Using Multi-Source Data to Map and Model the Predisposition of Forests to Wind Disturbance

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Abstract

Natural disturbances such as wind are known to cause threats to ecosystem services as well as sustainable forest ecosystem management. The objective of this research was to better understand and quantify drivers of predisposition to wind disturbance, and to model and map the probability of wind-induced forest disturbances (P_{DIS}) in order to support forest management planning. To accomplish this, we used open-access airborne LiDAR data as well as multi-source national forest inventory (NFI) data to model P_{DIS} in southern Finland. A strong winter storm occurred in the study area in December 2011. High spatial resolution aerial images, acquired after the disturbance event, were used as reference data. Potential drivers associated with P_{DIS} were examined using a multivariate logistic regression model. The model based on LiDAR provided good agreement with detected areas susceptible to wind disturbance (73%); however, when LiDAR was combined with multi-source NFI data, the results were more promising: prediction accuracy increased to 81%. The strongest predictors in the model were mean canopy height, mean elevation, and stem volume of the main tree species (Norway spruce and Scots pine). Our results indicate that open-access LiDAR data can be used to model and map the probability of predisposition to wind disturbance, providing spatially detailed, valuable information for planning and mitigation purposes.

KEYWORDS: wind damage, LiDAR, National Forest Inventory, Landsat, forest mensuration, risk modelling, open access

Introduction

Boreal forests are seen as complex and dynamic ecosystems (Drever et al 2006; Kuuluvainen 2009) where disturbances are a major process modifying forest structure and composition increasing heterogeneity, thus biodiversity (Kuuluvainen et al. 1998; Lewis & Lindgren 2000; Franklin et al. 2002; Kuuluvainen 2002; Rouvinen et al 2002; Levin 2005). Natural disturbances in forests appear in different forms, as abiotic (storm, drought, frost, snow, fire) or biotic agents (pest insects, diseases, mammals) (Dale et al. 2001; Fleming et al. 2002), and are seen as impediments to the productivity of managed forests (Quine 1995; Lyytikäinen-Saarenmaa & Tomppo 2002; Lyytikäinen-Saarenmaa et al. 2006). On the other hand, current forest management procedures may deteriorate the resilience of managed forest ecosystems to disturbances (Holling 2001). As ensuring biological biodiversity is one of the goals in modern sustainable forest management (Lindemayer & Franklin 2002), it has been suggested (Kuuluvainen 2009) that development of new forest management approaches (Vanha-Majamaa et al. 2007) is needed. Moreover, these practices would maintain heterogeneity and biodiversity which are related to the disturbance resiliency of managed forest, a quality which may become even more important as a result of climate change and associated changes in disturbance regimes (Westerling et al. 2006; Seidl et al. 2011; Seidl et al. 2014).

Wind was the most significant abiotic factor causing losses in forest yield in Finland in 2012 (Heino & Pouttu 2013). During the summer of 2008, wind storms resulted in the loss of more than 8,1 million m^3 of wood from Finnish forests, which equals approximately 15% of the annual cut in Finland (Finnish Forest Research Institute 2010). During storms in the winter of 2011, 3,5 million m^3 of wood were damaged, having an estimated value of 120 million euros (Ministry of Agriculture and Forestry 2011). Since most of the forests in Finland are owned by private forest owners, losses of this magnitude have an impact on those who depend on their forest holdings for their livelihood. Forsell and Eriksson (2014) studied the influence of wind disturbance susceptibility on strategic forest management planning on a large forest estate (~1200 ha). When susceptibility was taken into account in forest management planning simulations, a slight increase (< 2%) in net present value was obtained. In order to prevent pest outbreaks and protect forest value, Finnish forest regulations require forest owners to remove damaged trees if the volume of damaged timber exceeds a designated threshold (Metsälaki 1996; Metsäasetus 2010).

Wind disturbance also impacts those who rely in Finland’s electricity network. Power line networks are owned and maintained by electricity companies who are responsible for providing electricity to households connected to their networks. When electricity is unavailable, these companies must compensate customers. Wind damage is the main reason for interruptions in the supply of electricity, thus costs to electricity providers have increased in recent years (Finnish Energy

Industries 2013).

Airborne scanning light detection and ranging (LiDAR) is an efficient remote sensing tool for spatially accurate stand- and tree-level forest mapping applications. Airborne LiDAR-based mapping applications that are now in operational use were developed during the last 15 years (Hyyppä & Inkinen 1999; Næsset 2002; McRoberts et al. 2010; White et al. 2013; Wulder et al. 2013). In addition to producing accurate stand attributes for forest management, LiDAR data show great promise for monitoring and modelling to address forest information needs such as when estimating changes in aboveground biomass (Hudak et al. 2012; Næsset et al. 2012; Andersen et al. 2014). LiDAR data can provide wall-to-wall coverage, and the use of geometrically accurate multi-temporal data enables documentation of changes at the tree level (Yu et al. 2004; Vastaranta et al. 2012). However, airborne LiDAR is most capable of detecting highest trees (Kaartinen et al. 2012; Vauhkonen et al. 2012), thus it is suited best for monitoring of dominant trees. From the viewpoint of forest disturbance mapping, multi-temporal LiDAR is convenient for monitoring abiotic tree- or stand-level changes in the forest structure, such as thinnings (Yu et al. 2004; Vastaranta et al. 2013) or snow- and wind-induced disturbances (Vastaranta et al. 2011; Vastaranta et al. 2012; Honkavaara et al. 2013). Biotic changes that have more subtle effects on forest canopy structure within a short time window, such as defoliation (Solberg et al. 2006; Kantola et al. 2010), have been more problematic to map.

Increasingly, many areas in Europe, USA, and Canada are covered by LiDAR data. For example, free and open-access LiDAR data are currently available for approximately 75% of the land areas of Finland. Therefore, LiDAR data are increasingly being utilized as input information for spatial modelling purposes. To date, there exist only a few studies where LiDAR data have been used for spatial modelling of natural disturbances including examples of flood (Gueudet et al. 2004; Agget and Wilson 2009; Hohental et al. 2011) and landslide (Liao et al. 2011). In all these cases, the primary use of the LiDAR was to produce an accurate digital terrain model (DTM). In addition to the DTM, the digital surface model (DSM) is commonly produced by LiDAR data providers. In the forested areas, the DTM is used to normalize DSM heights to aboveground heights, resulting in a canopy height model (CHM).

