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A LiDAR method of canopy structure retrieval for wind modeling of heterogeneous forests

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The difficulty of obtaining accurate information about the canopy structure is a current limitation towards higher accuracy in numerical predictions of the wind field in forested terrain. The canopy structure in computational fluid dynamics is specified through the frontal area density and this information is required for each grid point in the three-dimensional computational domain. By using raw data from aerial LiDAR scans together with the Beer–Lambert law, we propose and test a method to calculate and grid highly variable and realistic frontal area density input. An extensive comparison with ground-based measurements of the vertically summed frontal area density (or plant area index) and tree height was used to optimize the method, both in terms of plant area index magnitude and spatial variability. The resolution of the scans was in general low (<2.5 reflections m⁻¹). A decrease of the resolution produced an increasing systematic underestimation of the spatially averaged tree height, whereas the mean plant area index remained insensitive. The gridded frontal area density and terrain elevation were used at the lower boundary of wind simulations in a 5 km × 5 km area of a forested site. The results of the flow simulations were compared to wind measurements using a vertical array of sonic anemometers. A good correlation was found for the mean wind speed of two contrasting wind directions with different influences from the upstream forest. The results also predicted a high variability on the horizontal and vertical mean wind speed, in close correlation with the canopy structure. The method is a promising tool for several computational fluid dynamics applications requiring accurate predictions of the near-surface wind field.

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1. Introduction

In computational fluid dynamics (CFD) simulations of complex forested terrain, imposing the correct canopy structure at all spatial scales is crucial to reduce the modeling uncertainty (Lopes Da Costa et al., 2006). In the vicinity of the trees, the flow is affected by the canopy elements and the horizontal and vertical variability in forest density. At larger scales, natural and man-made heterogeneities cause the flow to be in constant adaptation to the surface. It has been shown that the flow in and over the heterogeneities is closely correlated with the density of the forest (Schlegel et al., 2012; Dellwik et al., 2014). Several CFD applications require high accuracy numerical predictions of forest flows. These include wind energy assessments (Lopes Da Costa et al., 2006; Ayotte, 2008), aerosol dispersion (Katul and Poggi, 2010), wildfire propagation (Coen, 2005; Sun et al., 2009), carbon dioxide exchange between forests and atmosphere (Belcher et al., 2012), and wind damage on trees (Dupont and Brunet, 2006). In this study, a method to obtain the forest canopy structure using aerial light detection and ranging (LiDAR) scans (ALS) for CFD is presented and evaluated.

In wind modeling, the effect of the forest is often parameterized using drag forces in the momentum equations (see e.g. Finigan, 2000). Additional source terms are generally prescribed in a turbulence model to account for the modification of the turbulence length or velocity scale inside the canopy. In the Reynolds-averaged
Navier–Stokes (RANS) canopy model proposed by Sogachev and Panferov (2006) and Sogachev (2009), the drag terms $S_d$ and the source term $S_e$ in the dissipation equation read

$$S_d = -C_d |u| |u|,$$

$$S_e = 12C_m^2 |u| |u| / k,$$

where $u$ in m s$^{-1}$ is the mean velocity vector, $k$ in m$^2$ s$^{-2}$ is the turbulent kinetic energy (tke), $C_d$ is the drag coefficient and $a$ in m$^2$ m$^{-3}$, the frontal area density. The frontal area density represents the area of leaves, branches and stems opposing the wind flow per unit volume. Two parameters, $C_d$ and $a$, are required as input. $C_d$ is often assigned using approximations based on measurements (see e.g. Pinard and Wilson, 2001; Queck et al., 2012). The canopy structure enters as an input through $a$.

Different methods can be considered for the determination of $a$ (Jonckheere et al., 2004; Weiss et al., 2004). They can be classified as direct and indirect (Brdá, 2003). The direct methods consist of destructive sampling of trees, whereas indirect methods relate the forest density to the light absorption and the optical properties of canopies (Morsdorf et al., 2006). In wind modeling, performing labor-intensive, ground-based tree height and density distribution measurements is technically impracticable as the forest properties are needed for extended areas. Therefore, the canopy structure is often simplified in flow models and parameterized based on few measurements only. This can severely degrade the overall accuracy of the wind simulations. Thus, indirect methods such as the ALS technique are potentially useful for determining stand structure for applications requiring high accuracy description over extended areas.

