Evaluation of the Effect of Forest Input Data on Rockfall Simulations

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Rockfall simulation models are now able to take into account impacts on trees. Forest maps at operational scale can be derived from statistical inventories or remote sensing such as airborne laser scanning (ALS). The present study compares rockfall simulations results obtained with different forest inputs for three different stands. Results obtained with field and ALS-derived inputs showed little difference regarding energy values but sometimes large ones concerning the proportion of stopped blocks. It also turns out that the spatial heterogeneity and coniferous proportion of trees are critical issues which might be difficult to address at operational scale.

Key words: protection forest, rockfall simulation, airborne laser scanning

1. INTRODUCTION

The protective effect of trees against rockfall hazards has been known for a long time. However research on the interactions between tree stands and falling blocks only dates back to the 1980's. More recently, numerical models have been developed to simulate the trajectory of falling rocks in forested site [*Dorren et al.,* 2007]. In the more advanced modelling approaches, the trees are individually integrated into the site model. Modelling forest stands in this framework thus requires building virtual forest having the same characteristics as in the site. As an alternative to making field forest inventories, tree distributions and characteristics of each tree can be estimated using airborne laser scanning (ALS). However, the errors in modelling the quantitative characteristics of the trees may lead to non-negligible errors in the simulated trajectories of rocks as they move through the trees. Such error may yield erroneous evaluation of the forest protection. The objective of this study is to compare the results of rockfall simulations performed with forest models that are derived from two types of investigation: field investigation or ALS remote sensing.

2. MATERIAL AND METHODS

2.1 Rockfall modelling

The software RockyFor3D is used for rockfall simulations. It is a simulation model that calculates trajectories of single, individually falling rocks, in three dimensions [*Dorren et al.,* 2005]. The model combines physically-based algorithms with stochastic approaches, which makes Rockyfor3D a so-called "probabilistic process-based rockfall trajectory model". It simulates the rockfall trajectory by calculating sequences of classical parabolic free fall through the air and rebounds on the slope surface, as well as impacts against trees if required. Rolling is represented by a sequence of short-distance rebounds and sliding of the rocks is not modelled. The required input data consist of a set of rasters which define slope surface, forest and block characteristics and topography [*Dorren*, 2012]. The main components of the model are the parabolic free fall, the rebound on the slope surface, the impact against a tree and the calculation of the fall direction [*Bourrier et al.*, 2009]. Each time a simulated block surpasses or rebounds in a given raster cell, statistics of the block trajectory in that cell are recorded. Simulations are held on an archetypal virtual study site in order to focus on the effect of forest inputs on rockfall assessment. The topography is a slope of 35 degrees of compact soil with rock fragments. The roughness of the surface is expressed as obstacles with heights of 0.05 m, 0.1 m and 0.2 m for 70 %, 20 % and 10 % of the surface area respectively. Spatial resolution is 2 m. Spherical blocks with a volume of one cubic meter and of 2600 $kg.m^{-3}$ density are released from five meters height along a

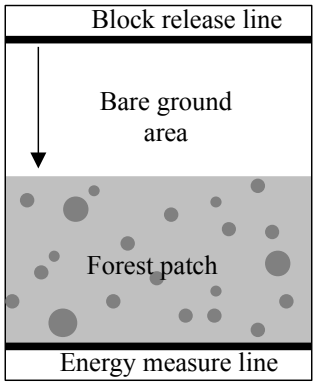

Fig. 1 Simulation scheme

contour line (**Fig. 1**). Their velocity increases across an unforested area of 50 m. Then they enter a forest patch where tree impacts might stop some blocks. The forest input data for Rockyfor3D are either a file with the trees positions and diameters, or files describing tree density, mean and standard deviatoin of diameter at breast height (DBH) in delineated polygons. The percentage of coniferous trees is in both cases supplied as a raster file.

2.2 Forest input data scenarios

2.2.1 Tree-level field data (*Field_Tree* scenario)

Tree positions, diameters and species are recorded on the field for three different forest stands presenting different forest structures and species (**Table 1**) and located in rockfall hazard areas. All trees with a diameter at breast height (DBH) above 7.5 cm (5 cm for Saint Paul) were inventoried and georeferenced. Additionally the heights of all trees were measured in Saint Agnan. In Valdrôme heights were measured in three transects including a total of 362 trees. For this scenario, the positions and diameters are known, and the coniferous percentage input is a raster image of 2 m resolution computed by retaining in each pixel the proportion of coniferous trees among trees whose centres are located inside this pixel.