As natural disturbances become increasingly common (e.g. Westerling et al. 2006; Seidl et al. 2011; Seidl et al. 2014), development of modern planning tools for forest sites that are highly susceptible to natural disturbance are needed (Lyytikäinen-Saarenmaa et al. 2008). As a proactive procedure, drivers associated with different kinds of disturbances need to be better understood and susceptible sites need to be identified. Based upon previous studies, tall trees are expected to be most vulnerable to wind disturbance (Lohmander & Helles 1987; Peltola et al. 1999; Jalkanen & Mattila 2000; Doppertin 2002). Diameter-at-breast-height (dbh) has been found to be a factor driving wind disturbance. Peltola et al. (1999) as well as Jalkanen & Mattila (2000) have discover that trees with smaller dbh were more vulnerable to wind whereas others (e.g. Simpson 1967; Lohmander & Helles 1987; Peterson 2000; Doppertin 2002) reported opposite; trees with larger dbh are more likely to suffer wind disturbance. Other reported factors associated with wind-induced disturbance are age of trees, crown size, health of roots, soil moisture, the amount of conifers, ditching, fertilisation, thinning, topography, and position in relation to wind direction (Lohmander & Helles 1987; Wright & Quine 1993; Jalkanen & Mattila 2000; Doppertin 2002). LiDAR-based CHM and DTM correlate with many variables that have been used to predict risk of wind damage such as tree height, crown size, stem density, and topography (Lohmander & Helles, 1987; Wright & Quine, 1993; Peltola et al. 1999; Jalkanen & Mattila 2000). As mentioned, with multi-temporal LiDAR data sets it is possible to monitor changes occurring in forests. Thus, we believe that utilization of these data sets will improve decision making in sustainable forest ecosystem management. These data sets could be utilized also in ecological modelling in regard to changes in forest structure as well as heterogeneity of forests.

In addition to the LiDAR data, forest attribute maps at resolution of 400 m^2 based on Finnish multi-source national forest inventory (NFI) are freely available for public use provided by the Finnish Forest Research Institute (part of Natural Resources Institute Finland). Multi-source NFI forest attribute maps, such as species-specific stem volume and biomass (per hectare) maps are produced by combining field plot information and Landsat thematic mapper (TM) satellite images. This information has limited accuracy for forest management but enables robust characterization of forested area (Päivinen et al. 1993; Hyyppä et al. 2000; Tuominen & Haakana 2005; Vastaranta et al. 2014). Detailed information used for forest management planning of privately owned forests is not available to third parties. For example electricity providers could benefit from knowing which areas are very susceptible to wind disturbance, but they do not have the access to this forest resource information at the stand level.

The main objective of the study was to test the applicability of open-access LiDAR data for modelling the predisposition to wind disturbance in forests. The main emphasis was to investigate variables derived from LiDAR data that explain probability of wind-induced forest disturbance (P_{DIS}). We also tested whether information about tree species would improve our modelling results. For this purpose we used multi-source NFI data to provide auxiliary information about tree species (which is challenging to obtain with open-access LiDAR data). The results were expected to support decision making in forest management planning and in other sectors (e.g. electricity providers), as well as increasing the value of these openly accessible data sources.

Materials

Study Area

The study area is located in southwestern Finland with centre coordinates 61°4′33″N, 22°52′3″E (Fig. 1) and covers approximately 173 km^2. The area is comprised primarily of managed boreal forests and agricultural fields. The main tree species are Scots pine (*Pinus sylvestris*, L.), Norway spruce (*Picea abies* [L.] H. Karst), and Silver and Downy birches (*Betula spp*.). Topography in the area is relatively flat, with an elevation range of approximately 50 to 111 m above sea level (asl) (standard deviation of 12 m). On 26th and 27th of December 2011, the area was subjected to heavy winter storm called the Tapani-storm, which was the strongest storm in Finland in a decade (Finnish Meteorological Institute 2011). The Tapani-storm caused extensive damage to the study area with the most damaging west and northwest winds blowing at an average speed of 18.3 m/s and a maximum speed of 28.7 m/s on December 26th 2011.

Figure 1. Study area.

LiDAR data

We used national open-access LiDAR data to characterize forest conditions in the study area before the Tapani-storm. The data, which are publically available and subject to open data policies, were obtained from the National Land Survey of Finland (NLS). The specifications for the data collections include a flying altitude of 2000 m, a maximum scan angle of ± 20° and a footprint of 50 cm; preferential collection occurred during a bare-ground season or during spring time, when the trees have small leaves. The minimum point density of the NLS LiDAR data is half a point per square meter and the elevation accuracy of the points in well-defined surfaces is 15 cm with a horizontal accuracy of 60 cm. The LiDAR data used in this study were collected in the spring of 2008.

Multi-Source National Forest Inventory data

In addition to field measurements, Landsat TM satellite images were utilized in multi-source NFI to predict forest attributes using a k-nearest neighbour approach (Tomppo et al. 2008). The results are presented as thematic maps (resolution of 20 m x 20 m) of site type, canopy cover, age, mean dbh and height, basal area, as well as species-specific stem volume and biomass per hectare. The expected accuracy of the predicted forest attributes at the sample plot level varies between 50 to 80% (RMSE) in stem volume, height and basal-area (Tuominen & Haakana 2005). Information from thematic maps of site type, species-specific volume, and biomass were used in this study. In Finland, site types are classified based on soil fertility and identified by means of surface vegetation by adopting indicator species (e.g. *Vaccinium myrtillus*) which are also applied when naming the site types.

Aerial images

Aerial imagery was acquired by Blom Kartta Oy © (Helsinki, Finland) to document the event of wind damage at the 8th of January 2012. The images were acquired using a Microsoft UltraCamXp (Microsoft UltraCam 2013), large-format mapping camera. The average flying height was 5370 m above ground level (AGL) provided a ground sample distance (GSD) of 32 cm. The images were taken in a block structure, with 16 image strips and approximately 30 images per strip; the forward overlap of the images was 65%, whereas the side overlap was 30%; the distances of the image strips were approximately 3900 m. The atmosphere was clear, and the solar elevation was as low as 5° to 7°. The data were collected between 11:56am and 14:11pm local time (UTC +2). Before the aerial images were collected, the first snow had fallen, so that there was approximately 10 to 20 cm snow cover on ground. It is likely that there was also some snow on trees, but visual evaluation on images indicated that the snow was tolerable for delivering accurate data on the study area. Photogrammetric processing of used panchromatic images is explained in more detail in Honkavaara et al. (2013).

Methods

Work flow

The relationship between probability of wind-induced disturbance (P_{DIS}) and LiDAR derived predictors as well as multi-source NFI forest attributes was explored and used to model and map the wind disturbance predisposition. An overview of the procedure adopted in our study is illustrated in Figure 2. Aerial images and visual interpretation were used as ground truth (i.e. reference) instead of field measurements and to build strata for selection of sample cells for modelling. DTM and CHM were developed from LiDAR data and used for extraction of the predictors describing local topography and canopy structure. Forest inventory attributes were extracted directly from multi-source NFI maps. A logistic regression approach was applied in order to identify the most relevant predictors. Final predictor variables were selected using logistic regression based on their significance to the model after investigating possible multicollinearity. The goodness of fit as well as strength and significance of overall model were tested when validating the models. The resulting probability surface was used as a map to identify areas of high predisposition to disturbance caused by heavy wind.

