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Assessing forest windthrow damage using single-date, post-event airborne laser scanning data

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One of many possible climate change effects in temperate areas is the increase of frequency and severity of windstorms; thus, fast and cost efficient new methods are needed to evaluate wind-induced damages in forests. We present a method for assessing windstorm damages in forest landscapes based on a two-stage sampling strategy using single-date, post-event airborne laser scanning (ALS) data. ALS data are used for delineating damaged forest stands and for an initial evaluation of the volume of fallen trees. The total volume of fallen trees is then estimated using a two-stage model-assisted approach, where variables from ALS are used as auxiliary information in the difference estimator. In the first stage, a sample of the delineated forest stands is selected, and in the second stage the within-stand damages are estimated by means of line intercept sampling (LIS). The proposed method produces maps of windthrown areas, estimates of forest damages in terms of the total volume of fallen trees, and the uncertainty of the estimates. A case study is presented for a large windstorm that struck the Tuscany Region of Italy the night of the 4th and the 5th of March 2015 and caused extensive damages to trees in both forest and urban areas. The pure field-based estimates from LIS and the ALS-based estimates of stand-level fallen wood were very similar. Our positive results demonstrate the utility of the single-date approach for a fast assessment of windthrow damages in forest stands which is especially useful when pre-event ALS data are not available.

Introduction

Wind is a major forest disturbance agent and a key component of the dynamics of many forest ecosystems, particularly in temperate forests (Gardiner, 2013). Large storms are complex and extreme meteorological events, and their behaviour and impacts are therefore largely unpredictable (Schütz *et al.*, 2006). In Europe, more than half of forest damages in terms of fallen volume are due to wind with the increasing trend in damage levels being of particular concern (Mason and Valinger, 2013).

Both the frequency and the severity of these large storms have been attributed to climate change. Multiple studies have reported that the number of windstorms has increased in recent years (Gardiner *et al.*, 2010; Schelhaas *et al.*, 2010; Schuck and Schelhaas, 2013; Saarinen *et al.*, 2015). The damage has increased since 1950, both in frequency and in magnitude. In Europe, the variation among years is very large, but in the period 1970–2010 storm damages doubled, increasing from about 50 million m^3 to about 100 million m^3.

Multiple potential factors contribute to explaining the increasing trend in windstorm damage: (1) forest management practices with longer rotation periods; (2) delays in thinning operations which result in greater growing stock volumes and stand ages (Seidl *et al.*, 2011); and (3) changing climatic conditions, such as warmer winter temperatures and greater precipitation (Usbeck *et al.*, 2010; Schuck and Schelhaas, 2013). If the current rate of increase in growing stock volume in European forests and the increase in numbers and intensities of extreme windstorms continues, the probability of forest damage occurrence is expected to at least double, and possibly quadruple, by the end of the century (Gardiner *et al.*, 2010). Based on an ensemble of climate change scenarios, the damage from wind, bark beetles and forest fires is likely to increase in the coming decades at a rate of 0.91 million m^3 of timber per year until 2030 (Seidl *et al.* 2014).

Since 1950, more than 130 windstorms have caused notable damage to European forests. Spatially, these storms have been concentrated in Western and Central Europe including France, Switzerland and Germany, but also increasingly in Northern Europe including Sweden and Finland (Schuck and Schelhaas, 2013) where they are caused by northern hemispheric mid-latitude cyclones (Usbeck *et al.*, 2009). Based on the damage caused, the 1990 storm 'Vivian' was considered the storm of the century in Switzerland with 120 million m^3 of timber damaged (Dobbertin, 2002). Less than 10 years after, in December 1999, storms 'Lothar' and 'Martin' caused the greatest damage to European forests ever recorded with more than 240 million m^3 of timber damaged across 15 countries; France was the most affected, followed by Germany and Switzerland (Schelhaas *et al.*, 2003; Schuck and Schelhaas, 2013).

After a storm, it is necessary to rapidly obtain information about the damaged area to support forest operations and future management strategies (Honkavaara *et al.*, 2013). Monitoring forest disturbances is typically based on comparisons between information acquired before and after the event (Honkavaara *et al.*, 2013). Conventionally, airborne and spaceborne remotely sensed data are used for this purpose with the resulting process commonly characterized as change detection. Frolking *et al.* (2009) summarized how spaceborne data can be used for forest disturbance detection.

For the current study, we focused on the use of airborne laser scanning (ALS) data which are currently widely used for forest inventory and monitoring applications because they provide accurate predictors of canopy height and structure (Hyyppä *et al.*, 2012; Mura *et al.*, 2015; 2016). Multiple studies have documented the efficient use of ALS data for predicting important forest structural attributes (Næsset, 2004; Clementel *et al.*, 2012; Corona *et al.*, 2012; Montaghi *et al.*, 2013). Recent research has featured multi-temporal ALS data for estimating forest damage (Dolan *et al.*, 2011; Rahman, 2011; Vastaranta *et al.*, 2011). Honkavaara *et al.* (2013) developed an automated method for storm damage detection based on comparisons of two digital surface models (DSMs) where a post-storm DSM was estimated using high-altitude photogrammetric imagery and a pre-storm DSM was estimated using national ALS data. Saarinen *et al.* (2015) used ALS data to better understand and spatially quantify drivers of wind damage, thereby supporting forest management planning. However, the number of such studies is still limited, and they are concentrated in Northern Europe. Moreover, multi-temporal ALS data are still usually not available on vast areas.

To the best of our knowledge, no single-date, ALS-based studies have attempted to estimate storm damage effects in terms of the volume of wood logs lying on the ground, an essential approach when pre-storm ALS data are not available. This study was conducted following a windstorm that hit the Tuscany Region in Central Italy the night of the 4th and the 5th of March 2015. The storm caused extensive damage to both urban green infrastructures and forestland, especially in coniferous plantations.

The aims of this study were fourfold: (1) to develop a two-stage sampling strategy exploiting post-event ALS information to estimate windstorm damage in terms of the volume of fallen trees, (2) to assess the precision of the proposed strategy by providing a statistically sound estimator of its standard error, (3) to document the utility of this approach for estimating the effects of the abovementioned windstorm in Tuscany as a relevant and typical case study and (4) to discuss the role of such an assessment as a component of a proactive forest management framework.