2.2.2 Area-level field data (*Field_Area* scenario)

This scenario is a degraded version of the tree-level field inventory. Tree positions are unknown and diameter distribution is modelled from its mean and standard deviation. The stand surface is divided in square pixels of 50 m width (40 m for Saint Agnan in order to have an integer number of pixels for the forest stand). From the tree-level field data, the mean and standard deviation of diameter are calculated for these pixels, as well as the coniferous percentage and stem density. For this scenario, tree positions and diameters are randomly generated by the software in each pixel to provide the required inputs for the rockfall simulations. Trees positions are randomly generated with uniform probability distribution. Tree diameters are generated from a

Table 1 Description of forest field data

Site	Saint Agnan	Saint Paul	Valdrôme
Structure	Uneven-aged	Coppice	Plantation
Dominant species	*Abies alba, Fagus Sylvatica*	*Acer opalus, Corylus avellanum, Sorbus aria, Quercus pubescens*	*Pinus nigra*
Size (m^2)	80x120	50x50	50x200
Basal area ($m^2.ha^{-1}$)	32.5	31.2	45.5
DBH (cm) (mean ± sd)	30.1±15.7	12.5±8.0	22.3±8.3
Stem density (ha^{-1})	357	1800	1025

Table 2 Description of airborne laser scanning data

Site	Saint Agnan and Valdrôme	Saint Paul
Pulse frequency (kHz)	170	120
Flight height (m)	600	600
Footprint size (m)	0.3	0.3
Flight year	2010	2009

Gamma probability distribution. Stem density is respected in each pixel.

2.2.3 Tree-level ALS data (*ALS_Tree* scenario)

ALS data were acquired over the three stands with a RIEGL LMS-Q560 scanner. Acquisitions settings are presented in **Table 2**. A tree detection algorithm based on local maximum filtering [*Popescu & Wynne,* 2004; *Monnet*, 2011] was applied to the Saint Agnan and Valdrôme datasets. It is not used in Saint Paul as it is not relevant in coppice stands. The detection outputs are the positions and heights of the local maxima of the canopy height model computed from the ALS data. Those local maxima should correspond to the tops of the dominant trees. In order to estimate the corresponding diameters, a linear regression is fitted between the natural logarithm of DBH and the measured height for a random sample of 10% the field trees. This relationship is then applied to the detected height in order to produce the input file for the simulations. The coniferous percentage file is the same as for the *Field_Area* scenario (average over large pixels).

2.2.4 Area-based ALS data (*ALS_Area* scenario)

For the Saint Paul and Saint Agnan datasets, statistical inventory data were also collected in circular plots located inside the ALS flight. A circular plot is a forest area where trees within a fixed radius from the plot centre are inventoried. Stand-level forest attributes are then derived for

Table 3 Statistics of the ALS estimation models: adj-R^2 of linear regression, root mean square error and its coefficient of variation obtained in cross-validation.

Site (Nb of plots)	Para-meter	adj-R^2	RMSE CV RMSE	ALS metrics in the model
Saint Agnan (96)	mean DBH	0.78	8.6 cm 34.5%	hs,60 + d67 + $prop_{CHM>2m}$
	sd DBH	0.72	2.6 cm 19.6%	hf,80 + d50
	stem density	0.79	220 /ha 26.6%	hs,60 + d50
Saint Paul (31)	mean DBH	0.64	2.3 cm 15.8%	hf,80
	sd DBH	0.77	1.5 cm 19.9%	hs,99 + hl,80 + d83
	stem density	0.59	390 /ha 22.5%	ha,mean + d50 + $mean_{CHM}$