Figure 2. Work flow of the study.

Sample selection

Prior to the spatial modelling of wind disturbance probability, areas with disturbance were mapped. We used the same study area and same remote sensing data sets that were used in Honkavaara et al. (2013). Honkavaara et al. (2013) developed and evaluated a method based on pre-storm LiDAR canopy height model (CHM) and post-storm aerial imagery-derived CHM (normalized with LiDAR-based digital terrain model (DTM)) to detect wind damage. With their approach they were able to map forest stands with disturbance with an accuracy of 100% for areas with and without disturbance, 52% for minor disturbance (1-5 fallen trees per ha), and 36% for low disturbance (6-10 fallen trees per ha). We used this automated disturbance detection (disturbance-no disturbance) as stratification for our sample selection to obtain approximately equal samples in forest areas with wind disturbance and no disturbance. A systematic grid (16 m x 16 m) was placed over the study area and 500 sample cells (250 in strata of wind disturbance and no disturbance each) were selected randomly within each stratum. The spatial resolution of the systematic grid was selected because it is the same resolution that is applied in LiDAR-based operational forest management planning inventory in Finland. Then, the classification of each sampled cell was verified visually from the orthorectified aerial imagery acquired in January 2012. A sample cell was determined to have disturbance if a group of fallen trees was detected within the cell. During the visual inspection, 70 samples were removed because they were located in an agricultural field, or as a result of their proximity to a road, a house, or other building, i.e. they were not entirely located in forest area. Following visual inspection, 430 grid cells remained: 196 were classified as damaged and 234 as undamaged.

Extraction of the predictor variables

In the LiDAR point clouds, the ground returns were already classified using the standard procedure developed by Axelson (2000). LasTools software (Isenburg 2013) was used to merge the map sheets of NLS LiDAR data that covered the study area and to make a DTM and a digital surface model (DSM) of the point cloud with 1 m grid spacing. A 1 m resolution CHM was generated from the DSM and DTM. Predictors for spatial modelling of P_{DIS} were extracted from the LiDAR and multi-source NFI data (Tables 1 and 2) for the sample cells (16m x 16m). We employed surface models, namely DTM and CHM, to extract the LiDAR predictor variables. DTM was applied to derive variables related to topography and elevation, such as slope and aspect as minimum, maximum, and mean elevation values. Mean elevation (also mean value of DTM), slope, and aspect were extracted for each sample cell but also for a window of nine 16m x 16m grid cells centred by the sample cell to include more information about the surroundings of the sample cells. In addition, aspect was calculated as a categorical variable (i.e. northeast, southeast, southwest, and northwest) in order to correspond to the direction of the damaging winds, namely northeast. Furthermore, to extract variables characterizing forest canopy (e.g. minimum, maximum, and mean values), CHM was used. Mean value of CHM was derived for both the sample cell and nine-grid-cell window (including sample cell) again to incorporate additional information from enclosing forest. In contrast, mean value of CHM only from surroundings of the sample cell was calculated as eight-cell-window around the sample cell (CHM_{sur}) (i.e. sample cell was not included). Moreover, mean value of CHM was determined where the most destructive winds were blowing, that is in northeast of each sample cell (CHM_{wind}).

An estimate for forest vertical canopy cover (VCC), which can be expected to describe density of forest, was computed by including all the points that were higher than 2 meters (CHM > 2m), which is a commonly used threshold value for vegetation points (White et al. 2013). Open areas were extracted from the CHM where there was no canopy cover (defined using VCC) and contiguous areas were larger than 1 ha. Although there may have been vegetation in areas where CHM was less than 2 m, it was presumed that wind can also cause disturbance to forest sites next to low vegetation, e.g. sapling sites do not protect neighbouring forest from wind. Distance to an open area (DIST) was calculated as shortest distance to the nearest open area of each sample cell. Proximity (Close), on the other hand, was determined as categorical variable describing whether a sample plot was located next to an open area or not (Table 2).

Disturbance probability modelling
The discrete nature of the dependent variable in our study (i.e., disturbance, no disturbance) was well suited to the use of logistic regression (LR). Logistic regression is commonly used for modelling the probability of an event based on predictor variables (e.g. elevation, slope, tree species, and height of trees). It has been applied in forestry to estimate e.g. snow and wind damages (Valinger & Fridman 1997; Canham et al. 2001; Scott & Mitchell 2005; Vastaranta et al. 2011; Vastaranta et al. 2012).

The logistic regression model for *n* independent predictor variables (x_n) can be described as:

$$logit(p) = ln\left[{}^{p}/_{(1-p)}\right] = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n \quad (1)$$

When using the logistic model to predict probability of wind disturbance (P_{DIS}) for the study area, the predicted probabilities were calculated by transforming them back to their original scale:

$$P = \frac{e^{ln\left[{}^{p}/_{(1-p)}\right]}}{\left[1+e^{ln\left[{}^{p}/_{(1-p)}\right]}\right]} \quad (2)$$

LR coefficients are exponentiated from logarithmic scale and they ($e^{\beta 0}$, $e^{\beta 1}$, etc.) can be interpreted as change of the odds of the event of interest (disturbance event) when a predictor variable changes one unit. The signs of the coefficients (β_0, β_1, etc.) indicate if the ratio-change in the odds of wind disturbance is increasing or decreasing.

We used logistic regression to form two separate models, one with LiDAR-derived predictors only (LR_{LiDAR}) and one where also multi-source NFI variables were included ($LR_{NFI+LiDAR}$). Thus, we were able to see if information about e.g. tree species would improve our results. There were various combinations with the LiDAR-derived predictors and variables describing the forest (tree species, species-specific volumes and total stem volume (m^3 ha^{-1})) to enter the predictor selection. We tested several combinations of predictor variables including LiDAR-derived variables and tree species information. There were highly correlated predictor variables (e.g. DTM_{mean} and DTM_{max} r=0.99 as well as VOL_{spruce} and VOL r=0.9). To avoid multicollinearity we only used predictor combinations with r<0.5 when modelling the probability of wind disturbance. Potential predictor variables were tested using logistic regression analysis in R (v. 3.1.1, R Development Core Team, 2007) with both stepwise forward and backward elimination of variables. The maximum number of steps to be considered was 1000. The final predictors of P_{DIS} were selected based on previous studies (Peltola et al. 1999; Jalkanen & Mattila 2000; Hanewinkel et al. 2008), by analysing the sample, correlations, cross-classification tables, and on preliminary modelling results. In other words, predictors were chosen on the basis of biological plausibility as well as statistical significance. Preliminary models of LR_{LiDAR} and $LR_{LiDAR+NFI}$ were also compared separately by using Akaike's information criterion, AIC (Akaike 1974). AIC is an approach to seek the most parsimonious model, i.e., it tries to find a model that is best balanced between over or under fitting..

