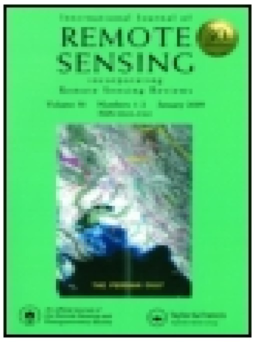

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International Journal of Remote Sensing

ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: http://www.tandfonline.com/loi/tres20

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International Journal of Remote Sensing
Vol. 31, No. 5, 10 March 2010, 1133–1153

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An application-oriented automated approach for co-registration of forest inventory and airborne laser scanning data

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Airborne laser scanning (ALS) data can be used for downscaling point-based forest inventory (FI) measurements to obtain spatially distributed estimates of forest parameters at a more detailed, local scale. Such downscaling algorithms usually consist of a direct coupling between selected FI parameters and ALS data collected at the field sampling locations. Thus, precise co-registration between FI and ALS data is an essential preprocessing step to obtain accurate predictive relationships.

This paper presents a new, automated co-registration approach that searches iteratively for the best match between an ALS-based canopy height model and the tree positions and heights measured during the FI. While the basic principle of the algorithm applies to various types of FI sampling configurations, the co-registration approach was developed specifically to take into account the tree selection criterion posed by angle count sampling. The angle count sampling method only includes trees that at a given distance from the sample plot centre have a minimum required diameter at breast height (DBH). This tree selection criterion leads to maximum plot radii and number of inventoried trees that strongly vary from sample plot to sample plot. In the automated co-registration procedure, several criteria (e.g. the occurrence of more than one spatial cluster of minimum residuals and a predominance of deciduous trees in a sample plot) were used to detect possible uncertain solutions and to reduce post-processing efforts by an image operator. Model calibration and validation were based on national forest inventory (NFI) and ALS data from the Austrian federal state of Vorarlberg. Transferability and robustness of the approach was verified using an independent local FI.

The results show that 68% of the NFI sample plots and 74% of the local FI plots could be automatically co-registered to a location at a distance of less than 5.0 m from the reference location. The maximum difference of 5.0 m used for marking a solution as correct was based on the relatively small influence that deviations of up to this value have on ALS-based predictions of biophysical forest variables at a stand level. The quality flagging criteria adopted were very successful in identifying uncertain solutions; only one out of 153 co-registered sample plots with a deviation from the reference data set greater than 5.0 m was not identified as uncertain.

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International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2010 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160903380581

Applying the automatically co-registered sample plots in calibration of a growing stock model provided estimates that were clearly superior to those obtained with the original plot positions and even slightly outperformed those based on manual co-registration. As the algorithm developed will be part of an operational processing chain for Austrian NFI data, it has a high practical relevance.

1. Introduction

National forest inventories (NFIs) are typically based on field measurements performed at regularly spaced sampling locations (Tomppo *et al.* 2008). Statistical measures of forest condition obtained from such a sampling approach (e.g. stem volume or tree density) are, depending on the sampling density, representative only for large- to medium-sized administrative units such as countries or regions (Gabler and Schadauer 2008, Tomppo *et al.* 2008). If information is required for smaller administrative units, such as municipalities or forest stands, dense local forest inventories (LFIs) are required or the available forest information has to be downscaled using additional, spatially distributed information sources such as multispectral satellite imagery (e.g. Koukal 2004, McRoberts and Tomppo 2007) or aerial photographs (Holmström *et al.* 2001). In recent years, airborne laser scanning (ALS) data have proven a very promising alternative data basis for such downscaling of point-based FIs (Lim *et al.* 2003, Næsset *et al.* 2004, Maltamo *et al.* 2007, Naesset 2007). The capability of ALS to accurately describe the horizontal and vertical distribution of canopy elements makes it well suited for the quantitative assessment of structural forest parameters such as tree density, tree height and stem volume.

The downscaling of FI parameters (either NFI or LFI) generally consists of two consecutive steps (e.g. Næsset 2002, Hollaus *et al.* 2009b): (i) establishing a consistent relationship between selected FI parameters and laser scanning data for the FI measurement locations (e.g. by *k*-nearest neighbour techniques or regression models) and (ii) applying the relationship obtained to the entire laser scanning data set to obtain the spatially distributed FI. Establishing a predictive relationship between FI and ALS data often relies on a direct coupling between various laser metrics derived from a fixed reference area around the centre of the FI measurements and the FI forest and tree attributes measured at those locations. Thus, accurate relative orientations between FI and ALS data are required to calculate reliable reference ALS metrics for input to the calibration of the predictive model (Farid *et al.* 2006, Gobakken and Næsset 2008, Hollaus *et al.* 2009a,b). Gobakken and Næsset (2008) showed that increasing the positioning errors of FI data led to a continuous decrease in accuracy of predicted mean tree height, stand basal area and stand volume predicted from ALS data. The effects were more prominent for sites of poor quality featuring a large number of scattered trees than for productive sites with denser canopies and more evenly distributed trees.