An ALS is performed using an aircraft with a combined LiDAR and global positioning system (GPS) (e.g. El-Shemy et al., 2005). The $x$, $y$ and $z$ positions, where the reflection of each LiDAR pulse occurs, form a so-called point cloud. In addition to the terrain elevation, the beam penetration gives information about the structure of the canopy. Several forest attributes can be recovered from the point cloud (see van Leeuwen and Nieuwenhuis, 2010, for review). These include, for example, tree height (e.g. Popescu and Wynne, 2004; Mcinerney et al., 2010) and plant area index (PAI) (e.g. Lefsky et al., 1999; Morsdorf et al., 2006; Solberg et al., 2006, 2009; Richardson et al., 2009). Although $a$ has not previously been derived from the point cloud, a few studies have included the vertical distribution of the LiDAR reflections for determining the canopy structure (e.g. Coops et al., 2007; Peduzzi et al., 2012). A good agreement was generally found between the ALS-derived properties and ground-based measurements in the various studies mentioned. However, the focus was put on a few local point validations and no systematic method to produce grid estimates of $a$ useful for CFD input has been proposed so far. In the present study, we propose such a method. An extensive grid validation with ground-based tree height, PAI and $a$ at various spatial scales was also performed. Today, ALS scans are becoming increasingly widespread and accessible, but the scans are often performed at low resolutions. We further explore how scanning resolution affects the forest description in the grid estimates of $a$. The scanning resolution was defined as the reflection density of LiDAR pulses per unit ground area in reflections m$^{-2}$.

The paper is divided into two major topics: (1) a method to organize ALS data into a 3D canopy structure input is proposed and validated and; (2) wind results are presented for a complex forested site located in Sweden where the input was coupled to a CFD model. For the first time, a large-scale numerical reconstruction of the 3D mean wind field for an actual forested site using a small-scale canopy structure description is presented.

### 2. LiDAR method of canopy structure retrieval

#### 2.1. Forest description

A three-dimensional description of $a(x, y, z)$ is considered. However, performing an extensive validation of $a(x, y, z)$ using a direct comparison with ground-based measurements is a difficult task to perform. For this reason, simpler forest parameters such as the tree height ($h_{max}$) in m and PAI in m$^2$ m$^{-2}$ were used for comparison. The tree height was defined here as the height difference between highest vegetation point above the ground and the lowest point on the ground within a given area. The PAI was a reduced two-dimensional variable of the three-dimensional distribution of $a(x, y, z)$ defined as:

$$PAI(x, y) = \int_0^{h_{max}} a(x, y, z) dz$$

and represents the projected canopy element area per unit ground surface area. Here, $a = a(x, y, z)$ and PAI = PAI($x, y$) include all possible canopy elements opposing the wind flow, i.e. leaves, branches and stems.

#### 2.2. Mathematical model

The ALS data was gathered as a point cloud, i.e. a set of reflections having $x$, $y$ and $z$ spatial coordinates (Fig. 1d). The Beer–Lambert law as a function of PAI was first introduced by Monsi and Saeki (2005). Extending its definition to $a(x, y, z)$ we get:

$$l(x, y, z) = l_0 \exp \left[ -\gamma(\theta) \int_z^{h_{max}} a(x, y, z) dz \right]$$

where the incoming light of intensity $l_0$ at the top of the canopy decays exponentially to a $l$ value within the canopy. Assuming a spherical distribution of the canopy element surface angles, the extinction coefficient $\gamma(\theta)$ was given by:

$$\gamma(\theta) = \frac{0.5}{\cos(\theta_{LIDAR})}$$

where $\theta_{LIDAR}$ is the mean zenith angle of the LiDAR (Richardson et al., 2009). Using so-called voxels of a vertically discretized volume (or bin) (e.g. Fig. 2a), a relationship for $a_k$ values into a kth layer of thickness $\Delta z$ can be directly obtained from Eq. (4). Assuming that the incoming and outgoing intensities $l_0 = l_{k-1}$ and $l = l_k$ could be obtained from the count of the intercepted LiDAR pulses $R_k$ inside the kth layer, $a_k$ reduces to:

$$a_k = \frac{1}{\gamma(\theta) \Delta z} \ln \left( \frac{l_k}{l_{k-1}} \right), \quad \text{where} \quad \left\{ \begin{array}{l} l_k = 1 - \sum_{i=1}^{k} \frac{R_k}{R_0} \\ l_{k-1} = 1 - \sum_{i=1}^{k-1} \frac{R_i}{R_0} \end{array} \right.$$  \hspace{1cm} (6)

and $R_0$ is the total number of reflections counted inside a given bin.

#### 2.3. Griding algorithm

The proposed LiDAR method was based on a local binning procedure (see e.g. El-Shemy et al., 2005). A uniform grid of $\Delta x = \Delta y$ spacing in the horizontal was defined where cylindrical bins of variable radius $r$ were created around each grid point (the blue shaded