Model validation and mapping

Model validation was performed by calculating fit statistics and prediction accuracy. Nagelkerkes's R-Square (R^2) was used to assess the goodness of fit of the logistic regression model varying between 0 and 1, 0 indicating a weak model and 1 indicating a strong model (Nagelkerke 1991). Nagelkerke's R-Square (R^2) can be used the same way in model validation as the ordinary least square regression (OLS) multiple R^2, although it usually has lower values and is based on likelihood (Noruŝis 2005). We used Wald *z*-statistics and their associated *p*-values to verify the significance of each predictor variable for the model (Hosmer & Lemeshow 2000). When selecting the predictor variables we set a significance threshold of p=0.01 in order to keep only highly significant variables in the final model. Overall prediction accuracy was also used when comparing different combinations of predictor variables. A Likelihood Ratio Test (LRT) was used to measure how well our model fits (i.e., the significance of the overall model).

Maps indicating predisposition to wind disturbance were produced by applying the final models by using ArcGIS software. This allowed us to identify the areas with high probability of susceptibility to disturbance caused by wind (P_{DIS}) across the study area. In the maps a cell size of 16 m x 16 m was used which is the same cell size as the sample cells. Accuracies of wind disturbance predisposition maps were evaluated by comparing them to the reference obtained by visual interpretation of aerial images. If the predicted risk probability was over 0.5, the cell was interpreted to have disturbance and then two-scheme classification accuracy percentage and Cohen's kappa values (Cohen 1960; Gramer et al. 2014) were calculated for predisposition wind disturbance maps (Eq. 3).

$$K = \frac{\mathrm{Pr}(a) - \mathrm{Pr}(e)}{1 - \mathrm{Pr}(e)} \tag{3}$$

where Pr(a) is the overall agreement among raters, and Pr(e) is the expected chance agreement (if agreement occurs by chance only). If the raters are in complete agreement then K = 1. If there is no agreement among the raters other than what would be expected by chance (as defined by Pr(e)), K = 0.

Results

Factors explaining the event of wind-induced disturbance

Sample cells with wind-induced disturbance covered 45.6% of the entire sample. Conifer-dominated sample cells were the most exposed to disturbance: 82.1% of the entire sample was dominated by either Scots pine or Norway spruce and 94.4% of the sample cells with wind disturbance was conifer dominated. Variation of predictor variables describing topography, stand maturity and species distribution between sample cells with and without disturbance are presented in Table 3. Most of the sample cells (86.7%) were located inside forest stands and based on our analyses there was no trend that cells close to an open area would be more vulnerable to wind disturbance. VCC was higher for areas with disturbance (79.4%) indicating that dense canopies may be more sensitive to wind. Our findings indicate that mature conifer stands are most exposed to the wind disturbance. Variables derived from the DTM indicated that there was no substantial difference in topography-related attributes between sample cells with wind disturbance and without disturbance.

Mean height of nine grid cells (sample cell area included) gave better results than mean height within the sample cells only, thus CHM_{buf} was used over CHM_{mean} when estimating wind disturbance probability (P_{DIS}). For regression model where only LiDAR-derived variables were used (LR_{LiDAR}), the selected predictor variables included mean elevation (DTM_{mean}) and mean height of surrounding forest (CHM_{buf}) (Table 4). Based on the Wald test, the target significance level ($p<0.01$) was achieved with these predictors. CHM_{buf} has greater meaning to P_{DIS} compared to odds ratio of DTM_{mean}, although increment in either will increase the P_{DIS} (43.1% and 5.3% respectively).

When multi-source NFI information was included in the model, the selected variables included mean elevation (DTM_{mean}) and mean height of surrounding forest (CHM_{buf}) but also stem volume of pine and spruce (VOL_{pine}, VOL_{spruce}). Based on Wald statistics all of these variables were statistically significant in the model (Table 4). Per unit change, in any parameter, resulted in an increase in the odds of wind disturbance predisposition. For example, one unit change in CHM_{buf} will increase the disturbance predisposition by 21.4%. Increment in other parameters increases the predisposition much less although it should be noted that the scales of units vary between the predictors.

Final models for mapping the susceptibility of wind disturbance

We were able to predict P_{DIS} with accuracy of 73% with respective Kappa value of 0.47 when using LiDAR variables only (LR_{LiDAR}). When information about tree species from multi-source NFI was added, the model was in fact improved and resulted with prediction accuracy of 81% (Kappa value 0.61). The models were compared based on their AIC-value, prediction accuracy, and kappa-value as well as strength of the model (Nagelkerke's R^2). The model containing a combination of DTM_{mean}, CHM_{buf}, and stem volume of both pine and spruce in the combined approach ($LR_{NFI+LiDAR}$) was found to be best suited to address the probability of wind disturbance explaining 52% of the variation in wind disturbance. A comparison of different logistic regression model scenarios (i.e. LiDAR variable only and combination of LiDAR and multi-source NFI) is provided in Table 5.

Mapping the susceptibility of wind disturbance

The model with only DTM_{mean} and CHM_{buf} (LR_{LiDAR}) produced the smallest area with a high probability (90-100%) of wind disturbance (P_{DIS}), whereas the model that combined LiDAR and NFI predictors ($LR_{LiDAR+NFI}$) resulted in the largest area of high predisposition (Table 6 and Figure 3). On the other hand, $LR_{LiDAR+NFI}$ also produced larger areas with very low P_{DIS} (0-10%) compared to LR_{LiDAR}. Thus, higher disturbance probabilities were difficult to obtain with only LiDAR.

Figure 3. Maps indicating predisposition to wind disturbance derived from two models. Left panel LR_{LIDAR} (using DTM_{mean} and CHM_{buf} only) and on the right $LR_{LiDAR+NFI}$ (model of combination of DTM_{mean}, CHM_{buf}, VOL_{pine}, and VOL_{spruce}).

Discussion

With increasing frequency of disturbance events caused by wind storms (Schelhaas et al. 2003), there is a need to identify areas of high predisposition to wind disturbance in order to inform forest management planning and respond to information needs in other sectors (e.g., electricity providers). Remote sensing data such as LiDAR brings cost efficient and accurate data for spatial modelling, particularly when these data are freely and openly available to the public.