For economic and logistical reasons, coordinates of sampling locations and tree positions are often measured using only a non-differential Global Positioning System (GPS) unit. In densely forested areas this may lead to positioning errors of up to several metres. Inaccuracies are even larger in mountainous terrain, where the number of visible satellites is significantly reduced compared to flat terrain. By contrast, ALS data typically have planimetric errors of less than 0.50 m (Kraus 2007), making them suitable as a geographic reference for the FI data. If relative tree positions and heights of the trees within the sampling units are known, a data analyst can adapt the positions of the FI data to the ALS data set by visual interpretation. This can, however, be a time-consuming and tedious task, especially if several thousands of sampling units have to be co-registered, such as in the case of NFIs. Olofsson *et al*. (2008) developed an automated co-registration method for linking field-surveyed trees and single trees identified from high-resolution ALS data. Their method is based on sample plots with a fixed radius and accounts simultaneously for horizontal displacements and angular distortions due to compass errors. Based on a simulation study and experimental ALS data they proved that very high co-registration accuracies can be obtained if position errors of single trees are small. However, accuracies were significantly reduced with increasing position errors, trees per hectare, and the number of undetected trees in the ALS data.

The single tree-based method proposed by Olofsson *et al*. (2008) requires ALS data with high point densities ($\sim$10 points m^{-2}), a condition that often is not met for data available from commercial terrain mapping campaigns, which have typical point densities of around 1 to 5 points m^{-2}. To overcome this prerequisite, the current paper presents an automated approach for the co-registration of FI and ALS data that does not require the detection and delineation of single trees and therefore should be less susceptible to lower point densities. While the basic principle of the approach applies to various types of FI sampling configurations, such as a fixed sample plot area, the approach concentrates on data collected using the angle count sampling method (Bitterlich 1948), which is used in many FIs throughout the world. For this sampling technique the probability of selecting a tree is equal to its diameter at breast height (DBH). The co-registration approach was developed and calibrated using NFI data for the Austrian federal state of Vorarlberg and ALS data collected during various commercial terrain mapping campaigns. An independent validation was performed using FI data provided by a local forest administration. As the approach is envisaged to be part of an operational processing chain for ALS-based NFIs, great importance is placed in providing accurate quality measures and aids for efficient post-processing, and especially in testing its robustness for very diverse data sets in terms of sample plot composition and data quality.

2. Study site and data

2.1 *Study area*

The co-registration procedure was developed using ALS and NFI data for the federal state of Vorarlberg in Austria (figure 1(*a*)). Elevation in the federal state of Vorarlberg ranges from 396 m to 3312 m asl. The landscape is mainly characterized by high alpine areas, coniferous and mixed forests, shrubs, meadows and sparsely settled areas in the valley floors. The average timberline ranges between 1700 and 2000 m. According to the NFI 2000/2002 (web.bfw.ac.at/i7/Oewi.oewi0002?geo = 8&isopen = 0&display_page = 0), Vorarlberg is covered with about 97 000 ha of forest, representing a forest cover fraction of 37.3%. The main tree species in Vorarlberg are spruce (*Picea abies*; 53.9% of the total area covered by forests), fir (*Abies alba*; 11.6%) and beech (*Fagus sylvatica*; 9.6%). In the forested area, 66.9% can be classified as coniferous forest and 23.8% as deciduous forest, while the rest consists of open spaces, shrubs and bare surfaces (web.bfw.ac.at/i7/Oewi.oewi0002?geo = 0&isopen = 3&display_page = 22).