Materials and methods

Study area and storm event

The Tuscany Region (22 994 km^2) is located in Central Italy and includes 11 515 km^2 (SE 0.7 per cent) of forest and other wooded lands (INFC, 2005). Broadleaf species such as Turkey oak, downy oak, pedunculated oak and sessile oak comprise 88 per cent of the total forest area. Coppice is the prevalent forest management system for broadleaves and it is applied on the 63 per cent of the total forest area (Bottalico *et al.*, 2014a; Laschi *et al.*, 2016). Coniferous species, being present mainly as artificial plantations, are dominated by maritime pine and black pine. Tuscan forests are estimated to account for a total of almost 132 million m^3 of growing stock volume (SE = 3.1 per cent) (INFC, 2005).

The windstorm that struck the Tuscan Region in the night of the 4th to the 5th of March 2015 included a dominating northeastern wind with gusts that exceeded 165 km/h. Atmospheric pressure in the affected areas exhibited a rapid drop of 16 hPa in 12 h with a rate of 1.3 hPa/h, which is a typical condition for an 'explosive' cyclogenesis. Furthermore, a sudden entrance of cold air in the lower and middle tropospheric layers caused a drop in temperature of 6–8°C generating katabatic winds (LaMMA, 2015).

Following the windstorm new ALS data were acquired to evaluate the forest conditions. Budget constraints limited the acquisition to those areas most affected by windthrow based on visual assessment by local forest authorities in the field. Photointerpretation was used to derive the area with new ALS data that were homogeneous with respect to pre-event species composition, height and tree density. The population under study is therefore defined as the set W consisting of N = 1354 damaged stands covering a total area of A = 43 623 ha (Figure 1).

Available data

Pre-event data included NIR orthophotos of the Tuscany region acquired in the spring of 2013 with 1 m resolution. Field data from the Tuscany Regional Forest Inventory (Regione Toscana, 1998) were available as a geocoded raster with one plot per 400 × 400 m cell. For each cell a large number of field variables was collected, but only information related to tree species composition was used for this study.

Between the 4th and 8th of May 2015 a flight was carried out over all the 1354 damaged stands using an Eurocopter AS350 B3 equipped with a RIEGL LMS-Q680i laser scanner and a DIGICAM H39 RGB and CIR optical instrument. The flying altitude was 1100 m above terrain level. Full-waveform ALS data were registered and discretized to a point density of 10 pts/m^2. Digital orthophotos with 0.2 m spatial resolution were also acquired. Standard pre-processing routines were used to remove noise in the ALS data (Terrasolid, 2005). ALS echoes were classified as ground/non-ground, and the relative heights above ground for echoes

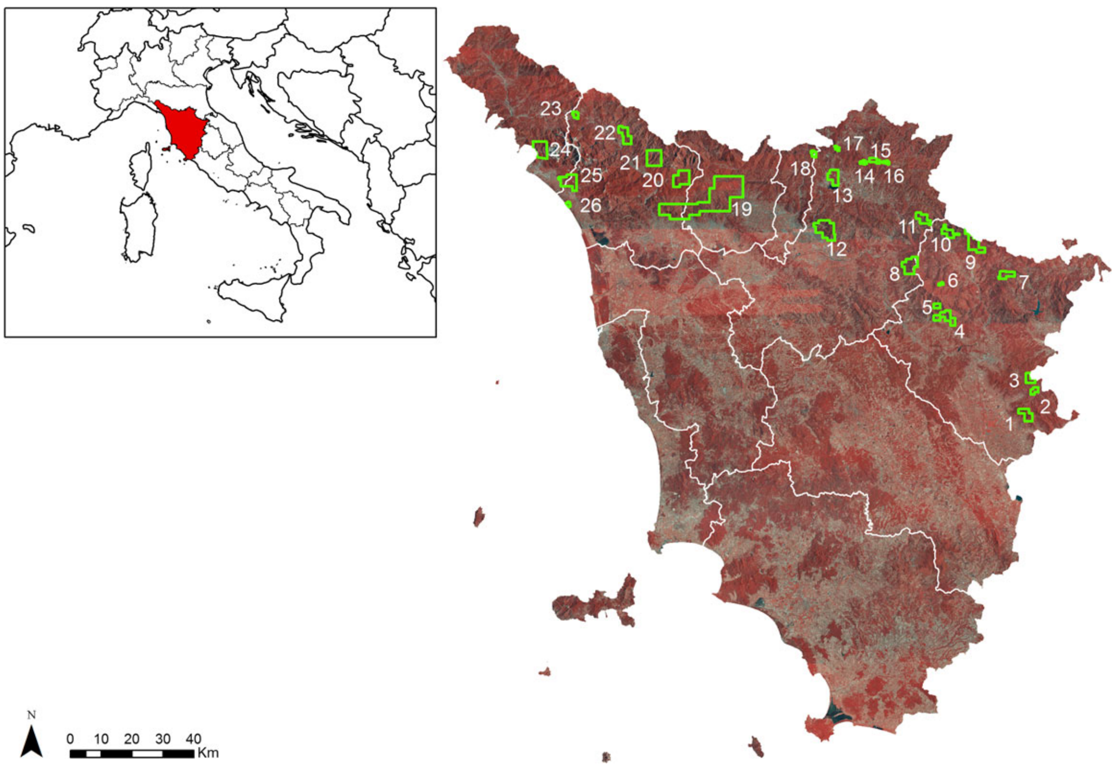

Figure 1 Study area location, continuous green lines mark the borders of the investigated areas in the Tuscany Region.

classified as non-ground were calculated and used to construct a canopy height model (CHM) with a geometric resolution of 1 m on the basis of the adaptive triangulated irregular network algorithm (Axelsson, 2000).

ALS-based damage evaluation

Remotely sensed data and other auxiliary information were analyzed using traditional photointerpretation techniques and advanced ALS data analyses (Figure 2) to map forest damages, to classify tree species, and to predict the number and the volume of fallen trees for the entire population W constituted by the 1354 damaged stands.

The damage evaluation was based on post-event ALS data using the area-based approach (Næsset, 2002).

Operators delineated the stands by digitizing vector polygons via manual photointerpretation of fine resolution pre- and post-event digital orthophotos aided by the post-event CHM. Photo-interpreters delineated the external boundaries of the stands without consideration of any groups of trees that may have remained standing and undamaged within the stand boundaries (Figure 4A).