each plot. For each site, these data are used to calibrate regression models between local statistical descriptors of the ALS point clouds extracted inside the circular plots, and the corresponding forest stand parameters: mean DBH, DBH standard deviation and stem density [*Næsset*, 2004; *Monnet*, 2011]. Those statistical descriptors, or ALS metrics, are computed with points whose height above ground is superior than 2 m. Height percentiles are abbreviated *hg,i* , where *g* refers to the point group (*s*: single, *l*: last of many, *f*: first of many) and *i* to the percentile value. The mean height for all points *ha,mean* is also computed. Density metrics are abbreviated *di* and correspond to the percentage of points with height lower than *i* % of the maximum height value on the plot. Two variables describing the canopy height model (CHM) are also computed: $prop_{CHM>2m}$ is the proportion of pixels with values above 2 m, and $mean_{CHM}$ is the mean value of the CHM on the plot. ALS metrics selected in the models and statistics about models accuracy obtained in leave-one-out cross-validation are summarized in **Table 3**. Those relationships are then applied to the point cloud contained in the three forest stands divided in square pixels of 20 m width in Saint Agnan and 16.7 m in Saint Paul. The positions and diameters of trees are then sampled using the same procedure as for the *Field_Area* scenario. The coniferous percentage input is the same as for the *Field_Area* and *ALS_Tree* scenarios.

2.3 Rockfall simulations

10 000 rockfall trajectories are simulated for each two-meter-wide pixel located on the release contour line. The number and the kinetic energy of passing blocks is recorded when the contour line immediately below the forest patch is attained. To avoid border effects, forest stands are laterally duplicated. The release line width is equal to the width of the forest stand and the measure line covers the whole width (including lateral buffers).

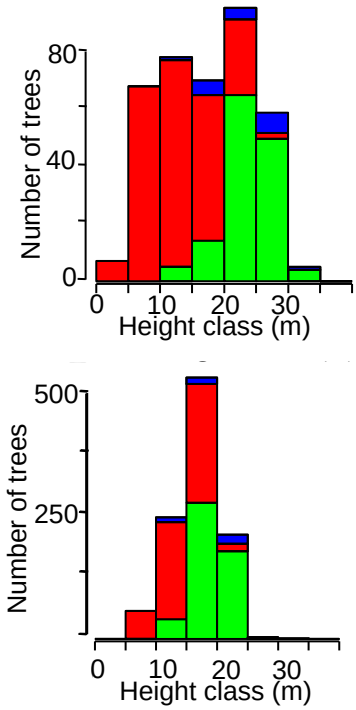

Fig. 2 Number of correctly detected trees (green), missed trees (red) and falsely detected trees (blue), in different height classes for the Saint Agnan (top) and Valdrôme (bottom) stands.

3. RESULTS

3.1 ALS estimation results

3.1.1 Tree detection

The assessment of detection accuracy is based on an automated procedure [*Monnet,* 2011]. In Saint Agnan, 136 (38.1%) of the 357 trees are correctely detected, with 18 false positives. In Valdrôme, 499 (48,7%) are detected, with 43 false positives. As usual with tree detection, dominant trees are well detected whereas trees in the lower layers are often missed (**Fig. 2**). For the detected trees, the height is slightly over-estimated by ALS in Valdrôme, with a mean difference of 0.2 m. In Saint Agnan the over-estimation is larger, with a mean value of 1.4 m. Standard deviation of errors are 1.5 m in both cases. Linear regression with measured height *h* as a function of the ALS height *hl* is $h=0.93*hl+0.49$ for Saint Agnan ($R^2=0.85$) and $h=0.9*hl+1.79$ for Valdrôme ($R^2=0.81$). Heights of tall trees tend to be over-estimated, whereas small trees are rather under-estimated.

3.1.2 Area-based estimation

In both Saint Agnan and Saint Paul, the mean and standard deviation of the diameter are generally