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1. Article from the same authors translated from a German version originally published in 1953.
Fig. 1. (a) Map of Sweden and neighbouring countries where the location of the study site is shown by the black dot. (b) Aerial photo of the study site investigated, where the red "×" marker in the centre of the domain indicates the mast location. The green square markers indicate the locations of the areas in Inventory B. The red square indicates the location of the Inventory A area. (c) Illustration of the stand in the Inventory A area in which the forest properties were calibrated and validated. Tree height, locations and species are represented in the figure (large-base cones: Picea abies, elongated cones: Pinus sylvestris, cylinders: Betula pendula). The crown shape is not to scale. (d) Raw point cloud distribution of xyz coordinates from the aerial LiDAR scans for the Inventory A area. The points in brown color indicate the ground reflections whereas the points in green, the vegetation reflections. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Fig. 2. (a) Sketch of the cylindrical volume, or bins, containing voxel slices of Δz thickness. The red line illustrates an incoming LiDAR beam where $\bar{\theta}_\text{LiDAR}$ is the mean zenith angle of the beams inside a given Δz thick voxel. (b) Illustration of the binning procedure viewed from the top for an equidistant grid of Δx = Δy. The bin radius r in this image was arbitrarily chosen. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)
area in Fig. 2b illustrates the grid arrangement). Each of the individual bins was discretized in the vertical by defining layers of Δz thickness. Ground and vegetation reflections were separated into two distinct data sets according to a method defined in Evans and Hudak (2007). Using Eq. (6), the number of vegetation reflections N_v contained inside each Δz layers was used to calculate the vertical distribution of n. A LiDAR beam may undergo multiple reflections when a pulse is emitted and reflected. Here, we only considered the first LiDAR reflections to be consistent with the definition of the Beer–Lambert law. The terrain height in each bin was set with the lowest first ground reflection. Last ground reflections could have been used to specify the terrain level but no significant difference were found on the tree height estimates for the considered point cloud. For the grid positions j in the x–y plane, the effective PAI (PAI_{eff}) was defined as the cumulative sum of each a^k_j voxels contained inside a given bin, given as:

\[ PAI_{eff}^j = \sum_{k=1}^{n_b} a^k_j \Delta z, \quad \text{where} \quad n_b = \left\lceil \frac{h_{max}^j}{\Delta z} \right\rceil. \] (7)

The PAI_{eff} denotes the raw PAI without any corrections applied.

3. Test site and experimental method

3.1. Site description

The LiDAR method was implemented and tested on a 5 km × 5 km area, centered around the Skogaryd Research Catchment.2 (58°21′50.5″N, 12°8′59.4″E) The site is located ±50 km from the west coast of Sweden (Fig. 1a). The ALS was produced by the National Land Survey of Sweden in the context of the Swedish national digital elevation model project. The scans were performed from 3 to 4 June 2011 and had a mean scanning resolution of 1.42 reflections m⁻² for the whole area. The area is predominantly covered by coniferous forest, but also contains areas of low-crop agriculture. Two tall installations were present on the site, a mast and a scaffold tower.

3.2. Wind measurements

The 38-m-tall mast was the basis for the wind experiment. The mast was equipped with six sonic anemometers (Metek USA-1 Basic), which were mounted at 1.2, 6.5, 12.5, 18.5, 31.0 and 38.4 m above the local ground level. For the levels below the canopy top, the instruments were not closer than ±1 m from the nearest branch. The measurement campaign lasted from 19 August 2010 to 26 October 2011. The forest immediately surrounding the mast was an ±50-year-old forest dominated by Norway spruce (Picea abies). The forest height h_r was estimated to be 24–28 m near the mast. Data were sampled at 20 Hz and averaged over 30 min. The Metek sonic anemometer data were corrected for flow distortion and treated the same way as described in Bechmann et al. (2009). The friction velocity and Monin–Obukhov lengths L were calculated as in Dellwik et al. (2014). The selection for near-neutral data was based on two criteria: \( z_{nref} - d \mid L_{ref} < 0.05 \) and \( u_{38m} > 4.5 \text{ m s}^{-1} \), where \( z_{nref} = 38 \text{ m} \) denotes a reference height above terrain. L_{ref} the Monin–Obukhov length at the reference height \( z_{nref} \), \( d = 0.75 h_r \approx 20 \text{ m} \) was the assumed displacement height and \( u_{38m} \) the mean wind speed in the mean wind direction at \( z = 38 \text{ m} \). For the CFD model validation, we focused on the eastern and western wind directions, which had contrasting upstream vegetation density and terrain. A total of 222 samples centered around the 270° sector and 58 samples around the 90° sector were taken on a 30° wide angle.

3.3. Inventory A area

The 24-m-tall scaffold tower is located about 600 m to the north–west of the mast (Fig. 1b, red square). In October 2010, detailed measurements of tree height and PAI were performed for a relatively homogeneous 90 m × 90 m area centered around the tower. This area was denoted as the Inventory A area. All trees in Inventory A were classified into species and status (alive or dead). There were 515 trees in the area (450 × Picea abies, 42 × Pinus sylvestris and 23 × Betula pendula). Tree height measurements were taken for each of the 515 trees using a Vertex IV inclinometer (Haglöf, Långsele, Sweden), with an instrumental uncertainty of ±0.1 m (Vertex IV, 2007). The distribution and location of the trees were mapped (Fig. 1c) using Stand Visualization System software. For comparison, the ALS data for this area are also shown (Fig. 1d).