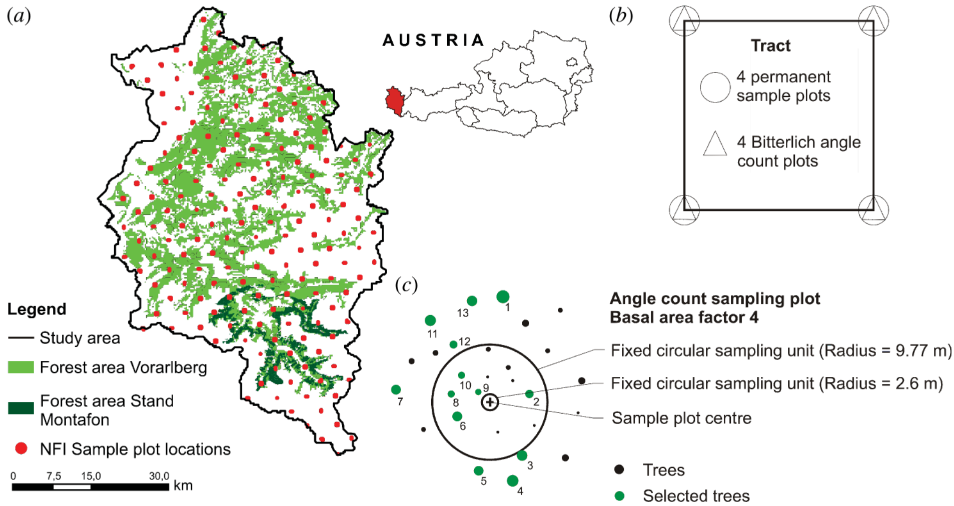

Figure 1. (*a*) Location of the Vorarlberg study site, showing the forested area overlain with the NFI sample units. (*b*) Configuration of sampling units within a tract as used at the Austrian NFI. (*c*) Configuration of a sampling unit.

2.2 *ALS data*

The ALS data were acquired within the framework of a commercial terrain mapping project covering the federal state of Vorarlberg. As terrain mapping campaigns require snow-free and leaf-off conditions, a prerequisite that is not usually met simultaneously for valley floors and high altitudes, the data were acquired during 10 different flight campaigns in the years 2002 to 2004. More than 1600 flight lines were acquired from a fixed-wing aircraft by the company TopScan GmbH, Germany, deploying Airborne Laser Terrain Mapper systems (ALTM 1225, ALTM 2050), and the company Terra Digital GmbH, Germany, which used a Leica-Scanner ALS50. The relevant sensor characteristics of the applied ALS systems are summarized in table 1.

The flying heights of the ALS campaigns vary between ~500 and ~2000 m above ground and minimum point density was 1 point m^{-2}. For this study, georeferenced three-dimensional (3D)-point clouds and digital terrain (DTM) and surface models (DSM) with a spatial resolution of 1 m were provided by the Land Survey Administration Feldkirch. Canopy height models (CHMs) were calculated by subtracting the DTM from the DSM.

Table 1. Summary of sensor characteristics of the ALS systems applied.

	Sensor		
Sensor characteristics	Optech ALTM 1225	Optech ALTM 2050	Leica ALS50
Beam divergence (mrad)	0.3	0.3	0.33
Field-of-view (°)	0–40	0–40	10–75
Wavelength (nm)	1064	1067	1064
Pulse repetition frequency (kHz)	< 25	< 50	< 83
Multiple targets	≤ 2	≤ 2	≤ 4

2.3 *National FI data*

The development of the co-registration procedure was based on Austrian NFI data from the assessment period 2000/2002. The NFI is carried out at regular time intervals of 6 to 8 years and comprises more than 170 attributes that provide information on quantity, quality and trends of the Austrian forests (Schieler and Hauk 2001, Gabler and Schadauer 2008). The attributes relevant for this study are given in table 2. The sampling design of the NFI is a permanent sampling grid pattern, where tracts are distributed regularly (3.89 km grid size) over Austria. Each tract is made up of four sampling units spaced in a square at a distance of 200 m (figure 1(*b*)). The single sampling units comprise a fixed large circular sampling area of 300 m^2 (radius = 9.77 m), a fixed small sampling area of 21 m^2 (radius = 2.60 m), and an angle count sampling plot, also called a Bitterlich plot (Bitterlich 1948). While the fixed large circular plot is used to capture site-specific properties, within the small sampling circle every tree with a DBH between 50 and 105 mm is characterized. The angle count sampling selects trees based on relascopic measurements of DBH taken from the centre of the circular plot of 300 m^2, while applying a basal area factor of 4 (figure 1(*b*)). Thus, at a given distance from the sample plot centre, a tree is only selected for sampling if it has a minimum DBH, while the minimum required DBH increases with increasing distance from the centre location. These tree selection criteria lead to maximum plot radii and number of inventoried trees that vary strongly from sample plot to sample plot. For more detailed information about the design of the Austrian NFI, refer to Schieler and Hauk (2001). Tree heights of a subset of the sample were measured with a Haglof VERTEX III (Haglof, Sweden), and data models were used to estimate heights of the remaining sample trees (Gschwantner and Schadauer 2004).