Information from the cells of the Tuscany Forest Inventory was used to identify the species of fallen trees in each stand. The pre-event dominant heights and tree densities for the stands were determined by the operators using the post-event CHM, and the pre- and post-event orthophotos were interpreted to obtain the species of trees in neighbourhoods of undamaged trees. The latter task was not difficult because most of the damaged stands were artificial, monospecific, coniferous plantations that were homogeneous in terms of tree stem size and height with all the canopies in a single vertical stratum.

To mask out areas with standing trees inside the damaged stands we reclassified the CHM using a vertical threshold of 8 m. This value was chosen after field surveys in some of the stands to separate standing trees from fallen wood that accumulated on the ground (Figure 3).

Based on the reclassification of the CHM, for each stand k in the population of damaged stands W, we obtained the effective area with fallen trees, $EAFT_k$ (Figure 4B).

The number of fallen trees, NFT_k, in stand k was calculated by multiplying the effective area of the stand (Figure 4B) by the pre-event number of standing trees per hectare, NST_k, i.e.

$$NFT_k = EAFT_k \times NST_k,\ k \in W$$

To estimate the volume of fallen trees, VFT_k, in stand k, we used the models developed by the second Italian National Forest Inventory to predict the growing stock volume of a tree using tree diameter at breast height (DBH) and height as independent variables (Tabacchi *et al.*, 2011). These models are available for all forest tree species in Italy. For the pre-event mean height of stand k, we determined a mean DBH of the fallen trees considering an average site class from Tabacchi *et al.* (2011). Then, we used the mean stand height and mean stand DBH with the volume models to estimate the mean volume of the fallen trees, $AVFT_k$, within stand k. Finally, the volume of fallen trees was calculated using the estimated number of fallen trees as

$$VFT_k = AVFT_k \times NFT_k,\ k \in W$$

The total effective damaged area with fallen trees, the total number of fallen trees and the total volume of fallen trees for the entire population W of 1 354 damaged stands were estimated as $EAFT = \sum_{k \in W} EAFT_k$, $NFT = \sum_{k \in W} NFT_k$, and $VFT = \sum_{k \in W} VFT_k$, respectively.

Sample-based estimation

For ALS-based evaluations of volumes of fallen trees at both stand and total level presented in section 'ALS-based damage evaluation', there is no possibility to achieve objective evaluations of precision since they are

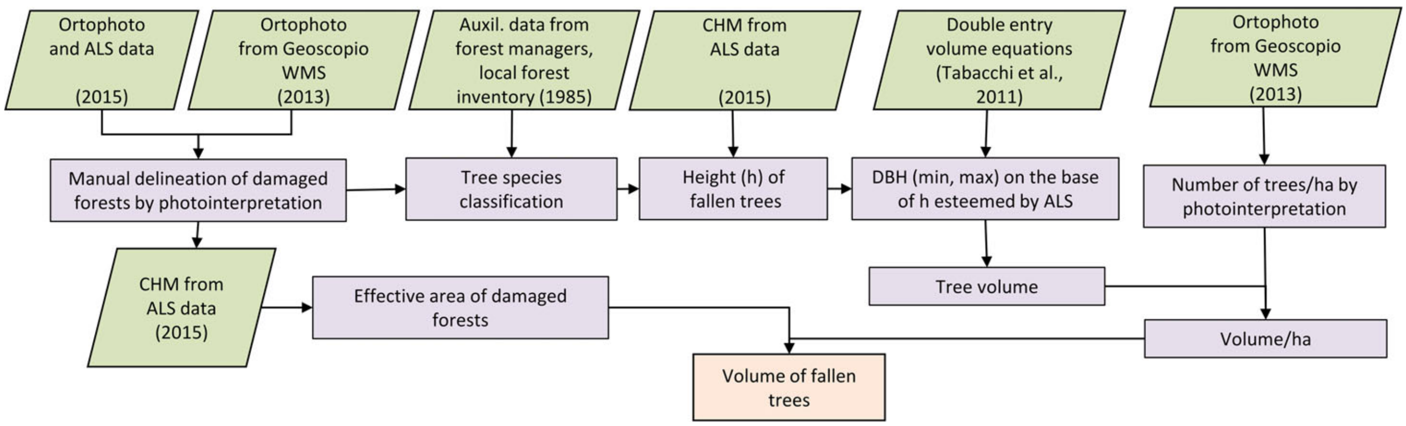

Figure 2 Data processing flowchart.

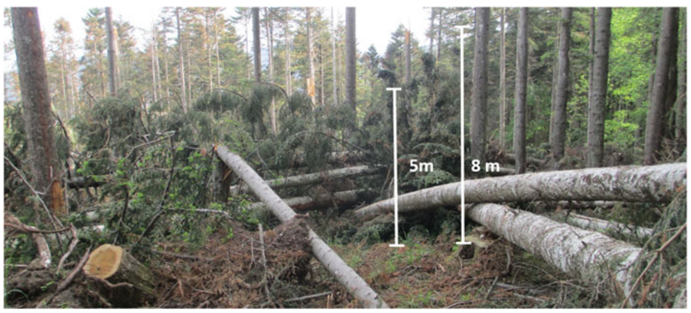

Figure 3 Example of the threshold separating undamaged trees from accumulated fallen wood.

not based on a statistical sampling design. For this purpose, the post-event ALS-based evaluations of the volumes of fallen trees for the 1354 stands were used as proxies for the true volumes for assisting a sample-based estimation of the total volume of fallen trees which allows for a subsequent estimation of the sampling error.

Denote by y_k the volume of fallen trees within stand k, and by

$$T = \sum_{k \in W} y_k,$$

the total volume in the entire set W of the $N = 1354$ stands. A two-stage strategy was used to estimate the total volume of fallen trees.

First stage

In the first stage, a sample Q of $n = 10$ stands was randomly selected using simple random sampling without replacement (SRSWOR) from the set W.