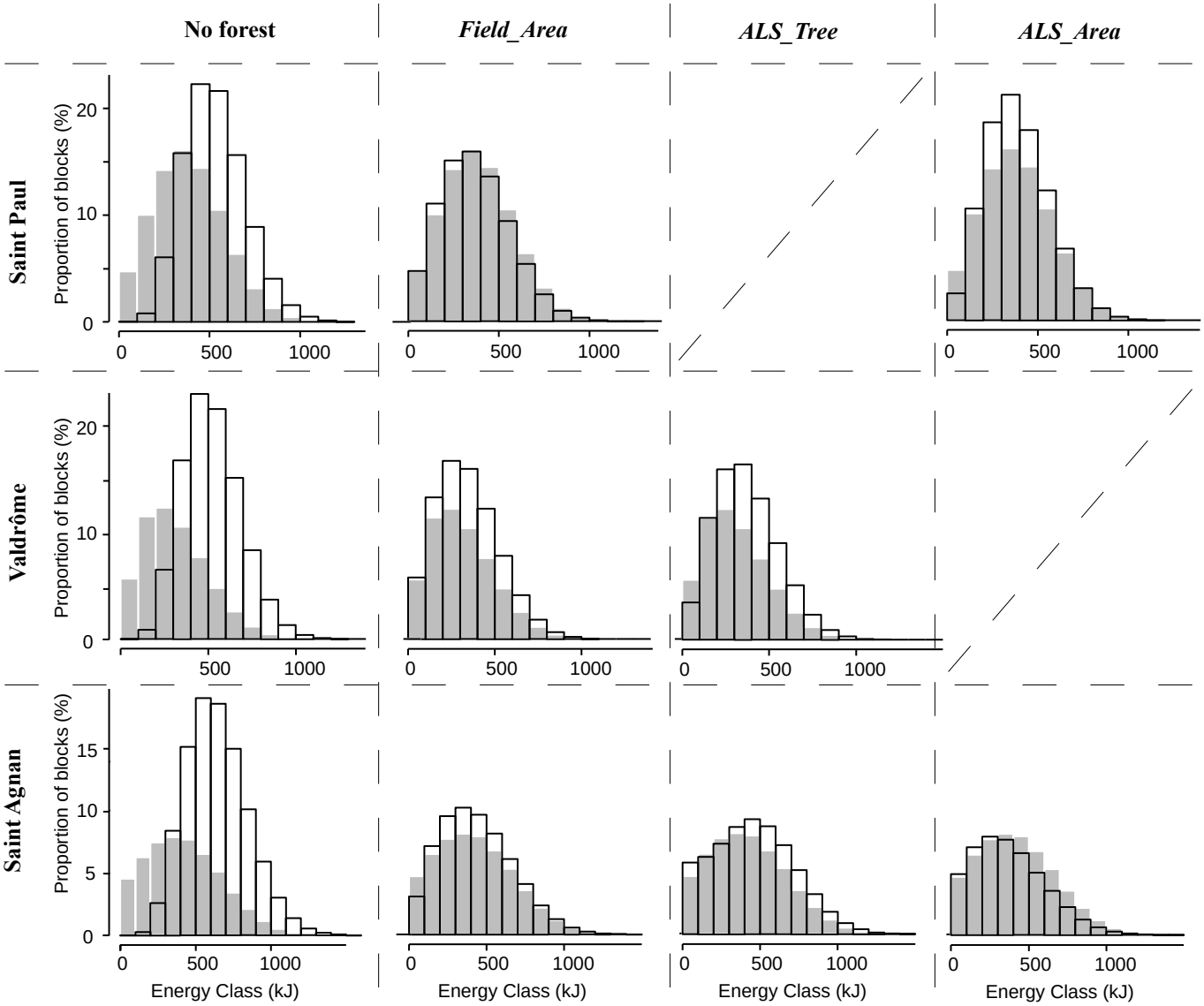

Fig. 3 Distribution of energies of passing blocks (blank bars) for the different input forest data scenario (columns), and for each forest stand (lines). Grey bars in the background correspond to the *Field_Tree* reference scenario.

Table 4 Statistics on the errors of the ALS estimation models at the pixel level

Site (Nb of pixels)	Parameter	Bias	Standard deviation
Saint Agnan (24)	DBH (cm)	-1.7	4.6
	sd(DBH) (cm)	-1.8	2.4
	N (ha^{-1})	190	120
Saint Paul (9)	DBH (cm)	-1.3	2.2
	sd(DBH) (cm)	-3.0	0.7
	N (ha^{-1})	260	430

under-estimated by the ALS estimation models. On the contrary, the stem density is over-estimated (**Table 4**).

3.2 Rocks propagation

The distributions of passing block energy are displayed in **Fig. 3**. With the coppice stand of Saint Paul, it is noteworthy that the energy distribution is similar for all forest inputs (**Table 5**). Relative differences in mean energies and 95th percentiles are below 4%. Mean energy is 37% higher when no forest effect is taken into account, compared to the *Field_Tree* scenario. However, the proportion of passing blocks is similar for the scenarios based on field data (around 82%) but almost all blocks roll through the forest in the *ALS_Area* scenario.

In the even-aged, coniferous forest of Valdrôme, the relative difference for mean energy is 7% for the *Field_Area* and 16% for *ALS_Tree* compared to the *Field_Tree* scenario. The mean energy for the *No_Forest* scenario is 64% higher. The same trend can be observed for the 95th percentile. Regarding the number of passing blocks, values with the *Field_Area* and *ALS_Tree* inputs (80%) are between the *Field_Tree* (58%) and *No_Forest* (100%) cases.