A logistic regression approach is well suited for estimating probabilities of forest disturbances, thus it was used to model the predisposition to wind disturbance. In our analyses, the most important spatial factors explaining the probability of wind-induced disturbance (P_{DIS}) were DTM_{mean}, CHM_{buf}, VOL_{pine} and VOL_{spruce}. Our finding that P_{DIS} was higher for sites at higher elevations is in keeping with the findings of Fridman & Valinger (1998) and Hanewinkel et al. (2004). Moreover, we found that taller trees are more vulnerable to wind disturbance, confirming the results of Lohmander & Helle (1987) and Doppertin (2002), and that the dominance of conifer species is also significant when modelling wind disturbance (e.g. Jalkanen & Mattila 2000; Doppertin 2002; Hanewinkel et al 2004).

In our models, slope and aspect were not significant factors in explaining the susceptibility to wind disturbance. This is similar to findings by Hanewinkel et al. (2004) and Hanewinkel et al. (2008), although it should be noted that many studies have produced contrary results (e.g. Baker 1915; Alexander 1964; Foster & Boose 1992; Wright & Quine 1993; Doppertin 2002). In our situation we assumed that this is due to uniform topography of the study area where terrain heights do not vary significantly (grid-cell level standard deviation of DTM is 12 m). Variables describing closeness and distance to an open area (Close and Dist, respectively) were expected to influence to the model but were actually found to be not significant to our model. This is inconsistent with the findings of Boe (1965), Cremer et al. (1977), Young & Hubbel (1991), and Valinger et al. (2000) and may in part be due to the unique configuration of open and forest areas in our study site and merits further investigation (e.g. did it have importance that the ground was not frozen at the time when the disturbance occurred).

Vertical canopy cover (VCC) describing stand density and structure did not contribute significantly with P_{DIS}, similar results were found by Doppertin (2002). The sample cells with wind disturbance had on average a higher mean value of CHM than areas located next to the sample cells in the direction in which storm winds were blowing. Thus, the wind disturbance predisposition decreased as the mean height of forest in the source wind direction increased. This demonstrates about shelter effect of large trees in northwest where the most destructive winds were blowing in our study area which is in line with the findings of e.g. Andersen (1954) and Boe (1965).

We did not want to use LiDAR 3D point metrics in the modelling because we wanted to have robust models without a need for campaign-to-campaign or sensor-to-sensor calibration which is required when 3D point metrics are used. Those metrics are generally used in area-based forest inventory using LiDAR (e.g. Næsset 2002; White et al. 2013). DTM and CHM are more robust for different flight and scanning parameters (Vastaranta et al. 2012). In addition, LiDAR surface models, such as DTM and DSM are readily available products that a user can order without a need of further knowledge about LiDAR processing (Vastaranta et al. 2013).

Species-specific stem volume information obtained by multi-source NFI increased the prediction accuracy and fit of our model. Presumably, the predicative power of multi-source NFI forest attribute maps comes from a rough classification of stand maturity (amount of stem volume per hectare) as well as the broad conifer-deciduous classification based on Landsat TM spectral values (Tomppo et al. 2008). We used volume instead of species proportions in basal area to describe the distribution of tree species because information on species-specific volume based on multi-source NFI was openly available. Our sample were mainly dominated by Scots pine and Norway spruce, which might have affected the result that sample cells with wind disturbance were also mainly conifer dominated. This might have also had an effect on the significance of VOL_{pine} and VOL_{spruce} in the $LR_{LiDAR+NFI}$. However, with LiDAR-derived predictors only, we were not able to find all sample cells where wind disturbance had occurred but information about tree species gave more accurate results. Winter storms happen in leaf-off season, thus deciduous stands have lower risk for wind disturbance (Peltola et al. 1999). In our models, increment in stem volume of pine or spruce

(m^3 ha^{-1}) increased the wind disturbance predisposition. It should be pointed out that information from the multi-source NFI is based on Landsat TM imagery and field plots. This means that predictions at plot level may include more uncertainty than it is typically expected from forest management planning information obtained by LiDAR (Tuominen & Haakana 2005; Peuhkurinen et al. 2007; Wulder et al. 2012; Vastaranta et al. 2013).

The output from the logistic regression is a probability of disturbance occurring and we used that to produce wind disturbance predisposition maps describing the likelihood that any given grid cell has wind disturbance. When predicting the probability of disturbance or no disturbance, we gained 73% and 81% prediction accuracies with LR_{LiDAR} and $LR_{NFI+LiDAR}$, respectively, compared to visual interpretation. This means if a similar storm would happen at similar site conditions (such as temperature, soil moisture, wind direction etcetera), we would be able to map the predisposition to wind disturbance with high accuracy. In practice, much lower accuracies will be obtained due to variation in many natural factors. In order for our results to be useful to forest practitioners, the resolution of 16 m was selected because this is the commonly used grid cell resolution for Finnish operational forest management planning applying LiDAR data. In addition, forest resource information from privately owned forests is typically provided at a 16 m resolution. Multi-source NFI forest resource maps have a spatial resolution of 20 m and resampling the multi-source NFI forest attribute maps to 16 m likely impacted our model results.

Maps indicating predisposition to wind disturbance produced with the logistic regression models could be extended to cover larger areas (e.g. circa 1 million ha) presuming that similar drivers are associated with a predisposition to wind damage as we found in our study area (i.e. elevation, stand height, and amount of conifers). The resulting maps could also be included in the database of forest attribute information provided by the Finnish Forest Centre. Forest managers could then incorporate this knowledge of wind damage susceptibility into their strategic planning when assessing operational environment and determining which management practices should be used in order to preserve biodiversity and maintain sustainable use of the ecosystem services that the forests provide. Our approach is best suited for mapping and modelling disturbance events that are associated with topography as well as forest height and density because these attributes can be obtained from LiDAR-based DTM and CHM. Other potential drivers, such as forest health, may also be related to a predisposition to wind damage, but are difficult to measure and are often not available as wall-to-wall data sources over large areas.

Our approach provides detailed 3D information about forest structure and topography and the spatial resolution of the model outputs (16 m) are advantageous when compared to Stadelmann et al. (2013), Thom et al. (2013), and Pasztor et al. (2014). Moreover, our approach enables the inclusion of predictor variables describing forest structure from CHM, such as mean height and vertical canopy cover, which have been discovered to act as a driver of wind disturbance (Fridman & Valinger 1998; Peltola et al. 1999; Jalkanen & Mattila 2000; Hanewinkel et al. 2008). Furthermore, LiDAR data, which are spatially extensive and openly accessible, could also be used to estimate P_{DIS} with acceptable levels of accuracy if NFI data are unavailable or outdated.

LiDAR and multi-source NFI data covering entire Finland have been freely and openly accessible to the public since 2012. Use of these data for estimating the predisposition to wind disturbance, as demonstrated herein, provides an example of additional beneficial uses for these data. Increasing the value of the data is one of the objectives in collecting detailed forest resource information in Finland and this study serves that purpose.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Table 1. Statistics of the extracted continuous predictor variables within sample cells (n = 430) derived from digital terrain model (DTM), canopy height model (CHM), and multi-source national forest inventory (NFI).