In accordance with the difference (D) estimator (Särndal *et al.*, 1992, chapter 6), our strategy is based on the assumption that the evaluation based on ALS presented in section 'ALS-based damage evaluation' of the stand-level volumes of fallen trees are good proxies for the true volumes, i.e. $y_k \approx VFT_k$. If the y_k s are assumed to be without errors within the sampled stands, the single-stage D estimator of the total volume of fallen trees is

$$\hat{T}_{(1)} = VFT + \frac{N}{n} \sum_{k \in Q} (y_k - VFT_k). \quad (1)$$

From Särndal *et al.* (1992), the D estimator is unbiased with sampling variance,

$$\mathrm{Var}_1(\hat{T}_{(1)}) = N(N-n)\frac{S_e^2}{n},$$

where $\bar{E} = \frac{1}{N}\sum_{k \in W} e_k$ and $S_e^2 = \frac{1}{N-1}\sum_{k \in W}(e_k - \bar{E})^2$ are the mean and the variance, respectively, of the errors, $e_k = y_k - VFT_k$, occurring when predicting y_k using VFT_k, and the subscript 1 denotes expectation and variance with respect to the first stage of sampling, i.e. the selection of the sample Q. The D estimator is efficient when the errors are small.

Second stage

The first-stage estimator (1) is only virtual because, besides knowledge of the ALS-based estimates of the stand-level volumes for the entire set of stands, W requires knowledge of the real fallen wood volumes within the selected stands $k \in Q$. On the other hand, the real volumes in these stands are unknown because a complete census in the field is not feasible. An effective option, as used for this study, is to estimate those volumes in a second stage by means of line intercept sampling (LIS) (Kaiser, 1983). In each stand k selected in the first stage, R_k transects of fixed length L and random direction were randomly located within the stand, and the pieces of fallen trees on forest floor - henceforth referred to as the secondary sampling units (SSUs) – crossed by a transect are selected into the sample (Kaiser, 1983, Gregoire and Valentine, 2003). Under LIS, the first-order inclusion probability of the j-th SSU in stand k is $p_j = (2Ll_j)/(\pi A_k)$, where l_j is the SSU length and A_k is the surface of the stand. Thus, the Horvitz-Thompson (HT) estimator of the wood volume of fallen trees in stand k estimated from the i-th transect is,

$$\hat{y}_{ik} = \sum_{j \in S_{ik}} \frac{v_j}{p_j} = \frac{\pi A}{2L} \sum_{j \in S_{ik}} \frac{v_j}{l_j},$$

where S_{ik} is the set of SSUs in stand k intersected by the i-th transect, and v_j is the wood volume (m^3) of the j-th SSU. If the volumes of the intersected SSUs are measured using Huber's method (Van Laar and Akca, 2007), i.e. $v_j = \pi(d_j/2)^2 l_j$, where d_j is the diameter measured at the intersection point, the HT estimator reduces to,

$$\hat{y}_{ik} = \frac{\pi^2 A}{8L} \sum_{j \in S_{ik}} d_j^2.$$

Conveniently, LIS-based estimation entails measuring only the diameter of each piece of fallen trees intersected by a transect.

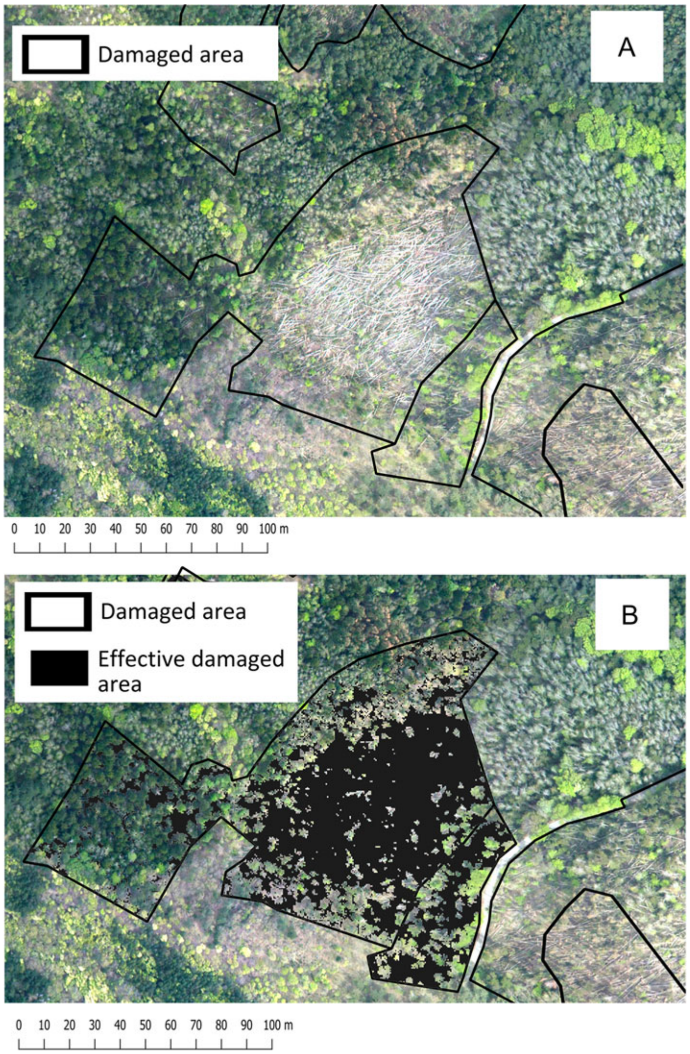

Figure 4 Example of damaged area delineated using orthophotos (A), and the map with effective fallen trees obtained from the ALS survey (B).

The number of transects, R_k, in each damaged stand $k \in Q$ can be selected as a trade-off between the need for precise estimates and the fact that the field work in windthrown areas is extremely time consuming and potentially dangerous for the operators who must work inside large and sometimes unstable accumulations of lying trees and wood logs. As is customary in forest surveys, the estimator of the wood volume of fallen trees in stand k was the mean of the R_k individual estimates, i.e.

$$\hat{y}_k = \frac{1}{R_k}\sum_{i=1}^{R_k}\hat{y}_{ik}. \qquad (2)$$

Because the transects are randomly positioned, equation (2) is an unbiased and consistent estimator of y_k, with variance $\mathrm{Var}_2(\hat{y}_k|Q) = \sigma_k^2/R_k$, where σ_k^2 is an unknown constant representing the variance that would be obtained for stand k using a single transect (Barabesi and Fattorini, 1998), and the subscript 2 denotes expectation and variance with respect to the second stage of sampling (i.e. the selection of the SSUs by LIS) conditional on the sample of stands selected in the first stage. An unbiased estimator of $\mathrm{Var}_2(\hat{y}_k|Q)$ is simply $v_k = s_k^2/R_k$, where

$$s_k^2 = \frac{1}{R_k - 1}\sum_{i=1}^{R_k}(\hat{y}_{ik} - \hat{y}_k)^2$$

is the sampling variance of the R_k estimates.