3.4. Ground-based measurements of PAI

The PAI measurements in Inventory A were taken with a plant canopy analyzer (PCA) (LAI-2000, LI-COR, Inc., Lincoln, Nebraska). The PCA was used in its two-sensor and five rings mode with 45° view caps on both sensors. The reference sensor was mounted at 25 m on top of the scaffold tower and set to measure once every 15 s. The measurements from the sensor inside the canopy were taken at breast height (\( z = 1.3 \text{ m} \)). The PAI_{eff} values were recorded every 6 m in a 16 × 16 equidistant horizontal grid (256 measurements). The vertical distribution of PAI_{eff} was also measured at different heights on the tower: 2, 11, 15, 19 and 23 m. The measurements of the vertical PAI_{eff} variation were made using 180° view caps.

3.5. Inventory B areas

A similar inventory denoted Inventory B, consisting of 15 randomly selected 15 m × 15 m areas (Fig. 1b, green squares), was made between 26 June and 27 August 2012 (see also Shendryk et al., 2014). The height of all trees was measured using the Vertex IV inclinometer, but the PAI was not measured. Compared with the Inventory A area, the fifteen areas contained more variability in stand age and height. The mean stand density for all 15 areas was 0.0877 tree m⁻².

3.6. Forest growth

To account for the time difference of ±1 year between the tree height measurements in the Inventory B areas and the ALS data, the ALS-based estimates were corrected for growth. Based on local field observations, 0.4 m was added to the tree height results of the ALS. The growth was neglected for the comparison between the ALS data and the data taken in Inventory A. This assumption was based on the shorter gap between the time the ALS and the inventory measurements were acquired (≈8 months) and the reduced growth rate during the winter season.

4. CFD model

4.1. Model details

The CFD model was based on a neutrally stratified RANS analysis using the standard \( k – \varepsilon \) model (Jones and Lauder, 1972). The source terms \( S_k \) and \( S_\varepsilon \) in Eqs. (1) and (2) were added to the \( k – \varepsilon \) equations to model the effect of the canopy (Sogachev and Panferov, 2006; Sogachev, 2009). The drag coefficient in the source terms

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2 A research station within the Swedish Infrastructure for Ecosystem Research Science, SITES (www.fieldsites.se).
was set to $C_g = 0.2$. The $k - \epsilon$ equations in the form used can be found in Wilcox (2006) where the constants of the model were set to $C_{\mu} = 0.06$, $\kappa = 0.4$, $\sigma_k = 1.0$, $\sigma_\epsilon = 2.1$, $C_{\epsilon_1} = 1.52$ and $C_{\epsilon_2} = 1.83$. The Coriolis force was added to the momentum equations and a length-scale limiter was added to limit the growth of the modeled mixing length following Apsley and Castro (1997). The maximum length scale $l_{\text{max}}$ in the limiter was prescribed using the relationship of Blackadar (1962):

$$l_{\text{max}} = \frac{0.00027G}{f_c}$$

where $G$ is the geostrophic wind and $f_c = 1.2 \times 10^{-4}$ is the Coriolis frequency.

4.2. Domain and grid specifications

The domain specification in the following description is illustrated in Fig. 3. A box-type computational grid having a 50 km length and 20 km width centred on the mast location was used. The computational grid had an equidistant $x$-$y$ resolution of 10 m near the domain centre. The grid cells were stretched towards the exterior boundaries. A hyperbolic mesh generator (Sørensen, 1998) was used to make a three-dimensional volume grid. The domain height was set to 4 km with a vertical near-wall resolution of 0.03 m, from where it was expanded to a resolution of about 1 m at a 30 m height above the ground. Simulation tests indicated that the numerical solution was sufficiently grid-independent. Based on measurements made at the site (see Section 5.1 for details), a 5 km $\times$ 5 km forest grid was generated from the ALS, as described in Section 2, using a bin radius of $r = 10$ m, a grid spacing of $\Delta x = \Delta y = 10$ m and layers of $\Delta z = 1.0$ m thickness. The forest grid was interpolated in the central area of the CFD grid. Inside the forested area, a roughness height of $z_0 = 0.1$ m was used at the ground boundary below the canopy. Outside this area, a roughness of $z_0 = 1.5$ m was set to reproduce appropriate farfield conditions.

4.3. Numerical setup

The set of model equations were solved using the EllipSys3D flow solver (Michelsen, 1992, 1994; Sørensen, 1995). The Leonard’s third-order accurate QUICK scheme (Leonard, 1979) was used on the advective operators and the standard second-order central difference scheme was used for all remaining terms. Periodic conditions were used on all the vertical boundaries and symmetry conditions (zero normal gradients) were used at the top boundary. Standard log-law wall functions were applied at the ground boundary, as described in Sørensen (1995). The flow was forced with a lateral pressure gradient equivalent to the Coriolis force to simulate a geostrophic wind $G$. The forest grid and the terrain were horizontally rotated with an angle $\theta$ such that the wind vector at 38 m above ground level (AGL) was aligned with the desired wind direction at the mast location. The magnitude of $G$ was imposed at the top boundary such that the calculated mean wind speed at 38 m AGL was matching the measured wind speed magnitude at the mast location.

5. Results

In this section, the tree height and PAI obtained using the LiDAR method proposed (Section 2) is first compared with ground-based measurements. Second, results of CFD simulations using the method are presented. The simulations were performed for western and eastern wind directions to highlight asymmetric influence of the canopy structure on the wind field.