With the uneven-aged, mixed forest of Saint Agnan, energy distributions for the *Field_Tree*,

Table 5 Statistics of the energy (kJ) of blocks passing through the forest stand. Mean, standard deviation, 95th percentile and number of passing blocks expressed in percentage of the number of released blocks. The second value is the variation compared to the *Field_Tree* scenario, expressed in percentage.

Sce-nario	Statistic	Saint Agnan	Saint Paul	Valdrôme
Field Tree	Mean Std. dev. 95th perc. Nb blocks	426 247 865 53%	385 192 723 84%	317 181 652 58%
Field Area	Mean Std. dev. 95th perc. % blocks	436 +2% 232 -6% 852 -2% 60% +13%	369 -4% 187 -3% 700 -3% 81% -4%	340 +7% 179 -1% 663 +2% 81% +40%
ALS Tree	Mean Std. dev. 95th perc. % blocks	459 +8% 259 +5% 905 +5% 63% +19%		368 +16% 180 -1% 692 +6% 80% +38%
ALS Area	Mean Std. dev. 95th perc. % blocks	377 -12% 229 -7% 797 -8% 46% -13%	388 +1% 174 -9% 698 -3% 97% +15%	
No Fo-rest	Mean Std. dev. 95th perc. % blocks	641 +50% 205 -17% 1005 +16% 100% +88%	529 +37% 167 -13% 825 +14% 100% +19%	521 +64% 164 -9% 812 +25% 100% +72%

Field_Area and *ALS_Tree* scenarios are very similar, with relative difference lower than 8% for mean energy and the 95th percentile. However, the number of passing blocks is almost 20% higher. The *ALS_Area* scenario is the only case where the energy and proportion of blocks have much lower values than the *Field_Tree* reference.

4. DISCUSSION

4.1 Coniferous proportion

Considering the reference scenario (*Field_Tree*), there is one limitation regarding the way the proportion of coniferous trees is taken into account. This parameter is critical as the energy dissipation by broadleaved trees is 1.7 times higher than for coniferous trees [*Dorren & Berger,* 2005]. In our study, the raster cell size for the simulation is two meters, so that the information about specie is not integrated in the simulation at the tree level, but averaged at this spatial resolution. However in Saint Agnan cases where both coniferous and broadleaved trees are located in the same pixel are rare. In case rockfalls are simulated at a coarser resolution, such as 5 or 10 m, using the average coniferous percentage may lead to inappropriate imputation of specie to the diameter class. If in the same cell two trees are present, one big broadleaved and a smaller coniferous, the coniferous proportion is 50%. The simulation software will consider that impacts on the biggest tree have an equal probability of being on a broadleaved than on a coniferous tree, and it is the same for the smallest one. This is different from considering that all impacts on the large tree are on a broadleaved tree and all impacts on the small one are on a coniferous tree. For a better integration of specie the coniferous proportion should be weighted by diameter. Besides in field inventories it is not more costly to count the specie-dependant diameter distribution than to measure diameters and count species independently.

This issue of the coniferous percentage is exemplified by the comparison of the *Field_Tree* and *Field_Area* scenarios in the mixed stand of Saint Agnan. Indeed, the energy distribution is quite similar but the proportion of passing blocks is over-estimated by 14%. The major difference between those scenarios is that the average of the coniferous percentage over large pixels (40 m width) is used for the *Field_Area* scenario. Other differences are a slightly different diameter and spatial distribution, due the generation procedure. In order to test the effect of the coniferous percentage input data, the average coniferous proportion was used as input data with the original tree diameters and positions in an additional scenario. In that case, the energy results were closer to the *Field_Area* scenario, with a mean energy of 435 kJ and a proportion of passing block of 59%. This demonstrates that the issue of the coniferous percentage is critical for a better rockfall propagation assessment.

4.2 Position and diameter

Another error source is linked with the probability distribution used to sample the tree positions and diameters in the case of area-based inputs (*Field_Area* and *ALS_Area* scenarios).