Substituting for actual (unknown) volumes, y_k, with their second-stage estimates $\hat{y}_k$ into equation (1), the second-stage D estimator of the total volume of fallen trees is,

$$\hat{T}_{(2)} = VFT + \frac{N}{n}\sum_{k\in Q}(\hat{y}_k - VFT_k). \qquad (3)$$

From the theory of two-stage estimation, equation (3) is an unbiased estimator of T with variance,

$$\mathrm{Var}(\hat{T}_{(2)}) = N(N-n)\frac{S_e^2}{n} + N\frac{S_W^2}{n}$$

where the first term is the variance of the first-stage estimator (1) that gives the variability induced by the selection of stands performed in the first stage and the second term represents the increase in variance due to the second-stage, while $S_W^2 = \sum_{k\in W}\frac{\sigma_k^2}{R_k}$ is the total of the variances due to the estimation of the y_k s within the stands.

Because $s_{\hat{e}}^2 = \frac{1}{n-1}\sum_{k\in Q}(\hat{e}_k - \hat{\bar{e}})^2$ is an approximately unbiased estimator of S_e^2, where $\hat{\bar{e}} = \frac{1}{n}\sum_{k\in Q}\hat{e}_k$ and $\hat{e}_k = \hat{y}_k - VFT_k$ is the estimated error for the k stand, and because $\hat{S}_W^2 = \frac{N}{n}\sum_{k\in Q}v_k$ is an unbiased estimator of S_W^2, an approximately unbiased estimator of $\mathrm{Var}(\hat{T}_{(2)})$ is given by

$$\hat{V}_{(2)} = N(N-n)\frac{s_{\hat{e}}^2}{n} + N\frac{\hat{S}_W^2}{n}. \qquad (4)$$

From equation (4) an estimate of the relative standard error (RSE) is $\hat{RSE}_{(2)} = \hat{V}_2^{1/2}/\hat{T}_{(2)}$. It is worth noting that once the estimates $s_{\hat{e}}^2$ and $\hat{S}_W^2$ are obtained, equation (4) can also be used to estimate the RSE which would be obtained if a sample of size n_0 stands had been selected in the first stage.

It is worth noting that equations (3) and (4) are the statistics to be computed when sample data are collected for estimating the total volume of fallen trees T and the precision of the sampling strategy.

Second-stage implementation in the case study

The total length of the transect line is an important variable when implementing the LIS method (Van Wagner, 1968). To select a suitable sampling intensity with respect to length per hectare of the transect line, a Monte Carlo simulation was carried out in one of the 10 stands selected in the first stage (silver fir forest located in Vallombrosa, near Florence; area of forest damage = 8.44 ha; effective cleared area = 5.23). In this area we first carried out a complete census of all the fallen trees and obtained a digital map of all the elements (Figure 5). Secondly, we extracted SSUs to simulate different LIS designs. Each transect was 20 m in length, and had random direction and random location. We tested sampling intensities between 80 and 1000 m/ha.

For each intensity, sampling was repeated 10 000 times. Based on the relative standard error obtained from the Monte Carlo distributions of the estimates, a total length per hectare of 500 m was selected (Figure 6).

In each selected stand, the LIS method was designed with a GIS system. Twenty-five points per hectare were randomly chosen, and a randomly oriented, 20-m transect centred on each point was used to select the fallen trees. To eliminate the edge effect we used the reflection method by line folding proposed by Gregoire and Valentine (2003). The diameters at the points of intersection between the transects and the

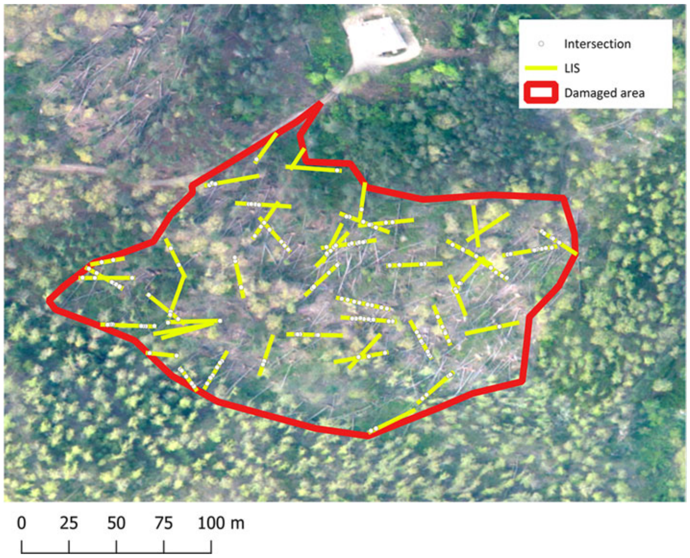

Figure 5 Example of line intersect sampling assessment.

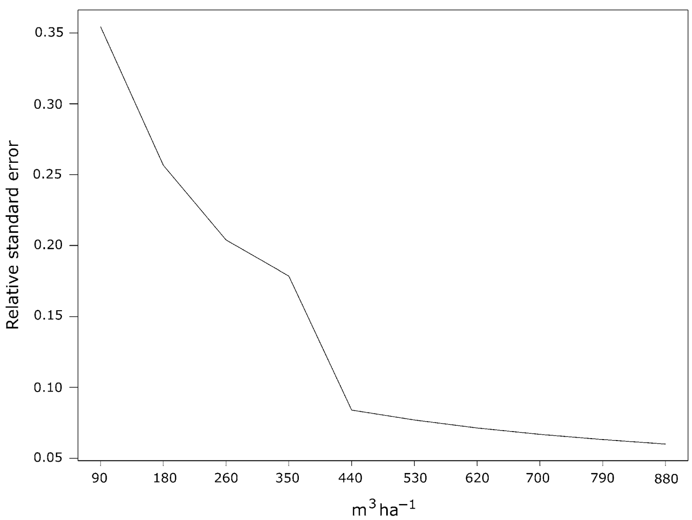

Figure 6 Monte Carlo simulation: relative standard error for different lengths per hectare of the transect line in the case study.