5.1. LiDAR method validation

An unknown to be determined in the LiDAR method was the correct bin radius $r$ (see Section 2.3). The PCA and ALS data were therefore assembled into grids and a statistical comparison of $h_{\text{max}}$ and $PAI_{\text{eff}}$ in Inventory A was performed. For the ALS grid, the thickness of the layers $\Delta z$ in the bins were kept fixed to a value of $\Delta z = 1.0$ m. The first near-ground layer in the $PAI_{\text{eff}}$ determination was excluded to be consistent with the PCA measurements, which were taken at breast height ($z = 1.3$ m). The ALS data was arranged in a grid having the same specifications in terms of $x$-$y$ grid point positions and spacing ($\Delta x = \Delta y = 6$ m), as the grid defined for the PCA data (Section 3.3). This grid was denoted the $16 \times 16$ grid. For $h_{\text{max}}$, the grid was reduced with a 18 m $x$-$y$ offset so that the bin radius does not exceed the area where the tree height data was recorded. For this reason, the $h_{\text{max}}$ grid had fewer grid points and the maximum bin radius was limited to $r = 18$ m. This grid was denoted the $10 \times 10$ grid.

The bin radius $r$ in the LiDAR method was varied to find the optimal grid value of $PAI_{\text{eff}}$ matching the grid value of $PAI_{\text{eff}}$. Both values agreed well for $r = 10$ m (Fig. 4a). The standard deviations $\sigma_{PAI_{\text{eff}}}$ became equal at $r = 10$ m (Fig. 4b). Regardless of the bin radius, $h_{\text{max}}$ was underestimated compared with the ground-based measurements (Fig. 4a) although their variability $\sigma_{h_{\text{max}}}$ was similar (Fig. 4b). The difference in grid values of $h_{\text{max}}$ for all $r$ was $\Delta h_{\text{max}} = 1.8$ m. Because the PAI as measured with the PCA is a well-known standard and because we aimed for the smallest possible binning area without altering the $PAI_{\text{eff}}$ estimates, we choose to fix the bin radius to $r = 10$ m. At this value, the same variability of $\sigma_{PAI_{\text{eff}}}$ occurred while the $PAI_{\text{eff}}$ remained comparable. A grid spacing of $\Delta x = \Delta y = 10$ m was chosen as $PAI_{\text{eff}}$ and $h_{\text{max}}$ did not vary significantly for higher resolutions (not shown).

Using $r = 10$ m, the scatter plot between $PAI_{\text{eff}}$ and $PAI_{\text{eff}}$ (Fig. 5a) showed a low correlation ($r^2 = 0.176$) and a root mean square error of $R = 0.864$, although the grid values of $PAI_{\text{eff}}$ were comparable ($PAI_{\text{eff}} = 2.98$ and $PAI_{\text{eff}} = 2.88$). To investigate if a stronger correlation was present for larger averaging areas, the $16 \times 16$ grids were averaged and aggregated on coarser $8 \times 8$ grids (Fig. 5b). The result showed an increased $R^2 = 0.336$ and a diminished $R = 0.591$. The tree height scatter (Fig. 5c) clearly indicated an overall underestimation ($\Delta h_{\text{max}} = 1.85$ m) by the LiDAR method compared to ground-based measurements. The correlation was low ($r^2 = 0.344$), but this was mainly due to the limited range of tree height values present in this specific area. To verify if a better correlation was present over a greater range of values taken in various areas, maximum tree heights derived from the ALS were compared with the maximum tree heights measured in Inventory B (Section 3.5, Fig. 5d). An improved correlation was obtained ($r^2 = 0.901$) with an overall tree height underestimation of $\Delta h_{\text{max}} = 2.04$ m.

An analysis was performed to determine whether the statistical properties of the ALS grid were changing with different scanning resolutions. A scanning resolution map for the 5 km $\times$ 5 km area is presented (Fig. 6a). The figure shows higher-resolution areas in the point cloud due to overlapping scans in the flight paths. The Inventory A area was located in a low-scanning-resolution area ($\approx 0.6$ reflections $m^{-2}$). Four different areas of 200 m $\times$ 200 m showing the highest scanning resolution were analyzed. The locations of these areas are indicated by black squares (Fig. 6a). The scanning resolution in these respective areas was intentionally lowered by successively removing every second pulse. The result is shown for four different resolutions (Fig. 6b). For all areas combined, the average lowest to highest resolutions were 0.3, 0.6, 1.2 and 2.5 reflections $m^{-2}$. For the resolutions of 0.3, 0.6 and 1.2 reflections $m^{-2}$, the average tree height respectively differed...
by 9.3, 5.1 and 2.1% from the average tree height calculated using the highest resolution (2.5 reflections m$^{-2}$). The calculated values of $PAI_{eff}$ differed on average by 1.7% between the lowest and the highest resolutions of 0.3 and 2.5 reflections m$^{-2}$. The tree height was therefore more sensitive than the $PAI_{eff}$ to the scanning resolution. These results indicated that even with relatively poor scanning resolution, a good description of $PAI_{eff}$ can be achieved. A mean tree height underestimation (≈5%) is however expected in specific areas of the ALS grid exposed to low scanning resolutions. Likewise, the variability $\sigma_{h_{\max}}$ and $\sigma_{PAI_{eff}}$ showed a negligible dependence on the scanning density (not shown).