Reconstructing the diameter probability distribution using a two-parameters model such as the Gamma distribution generally alters the shape of the distribution and fails to handle the case of a bi-modal distribution. Besides, the interval of the Gamma distribution is from zero to plus infinity, so that small diameters can be generated below the DBH threshold used for the inventory and very large diameters may occur. **Fig. 4** shows that for the coppice stand, the generated diameter distribution is smoothed compared to the real distribution, and that smaller and larger diameters are present.

The generation of the positions from a uniform probability distribution may also lead to different rockfall propagation estimations. The coppice data

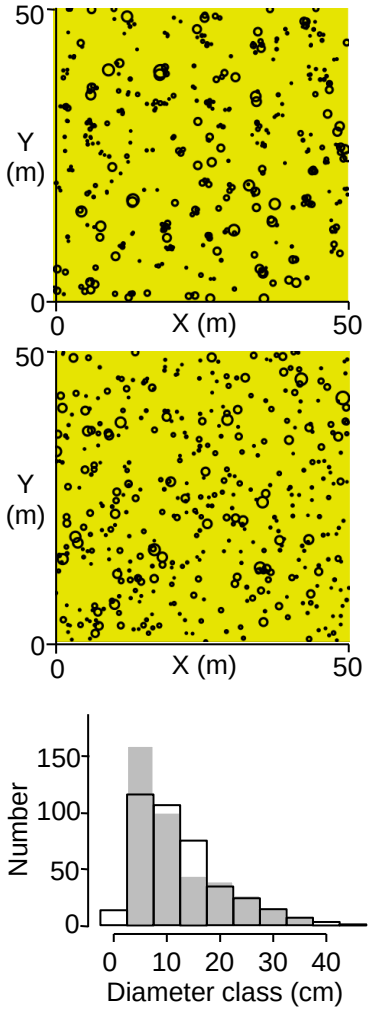

Fig. 4 Coppice stand. Top: positions of field trees. Middle: generated positions. Point size is proportional to tree diameter. Bottom: reference diameter distribution (*Field_Tree*, grey) and generated distribution (*Field_Area*, blank bars).

exhibit a clustered pattern that is not reproduced by the generation with uniform probability (**Fig. 4**). More simulations are required to test whether this aggregation pattern or the difference in the diameter distribution are responsible for the difference in the energy distribution of passing rocks.

In the Valdrôme stand, there is no aggregation but stem density is not spatially homogeneous inside the pixels considered in the *Field_Area* scenario. The density is higher near the upper border of the plot. This pattern is not accounted for in the generated positions (**Fig. 5).** Considering that the diameter distributions are similar, this difference in spatial heterogeneity might explain why the energy distribution is similar but with 40% more passing blocks in the case of the *Field_Area* scenario. Indeed in the *Field_Tree* case, there are higher chances that a sufficient number of consecutive tree impacts lead to a stop in the upper part. The integration of the spatial heterogeneity of tree positions is thus another important factor regarding

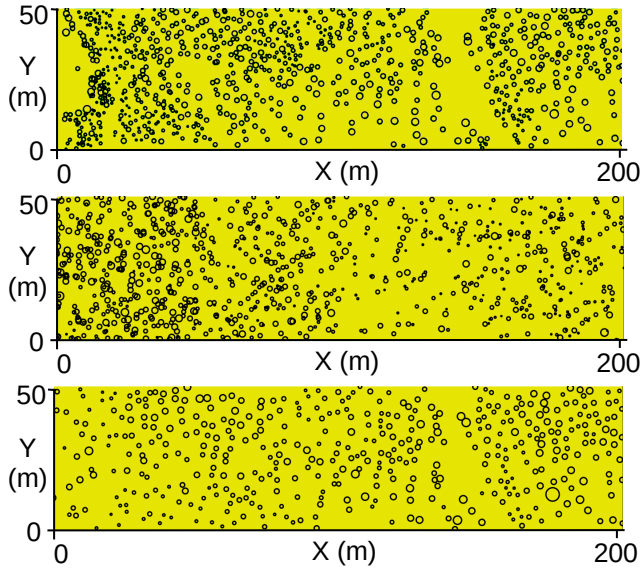

Fig. 5 Inventoried tree positions (*Field_Tree*, top) generated positions (*Field_Area*, middle) and detected trees (*ALS_Tree*, bottom) in Valdrôme. Symbol size is proportional to tree diameter. Uphill side is on top of the image.

the assessment of rockfall propagation.