SSUs were measured in the field. Finally, equations (3) and (4) were used to estimate the total wood volume (m^3) of fallen trees and the relative standard error, respectively. Field surveys were carried out during spring and summer of 2015, before any fallen wood was removed.

Results

The area covered by the ALS survey was 43 623 ha of which 81 per cent was forested based on the local land use/land cover map. The 1 354 damaged forest stands affected by windthrow covered an area of 2 017 ha, albeit with different degrees of damage. The mean area of the stands was 1.5 ha, while the largest was 28.7 ha. After subtracting the areas of standing trees, the effective cleared area (the area with felled trees) estimated using the ALS data was *EAFT* = 1127 ha. The ALS-based estimate of the total number of fallen trees was *NFT* = 331 802. Based on the ALS survey, the forest type most affected by the wind damages was coniferous plantation with an effective cleared area of 821 ha amounting to 73 per cent of the total damaged area. The damaged conifers areas represent 18.48 per cent of the total conifer forest covered in the ALS survey whereas only 1.8 per cent of the broadleaved forest where the ALS data were available was affected by damage. Among the broadleaf species, sweet chestnut and the black locust were the most damaged with 177 and 118 ha of effective cleared area, respectively (Table 1).

In coniferous forests, the most damaged stands had mean DBH ≥ 30 cm and height ≥ 20 m, while for the broadleaf forests the smallest DBH and height classes were the most damaged (Figure 7). These forests are managed as coppice, and often the entire stump with younger shoots was overturned. The H/DBH ratio for most damaged broadleaves species (*Castanea sativa* and *Robinia pseudoacacia*) was often greater than 70–80, indicating slender plants with lower stand stability. In the coniferous forests composed of *Abies alba*, *Pinus nigra*, *Pinus pinaster* and *Pseudotzuga menziesii* the H/DBH ratio was often less than 50–60, typical of older trees and coinciding with larger crowns in the upper part of the stems (Figure 8).

The ALS-based estimates of the total volume of fallen trees was *VFT* = 347 168 m^3. It is worth noting that all these ALS-based evaluations (sensu 'ALS-based damage evaluation' section) were achieved by non-statistical methods and as such there was no possibility to estimate precision.

The statistical estimation (sensu 'Sample-based estimation' section) was subsequently performed by means of equation (3) using the two-stage sample survey described in the previous section. In this case the sampling variance was estimated by means of equation (4). The sample survey was carried out in 10 of 1 354 stands for a total of 57.9 ha which represents 3.6 per cent of the effective cleared area. The LIS-based and ALS-based estimates of volume of fallen trees carried out in the 10 selected stands were very similar (Figure 9).

The data fitted by means of the simple linear regression model gave an intercept estimate of a = 18.7 and a slope estimate of b = 0.90 which suggested a regression line with intercept $\alpha = 0$ and $\beta = 1$. Actually, the composite hypothesis H_0: $\alpha = 0$; $\beta = 1$ assessed by means of the F-test was accepted (F = 1.83, degrees of freedom 2 and 8, p = 0.22) with a high fraction of the variability of the LIS estimates explained by the 1:1 line (R^2 = 0.96). Therefore, the ALS-based estimates accounted for nearly all the variability in the LIS estimates, thus confirming the utility of using ALS-based methods to predict fallen wood volumes in the two-stage difference estimator (3).

The two-stage estimate of the total fallen volume was 210 958.6 m^3. Based on 10 stands measured in the field, the relative standard error corresponding to this total volume estimate was 63 per cent. This RSE is large given the similarity between the LIS-based and ALS-based estimates of stand-level fallen wood (Figure 9) and is attributed to the very small sampling fraction used in the first stage (10 of 1354 stands). However, using equation (4), the sample estimates of S_e^2 and S_W^2 were 84 293 m^3 and 15 443 014 m^3, respectively, meaning that a sample of 75 stands (5.5 per cent of the total) instead of the 10 (0.74 per cent of the total) we used, would have been necessary to obtain an RSE of

Table 1 ALS-based evaluations of damaged forest areas per tree species.

Tree species	Total area acquired (ha)	Area of forest damage (ha)	Effective cleared area (ha)	Area damaged on total acquired %	% of effective area damage on the total acquired
Abies alba (Silver fir)	2001.47	372	124	18.59	6.20
Castanea sativa (Sweet chestnut)	13 771.04	285	177	2.07	1.29
Cupressus arizonica (Arizona cypress)	15.99	2	1	12.50	6.25
Fagus sylvatica (European beech)	2374.048	17	5	0.72	0.21
Ostrya carpinifolia (European hop-hornbeam)	1195.58	4	1	0.33	0.08
Picea abies (Norway spruce)	115.65	4	1	3.46	0.86
Pinus nigra (Black pine)	2541.74	331	171	13.02	6.73
Pinus pinaster (Maritime pine)	1964.31	655	461	33.34	23.47
Pinus pinea (Stone pine)	92.00	88	34	95.65	36.96
Pinus radiata (Monterey pine)	19.65	4	2	20.35	10.17
Pinus sylvestris (Scots pine)	12.34	9	3	72.93	24.31
Pseudotsuga menziesii (Douglas fir)	775.33	69	24	8.90	3.10
Quercus cerris (Turkey oak)	2625.22	4	2	0.15	0.08
Quercus pubescens (Downy oak)	1628.18	4	2	0.25	0.12
Robinia pseudoacacia (Black locust)	3854.07	170	118	4.41	3.06