PCA measurements were taken at several heights in the scaffold tower located in the Inventory A area (see Section 3.3). A comparison of the $PAI_{eff}$ measured with the PCA and the LiDAR method is shown in Fig. 7. In this comparison, the vertically varying $PAI$ at a given height $z$ was defined as:

\[ PAl(z) = \int_{z}^{h_{\max}} a(z)dz. \tag{9} \]

A single bin centred on the tower location was used to obtain the profile of $PAI_{eff}^{ALS}$. The $PAI_{eff}^{ALS}$ profile was similar to the profile of $PAI_{PC}^{eff}$, but with a small systematic underestimation ($R = 0.49$). The binning area was also increased from $r = 10$ to 15 m and the scanning resolution was lowered from 0.6 to 0.3 reflections m$^{-2}$ inside the bin. Both tests were only affecting the $PAI_{eff}^{ALS}$ estimates in the bottom part of the canopy (4.5% and 10.3% differences at $z = 2$ m respectively, Fig. 7).

5.2. Wind simulation results

In the following results, simulations are shown for the western and eastern wind directions. The magnitude of the velocity vector $u$ at the reference height $z = 38$ m AGL of the mast location was denoted $u_{\max}$. The x, y and z axes were oriented in the west–east, north–south and vertical directions, respectively (see Fig. 3). At the upper boundary, $G = 27.5$ m s$^{-1}$ was imposed for the western wind direction and $G = 25.0$ m s$^{-1}$ for the eastern wind direction (see Section 4). The LiDAR method produced a wind variability as low as ≈10 m in the x–y plane for the western results (Fig. 8). As expected, the wind field variations for the $u_x$ component were in great part influenced by the terrain elevation; but some recognizable forest signatures were observable (Fig. 8d and e). The most evident forest effect was produced by the patch of high $PAI$ and $h_{\max}$ in the central part (Fig. 8a and b), where the low wind velocity field was corresponding with the geometry of the patch (Fig. 8d and e). Small and even slightly negative velocities were obtained at $z = 10$ m AGL in the northern part of the area (Fig. 8e). The small velocities were present over large distances (≈500 m). The combined effect of the low forest density/height and higher terrain elevation (Fig. 8a–c) produced a high velocity field along $y = -400$ m from $-400 < x < 0$ m (Fig. 8d and e). The $u_z$ component was strongly correlated with the canopy structure (Fig. 8f). In areas where the terrain effect was not

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**Fig. 3.** Sketch of the computational domain and the forcing setup of the simulations. A geostrophic wind was imposed from the balance of a lateral pressure gradient and the Coriolis frame. The forcing was set such that the simulated wind velocity was oriented in the direction of the measured wind velocity at $z = 38$ m AGL (in the x–y plane) with the same magnitude.

**Fig. 4.** Variation of: (a) mean values and (b) standard deviations of plant area index and tree height with the bin radius $r$ for the PCA and ALS grids in Inventory A area. The dash lines indicate the results from the PCA grid and the plain lines, the results from the ALS grid. The vertical plain black line indicates the bin radius chosen in the analysis ($r = 10$ m). The shaded areas in (a) show the extent of the standard deviation around the mean.
dominating, positive values were observed where the forest was denser and higher than the surrounding environment. An evident example was the north–south row of trees located on the eastern side of the mast (x = 300 m, Fig. 8b) showing positive $u_x$ components (Fig. 8f). Negative values were obtained where the forest was sparser and lower than the surroundings.

Transects of the flow along the black line (in Fig. 8) are shown (Fig. 9). The raw point cloud data (Fig. 9a) showed various clearings (at $x = -140$ m, $x = 20$ m and $x = 110$ m), the height of the trees and the spatial distribution of the trees within the stands. The terrain elevation was fairly flat in this area, except from 125 < $x$ < 200 m where there is a small hill (Fig. 9a). The vegetation was also lower...
above the hill compared with the mast area (Fig. 9a). The α values extracted from the point cloud (Fig. 9b) showed regions of high-density crown and low-density trunk space in the western forest patches, as well as dense low trees around x = 130 m. For the western wind direction, the flow accelerated over the stand at 25 < x < 110 m due to west–east decreasing tree height (Fig. 9c) and over the hill. The wind was strongly decelerated in the forest patches located at x = 100 m. This was significantly different for the eastern wind direction (Fig. 9d), where the u0 component was adjusting to the forest only for x < 50 m. Small regions of recirculation were observed close to the ground between 100 < x < 200 m for both wind directions (Fig. 9c and d). These small-scale motions were induced by the large drag due to the high canopy density, the hill-induced adverse pressure gradient and the low pressure behind the forest edge at x = 110 m. For the eastern wind direction (Fig. 9f), the flow was mostly dominated by downward motions above z = 50 m from -200 < x < 50 m, an effect that was opposite in the western results (Fig. 9e). Inside the forest, the regions of updraughts and downdraughts were taking place at different locations for the eastern results compared to the western results (e.g. at x = 0 and x = -100 m). These differences suggest a strong wind directional dependence of the flow over and inside forests.