Predictor	***Description***	***Data source***	***Statistics within sample cells***			
			Min	**Max**	**Mean**	**Sd**
Slope	Slope, degrees	DTM	1.57	30.18	5.94	3.46
Aspect	Aspect, degrees	DTM	45.50	312.89	177.55	47.51
DTM_{min}	Minimum value of DTM, m	DTM	49.36	109.91	77.51	12.26
DTM_{mean}	Mean value of DTM(also elevation, m)	DTM	50.44	111.08	78.25	12.28
DTM_{max}	Maximum value of DTM, m	DTM	51.91	112.14	79.06	12.34
DTM_{sd}	Standard deviation in elevation, m	DTM	0.06	2.68	0.35	0.32
CHM_{min}	Minimum value of CHM, m	CHM	0.00	2.08	0.00	0.22
CHM_{mean}	Mean value of CHM, m	CHM	0.59	20.48	8.42	3.78
CHM_{max}	Maximum value of CHM, m	CHM	6,14	31,56	20,49	4.53
CHM_{sd}	Standard deviation in CHM, m	CHM	1.52	9.63	5.53	1.55
VCC	Vertical canopy cover over 2 m, %	CHM	8	100	74	21
DIST	Distance to the open area, m	CHM	0.00	151.44	22.37	29.86
VOL	Total stem volume per unit area, m^3 ha^{-1}	NFI	0	386	153	95.11
VOL_{pine}	Stem volume of pine, m^3 ha^{-1}	NFI	0	234	52.78	40.62
VOL_{spruce}	Stem volume of spruce, m^3 ha^{-1}	NFI	0	316	74.64	84.32
VOL_{birch}	Stem volume of birch, m^3 ha^{-1}	NFI	0	133	23.02	20.91
VOL_{OBL}	Stem volume of other broadleaved species, m^3 ha^{-1}	NFI	0	38	2.05	4.60
BM_{pine}	Total biomass of pine, kg ha^{-1}	NFI	0	14037	3334.38	2561.10
BM_{spruce}	Total biomass of spruce, kg ha^{-1}	NFI	0	20668	5282.77	5627.91
BM_{BL}	Total biomass of broadleaved species, kg ha^{-1}	NFI	0	12110	2205.26	1907.24
$BMcrown_{pine}$	Biomass of living crown for pine, kg ha^{-1}	NFI	0	1852	523.27	424.00
$BMcrown_{spruce}$	Biomass of living crown for spruce, kg ha^{-1}	NFI	0	4464	1210.92	1170.40
$BMcrown_{BL}$	Biomass of living crown for broadleaved species, kg ha^{-1}	NFI	0	2572	466.84	390.12
$BMroots_{pine}$	Biomass of roots for pine, kg ha^{-1}	NFI	0	2100	499.34	382.45
$BMroots_{spruce}$	Biomass of roots for spruce, kg ha^{-1}	NFI	0	3567	909.2	950.72
$BMroots_{BL}$	Biomass of roots for broadleaved species, kg ha^{-1}	NFI	0	2071	372.76	333.33
ASL_{buf}	Mean elevation from a window of nine grid cells (including sample cell), m	DTM	51.67	110.86	78.19	12.25
$Slope_{buf}$	Slope from a window of nine grid cells (including sample cell), degree	DTM	1.84	24.41	5.95	2.74
CHM_{buf}	Mean value of CHM from a window of nine grid cells (including sample cell), m	CHM	0.81	17.63	7.53	3.38
CHM_{sur}	Mean value of CHM around the sample cell (sample cell not included), m	CHM	0.29	7.26	1.23	0.59
CHM_{wind}	Mean value of CHM in the direction of storm winds, m	CHM	0.28	13.61	1.24	0.80

Table 2. Descriptions of extracted categorical predictor variables within sample cells (n=430).

Predictor	***Description***	***Data source***	***Number of classes***	***Distribution of classes***
$Aspect_{point}$	Aspect in compass points	DTM	4	NE: 113 SE: 107 SW: 108 NW: 102
Close	Sample cell location: Proximity to an open area	CHM	2	Next to an open area: 57 Not next to an open area: 373
SP	Main tree species	NFI	6	Pine : 174 Spruce : 179 Birch : 69 Other broadleaved : 1 Mixed : 4 No trees : 3
ST	Site type	NFI	7	Grove: 1 Grove-like: 78 Myrtillus type: 293 Vaccinium type: 42 Callunus type: 5 Lichen type: 1 Rock: 10

Table 3. Mean values of predictor variables in sample cells with and without damage.

Predictor variable	***Sample cells with damage***	***Sample cells without damage***
DTM_{mean} (m)	81.0	76.0
DTM_{sd} (m)	0.33	0.37
Slope (°)	5.5	6.3
Aspect (°)	175	179
CHM_{max} (m)	21.3	19.8
CHM_{mean} (m)	9.7	7.3
VCC (%)	79.4	68.8
H_{buf} (m)	9.1	6.2
VOL (m^{-3} ha^{-1})	209	105
VOL_{pine} (m^{-3} ha^{-1})	71	37
VOL_{spruce} (m^{-3} ha^{-1})	118	38
VOL_{birch} (m^{-3} ha^{-1})	19	27
VOL_{OBL} (m^{-3} ha^{-1})	1	3
Close (%)	5.1	20.3
SP_{pine} (%)	39.3	42.0
SP_{spruce} (%)	55.1	30.7
SP_{birch} (%)	5.1	25.5
SP_{OBL} (%)	0.5	1.7
Dist (m)	30.9	15.2

Table 4. Parameters and fit statistics for the logistic regression models with DTM_{mean} and H_{buf} (LR_{LiDAR}). and combination of these two with stem volume of pine and spruce per hectare ($LR_{LiDAR+NFI}$).

Predictors for LR_{LiDAR}	***Estimate***	***Std. Error***	***z value***	***Pr(>|z|)***	***e^{β}***	***% change in odds***	***Wald***	***Wald sig.***
Intercept	-6.974414	0.922634	-7.559	0.000			57.1	0.000
DTM_{mean}	0.051753	0.009717	5.326	0.000	1.053116	5.31	28.4	0.000
CHM_{buf}	0.358002	0.041574	8.611	0.000	1.430468	43.05	74.2	0.000
Predictors for $LR_{LiDAR+NFI}$	***Estimate***	***Std. Error***	***z value***	***Pr(>|z|)***	***e^{β}***	***% change in odds***	***Wald***	***Wald sig.***
Intercept	-7.567191	1.091151	-6.935	0.000			48.1	0.000
VOL_{pine}	0.021675	0.003310	6.548	0.000	1.02191	2.19	42.9	0.000
VOL_{spruce}	0.011135	0.001978	5.631	0.000	1.0112	1.12	31.7	0.000
DTM_{mean}	0.049585	0.011393	4.352	0.000	1.05083	5.08	18.9	0.000
CHM_{buf}	0.194245	0.048271	4.024	0.000	1.2144	21.44	16.2	0.000

Table 5. Validation for different logistic regression models for wind damage probability (P_{DIS}).