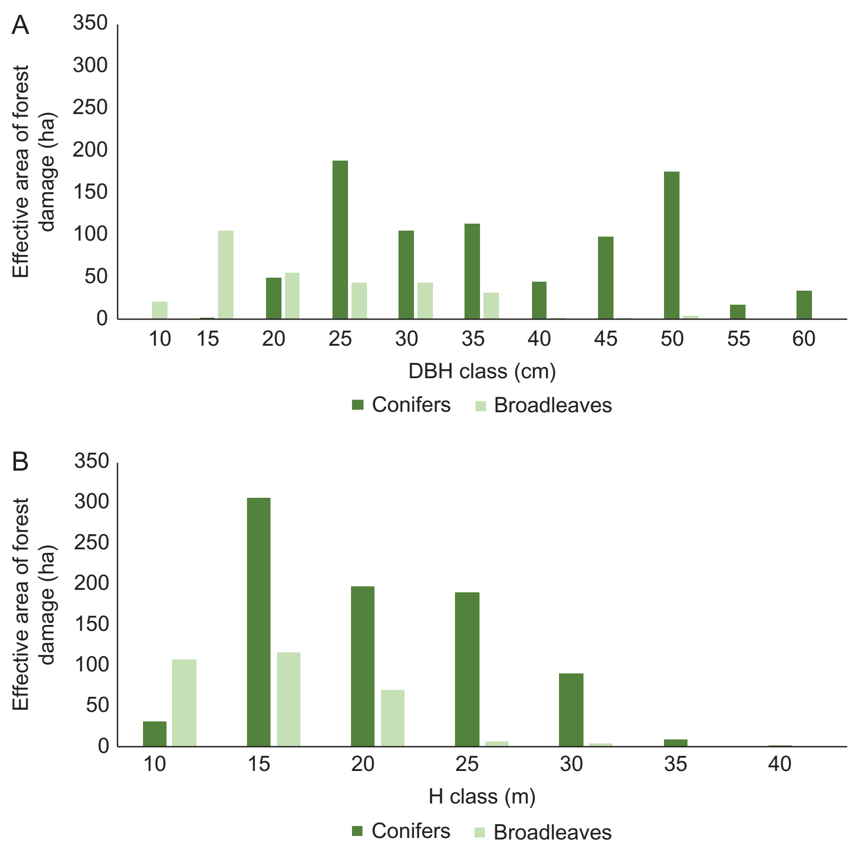

Figure 7 Effective areas of forest damage based on DBH class (A) and height class (B).

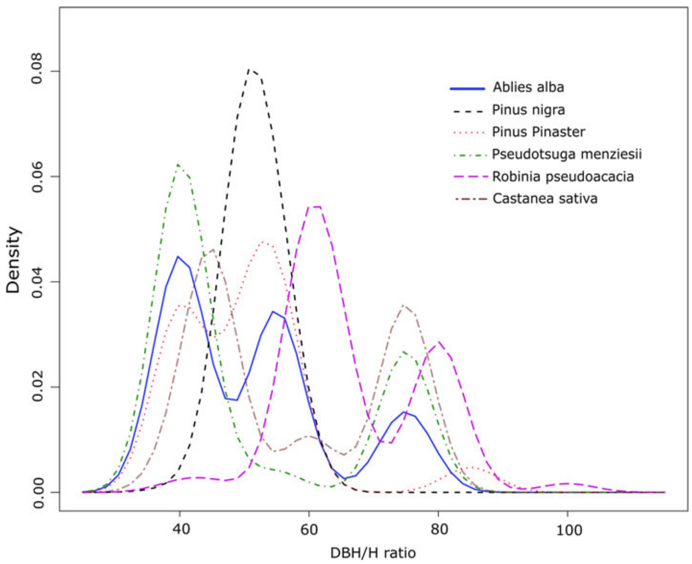

Figure 8 Height/diameter ratio of some of the main species referred to damaged stands.

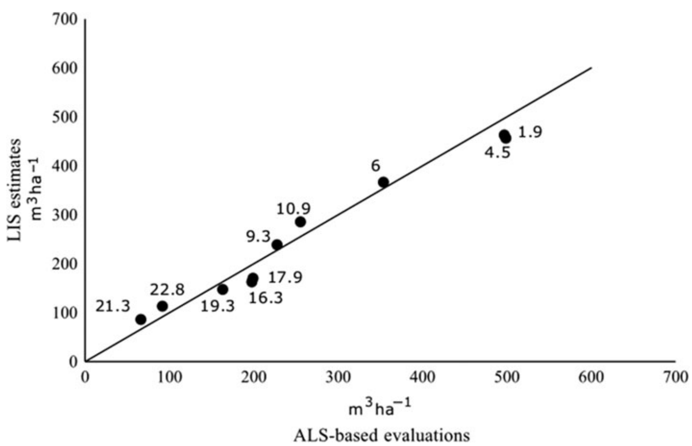

Figure 9 ALS-based estimates *vs* LIS-based estimates of fallen wood volume in the ten selected stands (the black line is the 1:1 line). Numbers on the dots represent the per cent relative standard errors.

about 15 per cent, while 150 (11 per cent of the total) stands would have been necessary for an RSE of about 10 per cent.

Discussion

Damage detection and estimation are critical steps in the management process after a windthrow event, because damaged areas must be quickly identified and mapped to facilitate selection of the best forest management actions and for supporting restoration planning.

For such an aim, we developed and applied a simple new method for estimating windstorm damages. The proposed approach is based on the availability of only post-damage ALS data which are used in conjunction with readily available data such as orthophotos, forest inventory data and models for predicting growing stock based on tree DBH and height. Thus, the method can be easily used as soon as a post-damage canopy height model is available, either from ALS data or photogrammetric analysis of optical images. We were able to produce maps, estimates of windthrown area, and estimates of forest damages in terms of total volume of fallen trees with associated uncertainties.

Methods traditionally adopted for forest damage assessment are based on change detection techniques using pre- and post-storm data, especially optical satellite images, digital orthophotos, radar data (Frolking *et al.* 2009), or in a few studies bi-temporal ALS data (Honkavaara *et al.*, 2013; Saarinen *et al.*, 2015). For cases for which pre-storm ALS data are not available, the method developed in this study can at least be a valuable option when undisturbed stands in proximity to damaged stands are available for estimating basic pre-event information (dominant species, dominant height, tree density).

On the other hand, the method we propose has some components based on photointerpretation and, therefore, implementation for large areas may be time consuming. For an initial delineation of damaged areas, classification of optical or radar images can at least partially replace photointerpretation. For this purpose, temporal segmentation methods (Kennedy *et al.*, 2010) merit consideration for long term monitoring of all the changes that occurred in a giving area.

For the case study, the LIS-based field estimates and the ALS-based estimates of stand-level fallen wood were very similar. On the other hand, the total estimate was relatively imprecise due to the small sampling fraction (selection of only 10 stands) used in the second stage. However, from the sample data, it can be inferred that a satisfactory precision of about 15 per cent could be obtained with a 5 per cent sample.