The profiles of u/uv3m (Fig. 10a) showed that the wind direction differences present in the measurements were captured in the CFD results. A better agreement was found for u/uv3m for the western wind direction (R = 0.026) compared to the eastern wind direction (R = 0.046). For the profiles of k/uv3m (Fig. 10b), the differences were small for the western wind direction (R = 0.009) but an over-prediction lying outside the measurement uncertainty range was obtained for the eastern wind direction (R = 0.036). Simulations performed with a flat terrain while preserving the forest information (not shown) indicated that the over-prediction was caused by the densely forested hill located upstream (x = 400 m, Fig. 8c).

### 6. Discussion

The discussion is divided in three parts, each containing specific topics emerging from the study: the uncertainties from the presented methods for determining (1) the plant area index and (2) the tree height; and (3) recommendations and issues related to the wind simulations.

<table>
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<th>Table 1</th>
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<td>in Inventory A for 14 measurement points taken on two different days (October 14 and 15) and for the day reported in the paper (October 12).</td>
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<tr>
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<td>October 15</td>
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### 6.1. On the plant area index

The vertical profile of PAI\textsubscript{eff} was consistently lower than the PAI\textsubscript{PC}\textsubscript{eff} (Fig. 7). In some cases, especially in the top part of the canopy, the PAI\textsubscript{PC}\textsubscript{eff} readings were made very close to the stem or directly under a branch, leading to recordings that were likely higher than the average conditions at these heights. These problems were more easily avoided near the ground (z = 2 m) where the recordings are therefore expected to be more representative. Since there was an unphysical decrease in PAI\textsubscript{PC}\textsubscript{eff} between z = 11 and 2 m (Fig. 7), we considered that the values of PAI\textsubscript{PC}\textsubscript{eff} at the top part were in fact overestimated.

At the bottom part of the canopy, PAI\textsubscript{AL}\textsubscript{eff} was reduced when the scanning resolution was lowered (Fig. 7). This local effect was due to higher amount of LiDAR reflections occurring in the top part of the canopy while fewer pulses penetrated the lower canopy. Although the observed differences were small, there could still be areas with very dense vegetation producing significantly poor estimates in the lower canopy. In wind simulations, most of the momentum is absorbed in the top part of the canopy (Wilson et al., 1982). For this reason, this effect was considered minor.

In this study, we assumed a spherical orientation of the canopy element surface angles — a specific approximation of the so-called G-function (Ross, 1981; Weiss et al., 2004). This function could be variable due to the variety of canopy element orientation, size and shape that can be observed for different types of forest. To test a different angle distribution on the vertical profile of PAI\textsubscript{eff} (Fig. 7), the G-function was lowered from 0.5 to 0.4 in Eq. 5. At z = 2 m, where the results were more representative as argued above, a closer agreement with the PAI\textsubscript{PC}\textsubscript{eff} results was found for 0.5. Richardson et al. (2009) also found that the G-function corresponded well to a spherical approximation for their analysis over a mixed-type forest, and mentioned that deviations from this theoretical distribution are not common. For these reasons, we considered the spherical approximation acceptable.

Compared with Solberg et al. (2009) and Richardson et al. (2009), low r\textsuperscript{2} values were obtained in Inventory A (Fig. 5a and b in Section 5.1). Several factors may have influenced the scatter between PAI\textsubscript{PC}\textsubscript{eff} and PAI\textsubscript{AL}\textsubscript{eff}. Among them, the uncertainty related to the spatial resolution of the PCA could be mentioned (Fig. 5a). To assess this effect, the data were analyzed using either four or five rings. The r\textsuperscript{2} values were similar using four rings (r\textsuperscript{2} = 0.178) compared to five rings (r\textsuperscript{2} = 0.176) indicating that the low correlation was not caused by the PCA resolution. Overall, the analysis was restricted to a small range of PAI values (PAI\textsubscript{eff} = 1 – 6) and there was different influence from local forest heterogeneities for the two PCA and ALS methods. We believe that these factors were the most contributing to the low correlation.

Suboptimal light conditions may have caused a bias in PAI\textsubscript{PC}\textsubscript{eff} (Leblanc and Chen, 2001). A sub-sample of fourteen of the grid points were measured on two supplementary days with predominantly clear and overcast conditions, respectively (Table 1). The differences in mean estimates of PAI\textsubscript{eff} for these points between the two supplementary days and the day the complete
measurements were recorded were below 6%. This result therefore provided a strong confidence in the PAI_{PCA} values reported in the study.