Model	***Number of predictors***	***AIC***	***Prediction accuracy. %***	***Kappa-value***	***Nagelkerke's R^2***	***Likelihood Ratio Test (LRT)***	
						Chi-square	**p-value**
LR_{LiDAR}	2 + intercept	477.52	73	0.47	0.33	121.22	<0.0001
$LR_{LiDAR+NFI}$	4 + intercept	393.04	81	0.61	0.52	209.70	<0.0001

Table 6. Percentage of the study area with certain probability of wind-induced forest disturbance (P_{DIS}) when using two different logistic regression models.

Damage probability (P_{DIS})	*Model with LiDAR-predictors (LR_{LiDAR})*	*Combination ($LR_{LiDAR+NFI}$)*
0-10%	36.72	58.07
10-20%	21.40	7.52
20-30%	9.20	4.97
30-40%	7.79	4.16
40-50%	7.32	3.71
50-60%	6.67	3.58
60-70%	5.36	3.77
70-80%	3.65	4.30
80-90%	1.70	5.34
90-100%	0.20	4.58

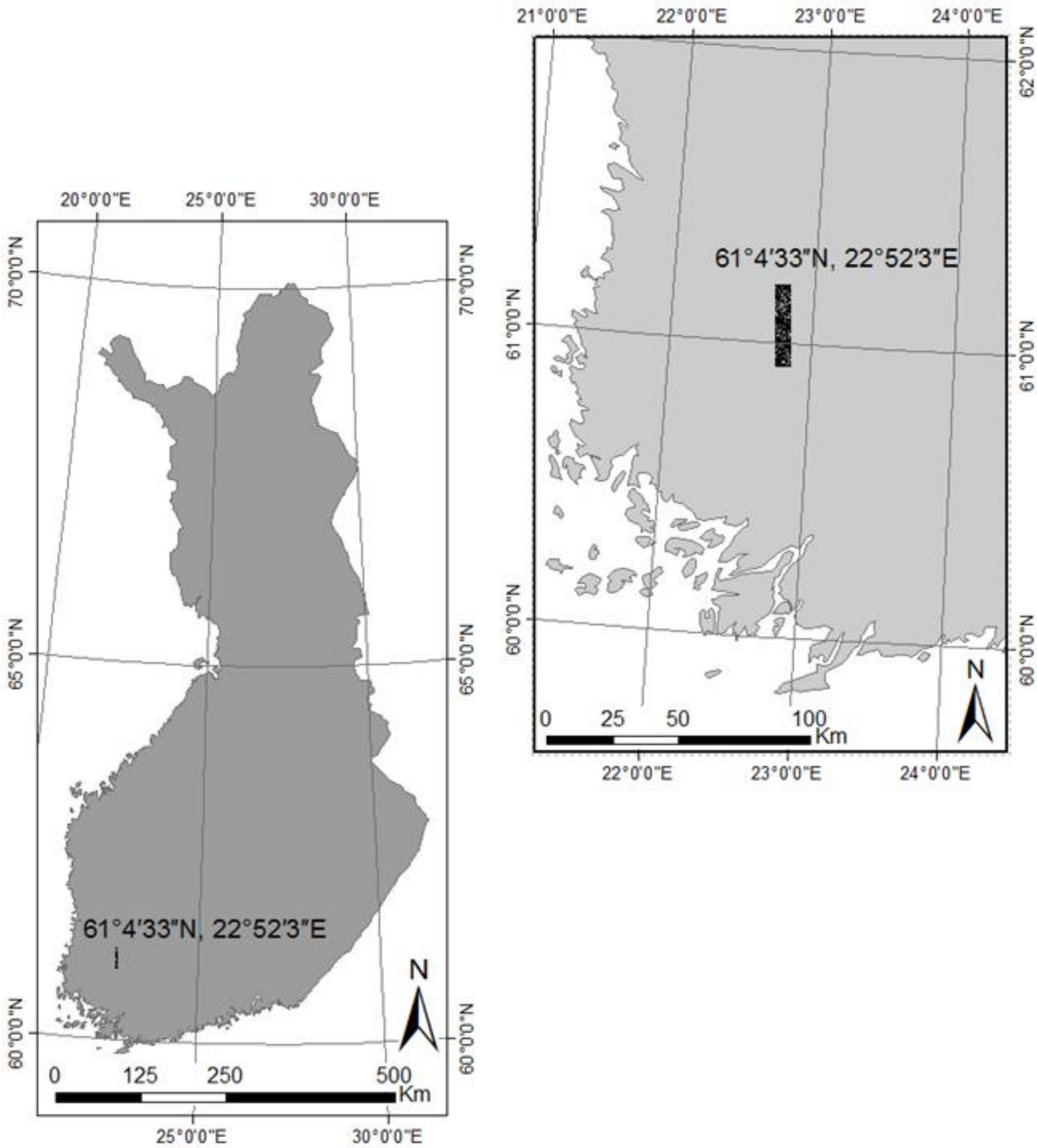

Figure 1. Study area.