Within the forested area of Vorarlberg, 132 sampling units are available (figure 1(*a*)). As no reliable differential GPS (dGPS) measurements were available to test the accuracy of the automated co-registration results, reference centre coordinates of each sample plot were determined by manually seeking the optimum fit between

Table 2. Attributes of the Austrian NFI that are relevant to the co-registration procedure presented.

Variable	Units	Measurement principle
Centre coordinates (x,y) of individual sample plots	m (GK Austria meridian 28 coordinate system)	Non-differential GPS. In case of insufficient satellites visible from measurement location (bad receiving) computed from GPS measurement in a nearby open space and eccentric
Polar azimuth from plot centre	grad	Compass
Distance from plot centre	cm	Ultrasonic range instrument
Diameter at breast height (DBH)	mm	Calliper, measuring tape
Tree height	dm	Ultrasonic measurement with VERTEX III
Tree species	–	–
Tree class (indicating vitality, growth stage, and relationship with neighbouring trees)	–	Using key proposed by Schieler and Hauk (2001)

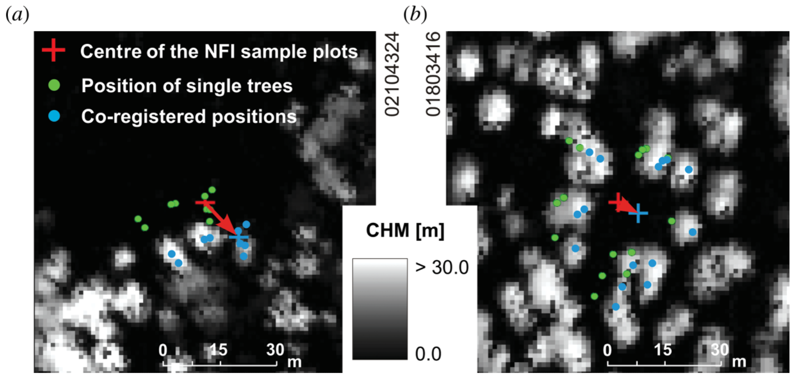

Figure 2. Relative orientation between tree positions, sample plot centre coordinates and the CHM for sample plots (*a*) 02104324 and (*b*) 01803416. The red arrow indicates the manual shift applied to co-register FI data to the CHM.

tree positions and heights measured by the NFI and the CHM. To do this, the absolute positions of the trees within each plot were calculated from the geographical coordinates of the sample plot centres and the polar coordinates of the individual trees. These coordinates were then converted into ArcGIS shapefiles, which, in combination with the NFI heights of each tree, facilitated a visual comparison with the CHM and finally a manual adaptation (figure 2). Errors of this manual co-registration method are expected to lie at the subpixel level (i.e. $<$ 1.0 m). Of the 132 sampling units, 98 could be unambiguously manually co-registered in the proposed way. Errors of the NFI centre coordinates measured with GPS were defined by computing their distance to the manually co-registered centre locations and ranged between 0.0 and 54.0 m, with an average of 8.5 m.

2.4 *Local FI data*

Transferability of the co-registration procedure was tested on an independent local forest inventory (LFI) data set operated by the forest administration Stand Montafon Forstfonds (www.stand-montafon.at/forstfonds). Similar to the NFI, the design of the Stand Montafon FI is based on permanent sample plots distributed in a regular grid of 350 m. Sampling trees were selected based on the angle count method (Bitterlich 1948). The basal area factor was set to four and the minimum DBH to 0.10 m. The centre coordinates of the sample plots as well as the tree locations were measured with a compass in combination with an ultrasonic range instrument. The accuracy of the measured relative tree coordinates within the sample plots is in the range of 0.3–0.5 m (Hollaus *et al.* 2006). For selected trees, heights were measured with a Haglof VERTEX III while heights of the remaining sample trees were estimated using data models (Hollaus *et al.* 2007). The tree species were determined as described in Hollaus *et al.* (2009b). In contrast to the NFI, the LFI does not describe the vitality and growth stage of each tree, nor the social relationship between neighbouring trees.