Through the binning process, we ensured that the mean and standard deviation (variability) of the forest properties were well represented for the Inventory A area, where the scanning resolution was uniform and was ≈0.6 reflections m⁻². A smaller value for the binning radius was however used in our study compared to other studies (r = 10 m compared with e.g., r = 17.8 and 15 m in Solberg et al. (2009) and Richardson et al. (2009), respectively). In our method, the binning represent a well-defined area but the PCA includes information from the local forest over an unknown area. Averaged over Inventory A, the PAI_{eff} results were almost independent of the binning radius (Fig. 4a). Moreover, varying the binning radius from r = 10 to 15 m produced a small effect on the vertical profile of PAI_{eff} (Fig. 7). Since we were aiming at obtaining a grid variability similar to the PCA (Fig. 4b) while keeping the bin radius small, this increased our confidence in applying a value of r = 10 m in our analysis.

6.2. On the tree height

A mean tree height underestimation was systematic over the four 200 m × 200 m areas (Fig. 6a and b). For low scanning resolutions, the top part of the canopy was missing in the point cloud which explained the high sensitivity for the tree height (Fig. 6b). Depending on the CFD application, a h_{max} underestimation could potentially affect the wind results. Here, we validated the RANS model with near- and within-canopy wind measurements, which demanded a precise description of the forest properties. By coincidence, the ALS scans in the immediate vicinity of the wind mast were of considerably higher resolution (>2 reflections m⁻²) than
the rest of the investigated area (Fig. 6a). Given that the mean underestimation of $\bar{h}_{\text{max}}$ for Inventory A and Inventory B was $\approx 2$ m and that $\bar{h}_{\text{max}}$ showed a uniform increase of $\approx 1$ m when the scanning density was increased from 0.6 to 2.4 reflections m$^{-2}$ (Fig. 6b), we estimated that the error on $h_{\text{max}}$ was $<1$ m, which corresponded to $\approx 5\%$ of the local tree height. In addition to being within the uncertainty of the CFD grid vertical resolution ($\approx 1$ m at 30 m), we considered this underestimation negligible.

6.3. On the wind simulations

CFD applications require input over large areas which may include sub-areas of different scanning resolutions (Fig. 6a). For the Skogaryd forest, increasing the scanning resolution had a small effect on the mean values of $\text{PAI}_{\text{eff}}$ (Fig. 6b). The vertical profile of $\text{PAI}_{\text{eff}}$ was also unaffected by the scanning resolution down to a certain level at the bottom of the canopy (Fig. 7). Nevertheless, we suggest using scans with a resolution exceeding 0.6 reflections m$^{-2}$ to avoid potential inaccuracies. At this resolution, an error of $\approx 5\%$ can be expected for the tree height and $\approx 2\%$ for the PAI.

The ALS technique gives a temporal snapshot of the forest properties. For wind-energy projects, the surface conditions evolve during the operating lifetime of wind farms (20–30 years). The average forest height growth over such a time period is significant (Liefers et al., 1996). This can substantially affect the wind field during the life-span wind farm projects. In this case, other techniques...
allowing the temporal variations of the growth to be monitored, such as synthetic aperture radar for example (Peduzzi et al., 2012), could be used to apply corrections to the ALS data (Clewley et al., 2012). On shorter time periods, the extinction coefficient of light $\gamma$ (Eq. 5) could change throughout the year (Breda, 2003). This is due to a particularly different light absorption behavior, for example, during the leaf-on–leaf-off periods in the summer and winter seasons. For coniferous forests, as was the case here, this effect could be ignored.

In the wind results, we showed that the LiDAR method produced a highly variable wind field above and within the canopy (Fig. 8d, e and f). Local phenomena such as flow separation were observed in hilly regions of dense forest (Fig. 8d and e). The $u_2$ component was more strongly correlated than $u_0$ with the canopy structure (Fig. 8f). By comparing results of two different wind directions (Fig. 9), a strong wind directional dependence was found. In Fig. 10a, the differences shown in profiles of mean velocity measurements between two opposite wind directions were correctly captured in the simulations. However, the $tke$ profile from the eastern wind direction showed a notable over-prediction (Fig. 10b). About 400 m upwind of the mast, a small hill (Fig. 8c) covered with dense forest (Fig. 8a and b) was identified as the source of the over-prediction (not shown). The $k-\varepsilon$ model is well-known to suffer from various drawbacks when applied to free shear flows and under conditions of adverse pressure gradient (Wilcox, 2006), which was the case over the forested hill. The results indicate that the CFD model may need further development for accurate predictions in complex forested terrain. For such development, the proposed method provides an easily applicable flow modeling test bed with low uncertainty inputs, where the performance of different CFD models can be assessed at sites with high-quality wind measurements.

7. Conclusion

A LiDAR-based method was developed to retrieve the canopy structure for CFD applications and was able to recover forest properties with a good agreement with ground-based measurements. Detailed wind profile measurements provided a strong validation case for the CFD simulations. The CFD simulations showed a high variability in close correlation with the canopy structure. The LiDAR method can reduce the gap between predictions in numerical wind models and the true flow processes observed in nature.

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References