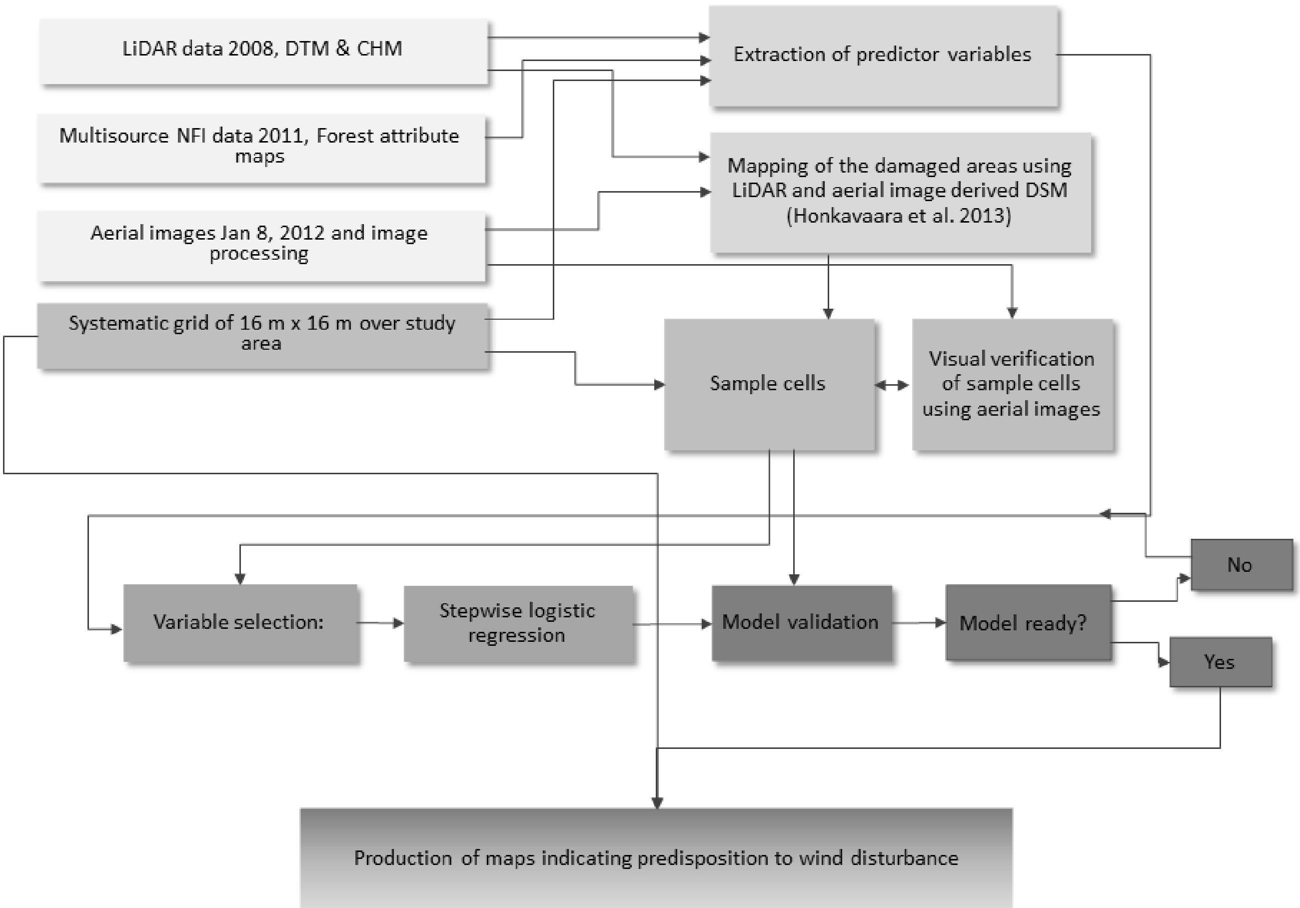

Figure 2. Work flow of the study.

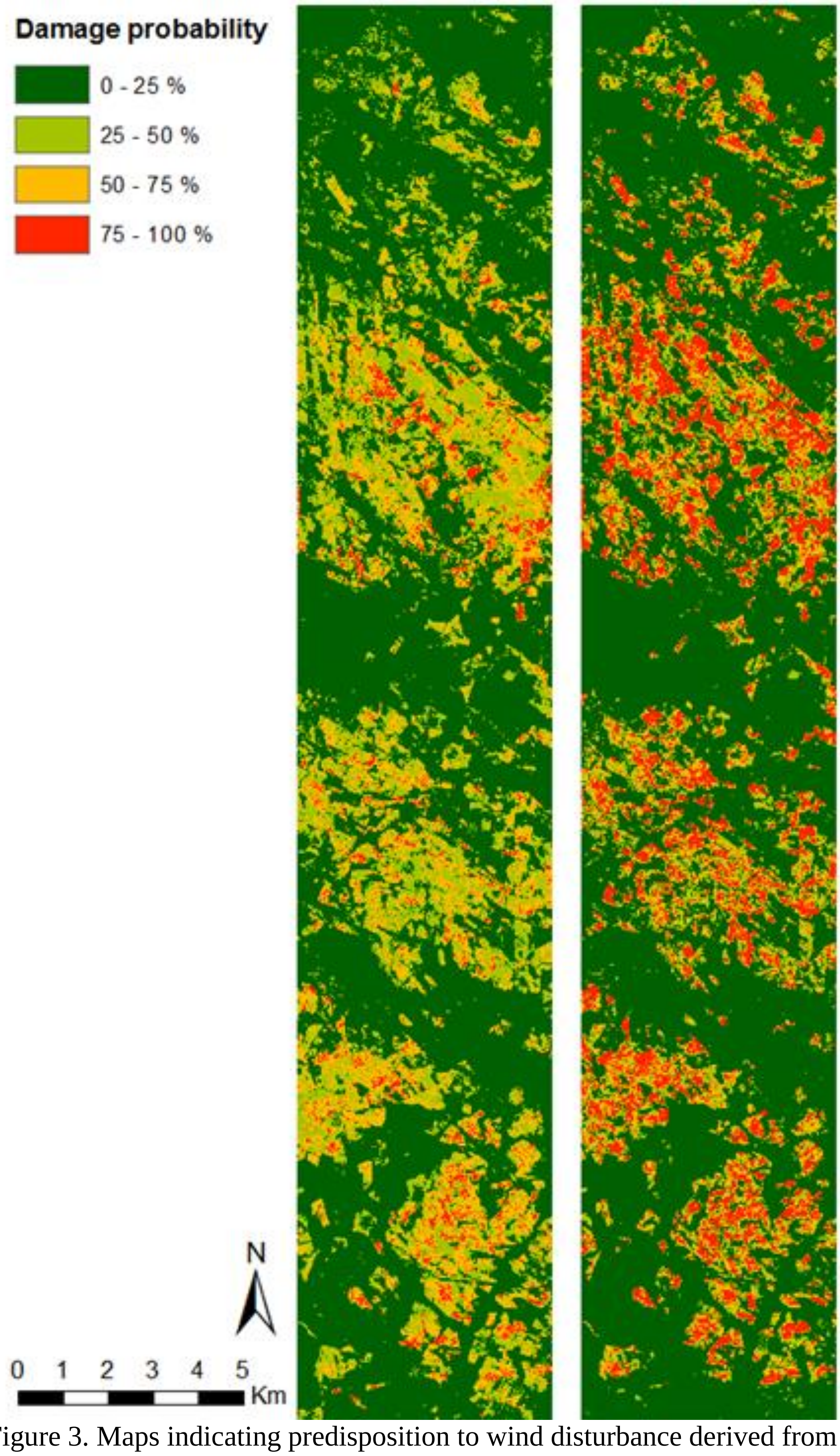

Figure 3. Maps indicating predisposition to wind disturbance derived from two models. Left panel LR_{LIDAR} (using DTM_{mean} and CHM_{buf} only) and on the right $LR_{LiDAR+NFI}$ (model of combination of DTM_{mean}. CHM_{buf}. VOL_{pine}. and VOL_{spruce}).