4.3 Tree detection

With the tree detection in the ALS data, the spatial distribution of trees should be better modelled. Indeed in Valdrôme (**Fig. 5**) and Saint Agnan (data not shown), major canopy gaps appear clearly. However stem density is not correctly estimated as detection proportion depends on the vertical and horizontal arrangements of trees. In Valdrôme almost all trees are detected in sparse areas, but in denser areas the proportion decreases. Indeed, detection performance highly depends on stand structure and algorithms that automatically adjust the detection parameters have yet to be tested. As a result, spatial heterogeneity is only partially modelled as the proportion of undetected trees is both variable and unknown. The number of false detections is also an issue but it has to be tackled with the proportion of missed trees as a trade-off in parameter optimization.

The question of diameter estimation is also problematic as ALS heights are biased estimators of field heights. In our cases, the heights of the taller trees are over-estimated because trees are tilted downslope [*Hirata et al.*, 2004]. Applying a diameter-height relationship calibrated with field measured heights thus leads to over-estimated diameters. It would be better to calibrate height estimation models directly with ALS-derived metrics (e.g. height, crown surface) in order to limit bias, but this requires tree-level field data. Species-specific relationships should also be considered but this requires that species is determined from ALS or

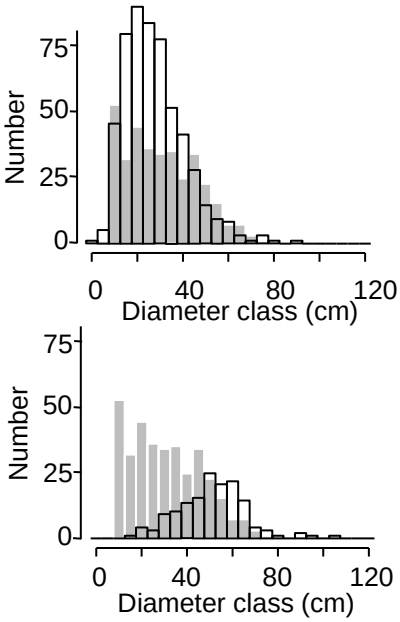

Fig 6 Diameter distribution of the *Field_Tree* (grey), *ALS_Area* (top, black) and *ALS_Tree* (bottom, black) scenarios in Saint Agnan.

other remote sensing data.

The area-based method for the estimation of stand parameters from ALS point cloud statistics is theoretically unbiased, but the errors can be locally important. In Saint Agnan and Saint Paul, the *ALS_Area* method leads to an over-estimation of stem density, whereas the mean diameter is better estimated (**Fig. 6**). These errors then propagate into the rockfall propagation simulations. Results obtained with *ALS_Area* should be handled with care as at this scale errors can be locally important and pixels are spatially correlated.

5. CONCLUSION

This study at the stand level identifies the prerequisites for a better integration of forest inputs in rockfall simulations from field and ALS remote sensing data. It shows that relatively to the large difference between the reference scenarios with and without trees, the forest inputs obtained from ALS data or from field data without tree positions lead to good estimations of the mean and 95th percentile of the energy distribution of passing blocks. However, the proportion of passing blocks displays larger errors. The study also points out some limitations due to the rockfall simulation software and to the methods used to generate the required input files from the field or ALS data.

Improvements could be made inside the software regarding the coniferous proportion. With the perspective to classify species at the tree level with remote sensing data it seems important to link this characteristic to each tree individually. In case of field inventory without tree positions, it seems important to weight the coniferous proportion with the diameter of trees. The diameter generation could also be refined by using a truncated distribution which would account for the minimum diameter of the inventory. A maximum diameter could also be imposed. Regarding the aggregation of trees in the case of coppice stands, methods developed to quantify it in field investigations could be integrated in the spatial generation procedure.

In the case of studies at larger scale, the field data do not account for the spatial heterogeneity of complex forests due to accessibility constraints and labour costs. The ALS area-based method provides stand parameters estimates at a resolution of around 20 m. The heterogeneity might only be partially rendered at local scale but over the whole area forest estimates are theoretically unbiased. With the ALS single tree detection, the heterogeneity is also only partially modelled due to algorithm and data limitations. The question of the propagation of local errors into rockfall simulation is open for both methods. However the dataset required to evaluate this will probably only be available from simulation. In the meantime, latest developments in the estimation of forest structure from airborne laser scanning and other remote sensing data should be integrated for a better characterization of species and dendrometrics.

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