As reliable dGPS measurements of the sample plot centre coordinates were lacking, positions were assessed manually using the same method as that used for the NFI data. Of the original 488 samples, 466 could be unambiguously co-registered in this way. Deviations between original and manually established centre coordinates varied between 0.0 and 47.2 m with an average of 10.5 m.

3. Automated co-registration

3.1 *Basic principles*

An automated co-registration procedure was developed to overcome the manual adjustment step between NFI data and CHM as described in §2. The approach searches iteratively within a specified search window for the best fit between the tree heights measured during the NFI and the heights contained in the CHM (figure 3(*a*)). Thus, the height difference (D) between the FI and CHM data for a given sample plot centre coordinates x,y within the search window can be given by:

$$D_{x,y} = \sum_{t=1}^{N} c_t \left| H_{\mathrm{NFI},t} - H_{\mathrm{CHM},t} \right| \tag{1}$$

where N is the number of trees measured in one NFI sample plot, $H_{\mathrm{NFI},t}$ is the height (m) assessed during the NFI for tree t, and $H_{\mathrm{CHM},t}$ is the value (in m) of the CHM at the location of tree t. Tree class parameter c is introduced in the cost function to account for the vigorousness of a tree and its social status with respect to the surrounding trees and is obtained from the NFI (Schieler and Hauk 2001). It is thus an indicator for the 'visibility' of a tree in the CHM. The tree class parameter can take a value of 1 (e.g. tree crown is part of the bottom canopy layer), 2 (e.g. tree crown belongs to the middle canopy layer), or 4 (e.g. dominant or solitary tree). The c factor is normalized for the total number of trees in the sample plot.

For angle count sample plots it is known that, within the plot, measured tree positions have an error of less than 0.5 m relative to the plot centre (Hollaus *et al.* 2006). To account for this small location error and other errors intrinsic to the measurements and the data used (e.g. tree apices that deviate from measured stem

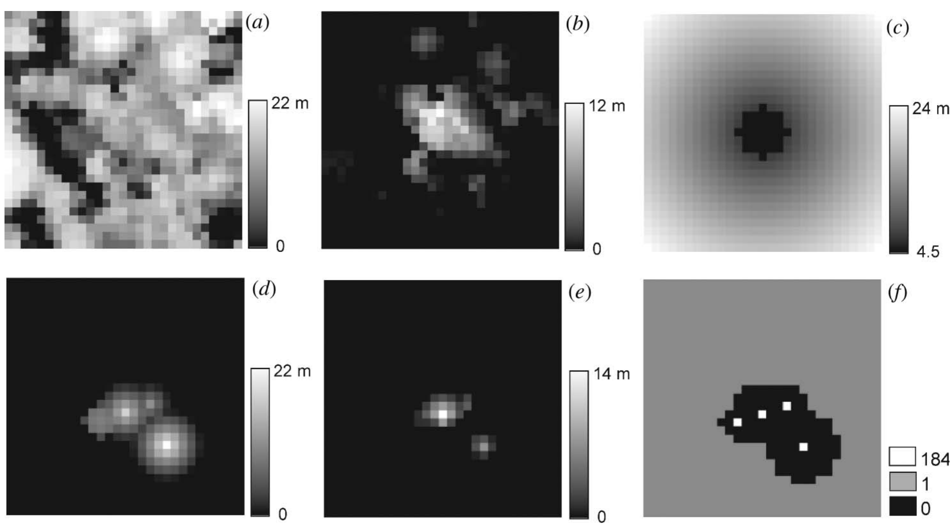

Figure 3. Example of data sets used for co-registration of sample plot 00504100: (*a*) subset extracted from the input CHM around position x,y within the search window; (*b*) difference between the CHM subset and the minimum tree height required for sampling in the Bitterlich plot (shown in (*c*)); (*d*) the simulated tree crown model; (*e*) the difference between the simulated tree crown model and the minimum required tree height (shown in (*c*)); and (*f*) weight every pixel receives in the cost function.

coordinates (leaning trees) and inaccuracies in the CHM), we assumed the total accuracy of the tree apices to lie within ±1.5 m from the measured tree stem coordinates. These errors were accounted for in the algorithm by comparing the NFI tree heights with the highest CHM value (i.e. the potential tree apex) in a 3 m × 3 m window around each tree location measured. For the current study a search window of 61 m × 61 m around the original (measured) centre coordinate was applied, which in most situations is large enough to encompass the target (true) centre position.

