fitting life data in biology and industry [Abernethy, 2000]. In forestry field, other distributions of parameters are modeled by this function. For example, the most commonly used probability density function for modeling diameter distri-
The two-parameter Weibull distribution has the following PDF:

\[
f(t) = \frac{b}{\eta} \left( \frac{t}{\eta} \right)^{b-1} e^{-\left( \frac{t}{\eta} \right)^b}, \quad (A1)
\]

where \( b \) is the shape parameter of the distribution and \( \eta \) is the scale parameter (\( b \) and \( \eta \) are positive). The Cumulative Distribution Function (CDF) of the Weibull distribution is

\[
F(t) = 1 - e^{-\left( \frac{t}{\eta} \right)^b}. \quad (A2)
\]

The calculations of \( b \) and \( \eta \) for each stand were realized with Matlab (MathWorks Inc.) using the simplex search method algorithm, minimizing the square difference between the Weibull CDF and the measured LAI CDF of the stand.

To get a theoretical model for the LAI distribution inside a “homogeneous” stand having only the mean LAI of the stand as driving parameter, parameters \( b \) and \( \eta \) have been plotted against the mean measured LAI of the stand. The scale parameter \( \eta \) appears to be linearly correlated to the mean LAI of the stand (Figure A1). This comes from the fact that the scale parameter is close to the mean of the Weibull function,

\[
\eta = 1.07 \times \text{LAI} \quad (r^2 = 0.99, 123 \text{ points}). \quad (A3)
\]

The shape parameter \( b \) is exponentially correlated with the mean LAI (Figure A1),

\[
b = 1.13 \times e^{0.23 \text{LAI}} \quad (r^2 = 0.77, 123 \text{ points}). \quad (A4)
\]

In Figure A1, all stands parameters are represented, even the ones that give a negative result in the Anderson-Darling test. However, only the stands with positive results are used for the regressions (123 points over 197). It is noteworthy that when the rejected stands are included in the graph, their Weibull parameters follow the same trend that the other stands even at low mean LAI. The only difference is that the relationship is more scattered. This result suggest that even if the Weibull model was rejected with the Anderson-Darling test, equations (A3) and (A4), further included in equation (A1), are suitable for modeling the LAI distribution.

A graphical representation of the modeled LAI PDF is given in Figure A2: Equation (A1) is used with the equations of \( \eta \) and \( b \) (equations (A3) and (A4)). Eight different distributions are represented: They are calculated for mean LAI going from 1 to 8 m\(^2\)/m\(^2\). One may note that the distribution is positively skewed for low mean LAI and negatively skewed for high mean LAI.

The switch from LAI distribution to NDVI distribution is achieved using a given within-stand LAI-NDVI relationship (we used here, for the graphic representation, the relationship given in Figure 2a, medium saturation case). The resulting NDVI distributions are represented in Figure A2b, according to the LAI distributions described above (mean LAI going from 1 to 8 m\(^2\)/m\(^2\), Figure A2a). Note that the PDF are normalized to get integrals normalized to 1, which leads to high ordinates for the narrow

<table>
<thead>
<tr>
<th>Distribution</th>
<th>A-D Test % of Success</th>
<th>CDF Fit Mean</th>
<th>RMSE (×10^{-3})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>47.2</td>
<td>32.0</td>
<td></td>
</tr>
<tr>
<td>Lognormal</td>
<td>37.6</td>
<td>38.0</td>
<td></td>
</tr>
<tr>
<td>Logistic</td>
<td>49.7</td>
<td>32.1</td>
<td></td>
</tr>
<tr>
<td>Weibull</td>
<td>62.4</td>
<td>30.1</td>
<td></td>
</tr>
</tbody>
</table>

*Test is the Anderson-Darling test, 197 samples, \( \alpha = 0.05 \). The fit mean RMSE is given as a goodness-of-fit criterion.
NDVI distributions. One may observe the decrease in width of the NDVI distribution when the LAI increases. This is this feature that is studied in the present paper.

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Figure A2. (a) Modeled LAI Probability Density Function. Eight different distributions are represented; they are calculated with a mean LAI going from 1 to 8 (indicated above each curve) with the equations (A3) and (A4) included in equation (A1). (b) Modeled NDVI Probability Density Function. These distributions come from the LAI distributions described in Figure A2a (LAI going from 1 to 8) and using the LAI-NDVI relationship given in Figure 3 (medium saturation).


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