Our approach produced reliable estimates of the wood volume of fallen trees, an advance when compared to the results of Honkavaara *et al.* (2013) for which ALS and photogrammetric data were used to distinguish damaged from undamaged areas and to identify damage classes. Furthermore, the approach developed in this study circumvents the limitations associated with using optical or radar imagery for which the effects of spectral or back-scattering from the lying biomass may be confused with undisturbed stands, especially when moderate resolution sensors are used (Frolkin *et al.*, 2009). This problem is even more important when considering that not all trees in a damaged area may be on the ground and dead. For this reason, we separated the islands of standing trees in damaged areas as a mean of estimating the effective area of forest damage.

For our particular case study, operational implementation of the method for estimating damage over an area of 43 623 ha required 60 days of photointerpretation, eight days for ALS data processing and elaboration, and 90 days for the field survey. For estimating the number of days we assumed a single operator.

Taking into account the cost of dedicated flights (38 000 euros) and a person/day cost of 150 euros, the total cost of damage assessment was 1.4 euro/ha. On the whole, the assessment took three months. It is also worth noting that if the field survey had been planned to achieve an RSE of about 15 per cent, the cost would be of 2.3 euro/ha.

Based on published studies, the most important predisposing factors for storm damage in forests are tree species composition, tree size and vertical and horizontal structure (Dobbertin, 2002; Xi *et al.*, 2008; Hanewinkel *et al.*, 2013; Hale *et al.*, 2015).

Conifers are considered more susceptible to damage than broadleaf species because of the greater drag of evergreen coniferous forests during winter storms when broadleaf species are leafless (Hanewinkel *et al.*, 2013). Our study confirmed this, as most of the damaged stands (89.7 per cent of total fallen wood) were conifers (including silver fir, douglas fir, black pine and maritime pine forests). Of the total area with conifer forests acquired in this ALS survey, we found that the 18.48 per cent were affected by windstorm damages.

These species were used in Italy in the past century for many reforestations projects, often at the geographical limit of their potential distribution area (Ciabatti *et al.*, 2009). These artificial forests in the Apennines have started to exhibit symptoms of decline and dieback with multiple trees and/or small groups of trees either dead or in poor health (e.g. Bottalico *et al.*, 2014b). The poor health condition of these stands has probably contributed to reducing their mechanical stability and thereby increasing their vulnerability to strong winds.

From our observations, broadleaf species suffered much less damage. In fact, only the 1.8 per cent of the broadleaved forest covered by ALS data was affected by damage. The most damaged broadleaf forests were sweet chestnut and black locust forests (9.1 per cent of the total fallen wood), probably because they are managed as coppices for which the weight of many shoots on the same stump may have contributed to overturning stumps. The most damaged broadleaf stands had DBH ≤ 30 cm and height ≤ 20 m. Recent studies confirmed that stands with trees with such dimensions are particularly susceptible to storm damage (Dobbertin, 2002).

In our case, wind inflicted serious damage mainly to older coniferous forests with greater values of growing stock, heights ≥ 20 m and DBH ≥ 30 cm, thus confirming similar evidence reported by Dobbertin (2002) and Hanewinkel *et al.* (2013) for the Lothar and Vivian storms. In most of the damaged forests included in our study, traditional rotation ages were exceeded, resulting in older and taller stands which are more sensitive to wind risk. It is interesting to observe that the majority of fallen trees were the most tapered (Figure 8). While conventionally, slender trees are considered to have associated lower critical wind speed (Ancelin *et al.*, 2004), and therefore should have the highest risk of damage in case of windstorm. More recently, Xi *et al.* (2008) observed that in case of strong but infrequent wind disturbances, larger trees are more susceptible to damage with the risk increasing with stand height. Most probably, following the recent robust theoretical suggestions by Virot *et al.* (2016), trees are broken or uprooted regardless of their diameter / height characteristics when the winds reach a critical speed of ~150 km/h.

The forest Regional administration has proposed two main forest management options to restore the disturbed stands. For damaged areas smaller than 2000 m^2, natural regeneration is preferred, with removal of only fallen or damaged trees. For damaged areas larger than 2000 m^2, reforestation with autochthonous broadleaf species is prescribed, together with conifers where these are an important component of the local forest landscape (e.g. *Abies alba* Mill., in the Appenines; *Pinus pinea* L., in coastal areas). This approach aims at favoring the re-naturalization of coniferous plantations by promoting mixed forests to be managed with more nature-oriented management. This approach should reduce future windthrow risks (Schelhaas, 2008).

In summary, because of the expected increase in the frequency and severity of windstorms and their expected greater adverse effects because of delayed forest management practices, forest management for the future requires a paradigm shift from deterministic planning to adaptive management with monitoring as a distinctive operational pillar (Wagner *et al.*, 2014; Corona, 2016). Specifically, future forest management strategies should be directed toward a gradual shift from over-simplified structures of coniferous plantations to stands with more diverse composition and more complex structures.

Conclusion

The major contribution of our study is the development of an efficient, fast and easy method for assessing forest storm damage using post-event ALS data.

Estimation of the effective area of forest damage using the method developed in this study, which integrates remotely sensed and auxiliary data, can support forest management and planning to reduce the risk of future windthrows. Our reports of spatial estimates for the most frequently affected stand types should be used to support identification of forests stands where more urgent fellings should be carried out to augment their mechanical stability.

Our results demonstrate that ALS data are useful for providing satisfactory estimates of storm damaged areas and volume of fallen trees, even if pre-event ALS data are not available. Because the method is based on input forest data that can be easily obtained, it is potentially transferable to any forest condition. Multiple future research topics are possible in these areas including the potential use of CHM produced from photogrammetric point clouds obtained by image matching of optical aerial images instead of the more expensive ALS acquisition or the implementation of more automated procedures for the initial delineation of damaged areas through change detection techniques (Pirotti *et al.*, 2016).

One of the most likely future effects of climate change is the increasing number of storms. In this light, policy, planning and management processes should seek to produce adaptive decisions that are evidence-based (Corona, 2014). To this end, it is important that the remote sensing, forest inventory and forest management communities work together to develop fast and operational methods for windthrow damage assessment on the on hand, and for the implementation of silvicultural practices for the reduction of windthrow risk on the other hand.

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Conflict of interest statement

None declared.

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