3.2 *Including angle count tree selection criteria*

Calculating the height difference by the method proposed above only considers tree height differences but does not account for the configuration of the angle count sampling. In fact, the angle count sampling only includes those trees that at a certain distance from the sample plot centre have an according minimum DBH, defined by the basal area factor. This means that the longer the distance between plot centre and tree location, the larger DBH is necessary to include the tree in the sample (Grosenbaugh 1958). To avoid solutions that conflict with this sampling principle, the minimum tree height required to fall within the sampling was introduced. Thus, for every distance from the centre coordinate the minimum required DBH was calculated. Based on all single tree measurements performed during the Austrian-wide NFI 2000/2002, tree type-specific empirical relationships between DBH and height could be established (table 3). Taking into account an uncertainty in these functions of 2 standard deviations, the minimum required tree height for each distance from the sample plot centre could be calculated from the minimum DBH (figure 3(*c*)). By subtracting the minimum required tree height from the CHM subset (which is defined by the position of the sample plot centre in the search window and by the distance of the outermost tree to the sample plot centre), we obtained the parts of the tree crowns that theoretically should be included by the angle count sampling (figure 3(*b*)), and are referred to as CHM_{diff}. Negative values of CHM_{diff} were set to zero.

Subsequently, the CHM_{diff} based on a measured CHM was compared to a difference model (CHM^*_{diff}) based on a simulated CHM. To obtain CHM^*_{diff}, hypothetical tree crowns were simulated from the NFI parameters by relating crown shape and extension to DBH according to the allometric functions proposed by Hemery *et al.* (2005) (figure 3(*d*)). Subtracting the minimum required tree height (figure 3(*c*)) from the simulated tree crown model provides CHM^*_{diff} (figure 3(*e*)), which is directly comparable to figure 3(*b*) and in the ideal case would look identical.

Figures 3(*d*) and 3(*e*) show that the simulated crown shapes are only a rough approximation of the actual crown shapes. As this would introduce too large an uncertainty in the result, we decided not to compare the complete measured and simulated canopy height difference models (CHM_{diff} and CHM^*_{diff}, respectively) but, instead, to compare only the apices of the trees while the rest of the simulated tree crown

Table 3. Empirical regression functions between DBH and tree height based on the Austrian NFI 2000/2002.

Type of forest	Regression function	No. of observations	R^2
Coniferous	Tree height = 7.3677 × $DBH^{0.5957}$	25 201	0.73
Deciduous	Tree height = 14.455 × $DBH^{0.4695}$	7459	0.66
Mixed	Tree height = 8.9211 × $DBH^{0.5604}$	32 660	0.70

pixels were excluded from the cost function. Thus, in the cost function the weight of all tree crown pixels other than the apices were set to zero (figure 3(*f*)). Tree and non-tree pixels were equally weighted in the cost function, that is the sum of the weights attributed to the tree apices (while still accounting for social stand differences) equalled the sum of the weights of all non-tree pixels. In the example shown in figure 3(*f*), this leads to a weight of 184 for each of the four tree apices while all 736 pixels that do not belong to a tree crown receive a weight of 1. Now, equation (1) can be written as:

$$D_{x,y} = \sum_{p=1}^{N} c_p \left| p(\mathrm{CHM_{diff}}) - p(\mathrm{CHM_{diff}}*) \right| \tag{2}$$

where $p(\mathrm{CHM*_{diff}})$ is pixel p in the adapted tree crown model containing N pixels (figure 3(*e*)), $p(\mathrm{CHM_{diff}})$ the equivalent pixel in the adapted CHM subset (figure 3(*b*)), and c_p the weight of the pixel analogous to figure 3(*f*). The D values are scaled between 0 and 1 according to the minimum and maximum observed values within the search window. The coordinates x,y within the search window providing the smallest D value eventually assume the new, co-registered sample plot centre coordinates.

3.3 *Quality flagging*

Even though the proposed iterative procedure always leads to a global minimum, it is possible that, due to errors in the CHM and NFI measurements and to model approximations, the minimum obtained does not correspond to the optimum (real) position. Identifying the sample plots that potentially have an ambiguous solution is a key element in the workflow because these samples may require manual post-processing by a data analyst. In this respect, all sample plots that require manual post-processing should be marked as 'uncertain' whereas as few as possible accurately co-registered samples should be denoted as such to reduce superfluous quality controls and post-processing efforts by the data analyst. Therefore, the following criteria were considered when marking a solution as 'uncertain':

1. When among the 10 smallest residuals more than one or a very broad spatial cluster exists. This is analysed using the spatial distribution of cost function residuals (figures 4(*b*) and 4(*e*)).
2. If residuals are sorted and plotted, a steep slope stands for a reliable solution while a flat slope suggests several plausible solutions (figures 4(*c*) and 4(*f*)). Detailed analyses revealed that a slope of 0.001 (no units) or less was best able to separate uncertain solutions from certain ones.
3. When a sample plot has a predominance (>50%) of deciduous trees, because these have less pronounced tree apices than conifers and because ALS data were acquired under leaf-off conditions.
4. When the distance between the original centre coordinate and the co-registration result is larger than 20.0 m.

A solution was marked 'uncertain' if at least one of the above criteria applied.

3.4 *Validation*

The accuracy of the automated co-registration procedure was investigated by computing the distances between the automatically co-registered sample plot centre coordinates and the centre coordinates that could be unambiguously manually allocated by

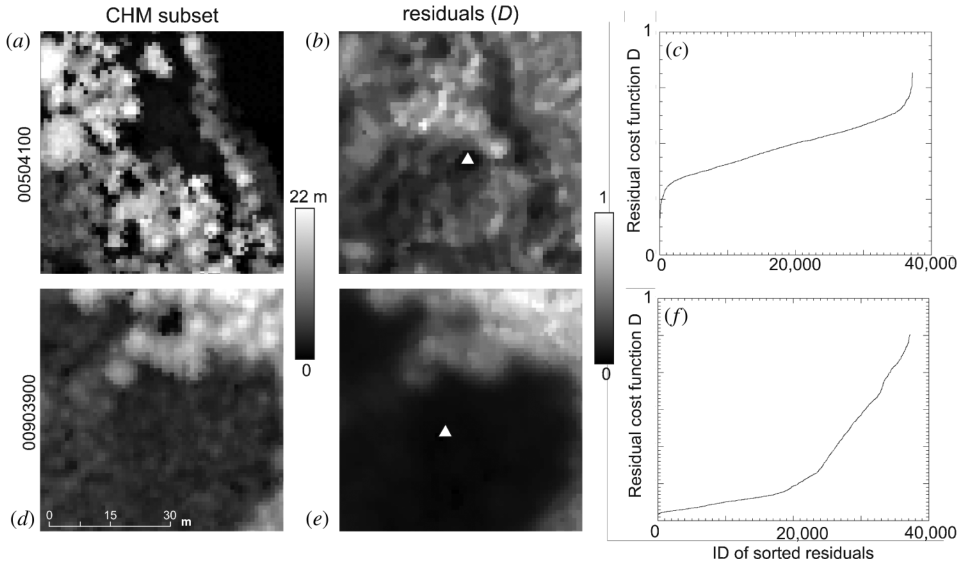

Figure 4. Two quality measures considered during co-registration, demonstrated for sample plots 00504100 and 00903900: (*a*) and (*d*) show the CHM of the respective sample plots; the spatial distribution of the cost function residuals is elucidated if more than one or very large clusters of minimum residuals exist (*b*, *e*), the triangle indicates the global minimum; the slope of the sorted residuals at the smallest absolute cost function residual D indicates whether the absolute minimum found is likely to be the global minimum or whether several local minima with slightly deviating minimum cost function values D exist (*c*, *f*).

the data analyst (§2.3). This was carried out for the NFI data set as well as for the 464 sample plots of the Stand Montafon LFI. The results obtained for this local FI guarantee a validation of the approach for an entirely independent data set.

Because of various uncertainties in the data (ALS and FI measurements) and methods (e.g. manual co-registration and model assumptions), it is very unlikely that manually and automatically established sample plot coordinates will match exactly. Therefore, small deviations between manually and automatically co-registered locations must be allowed for when considering whether a solution is correct. The decision on the maximum allowed distance between manually and automatically located plot coordinates was based on the work of Gobakken and Næsset (2008). They showed that, up to a plot position error of 5.0 m, stand-wise estimations of the Lorey's mean height, basal area and stem volume, based on a multiple regression model between FI data and laser metrics, are only modestly affected. For location errors up to 5.0 m, deviations in predicted values in most cases remained well below the 10% uncertainty generally attributed to large-area terrestrial FIs. The study of Gobakken and Næsset was based on sample plot sizes (232.9 m^2) that are comparable to those adopted in our study, so their results are assumed to be valid for the Austrian situation too. Based on their results we decided to mark as correct all differences between manual and automated co-registration of less than 5.0 m.

3.5 *Testing model sensitivity to angle count sampling criterion and tree class parameter*

In addition to a mere validation of model accuracy, the influence of two crucial model components was tested using the NFI data set. The two model components were: (i) the inclusion of the tree selection criteria posed by the angle count method and (ii) the influence of the tree class parameter. Applying the tree selection principle of the angle count method leads to sample plots that vary in spatial extent and do not necessarily include all trees present within the outermost radius of the sampling. To test the effect of introducing the angle count criteria in the cost function, automated co-registration was additionally performed and validated for data that were not corrected for minimum required tree heights at a given distance. In the cost function this corresponds to the difference between original and simulated CHMs as exemplified by figures 3(*a*) and 3(*d*), respectively.

It has been reported previously that not all angle count-based FIs incorporate a tree class parameter indicating vitality and growth stage of a tree and its relationship with neighbouring trees. To examine the robustness of the automated approach when it is applied to FIs where this parameter is lacking, such as in the Stand Montafon LFI, co-registration was performed on the NFI data set with all trees receiving the same weight, while all other parameters remained unchanged.

3.6 *Testing model robustness to changing input coordinates*

Sample plot coordinates measured with GPS contain a large random uncertainty that is to a high degree attributable to the satellite constellation at the time of data recording. The result of the co-registration procedure should be independent of these random errors in measured input coordinates and provide a solution that in every case points to the same location. In other words, the solution that is found for every model run should constitute a global solution that is independent of the content within the search window. Only if this is true can the approach be considered reliably implementable.

The dependency of model performance on the quality of GPS measurements was studied by adding additional location errors to the measured NFI coordinates and using the new coordinates as input to the comprehensive co-registration procedure (i.e. including the angle count criteria and weighting for tree stand characteristics). To study the effect of the magnitude of deviations, the procedure was repeated for different error levels. In five consecutive model runs the uncertainty added to each measured sample plot centre was randomly selected from a uniform distribution between 0.0 and 2.0, 4.0, 6.0, 8.0, and 10.0 m, respectively. The azimuthal direction of the error for each model run was selected on a uniform random basis between 0° and 360°.

3.7 *Quantifying the influence of co-registration on stem volume estimations*

To illustrate the importance of well co-registered data in creating more accurate ALS-based predictive models, and to show the improvement obtained when the results of the automated co-registration approach are integrated instead of the original GPS locations, we calibrated and cross-validated the stem volume model of Hollaus *et al.* (2009a,b) for three different co-registration states of the NFI, using (i) the original, (ii) the automatically co-registered, and (iii) the manually co-registered sample plot centre coordinates. Calibration and cross-validation were based on *in situ* stem volume measurements collected at each sample plot in Vorarlberg within the framework of the Austrian NFI (Gabler and Schadauer 2008). For more details on the growing stock model implemented, refer to Hollaus *et al.* (2009a,b).

4. Results

4.1 *Accuracy based on NFI data*

Figure 5 shows the distances between the automatically co-registered sample plot centre coordinates and the centre coordinates that could be unambiguously allocated manually by the data analyst. For better visualization the distances were sorted in ascending order. Table 4 shows that 67 of the 98 sample plots (i.e. 68%) were co-registered within a distance of 5.0 m from the manually assigned sample plot coordinates. The sharp rise in location errors observed around 5.0 m is noteworthy. The distance between correctly co-registered sample plots (i.e. distance $<$ 5.0 m) and manually obtained results ranged between 0.08 and 3.64 m, while more than half of these samples (34) showed a deviation of less than 1.0 m, which is the spatial resolution of the adopted CHM. The maximum deviation between automatically and manually obtained centre coordinates was 64.14 m. The latter value corresponded to a case in which the manually co-registered result was located outside the search window of the algorithm.

4.2 *Quality flagging*

Figure 5 and table 4 summarize the performance of the quality flagging criteria. It can be seen that all the points with a deviation $>$ 5.0 m from the manually allocated centre coordinates were marked as ‘uncertain’. This means that the set of quality flagging criteria was in all cases capable of identifying the incorrect solutions. Similarly, all plots that were marked as ‘certain’ had a deviation $<$ 5.0 m. By contrast, 25 plots showing a deviation $<$ 5.0 m from the manual co-registration results were tagged as ‘uncertain’. In these cases the set of rules applied to mark a solution as ‘uncertain’ also

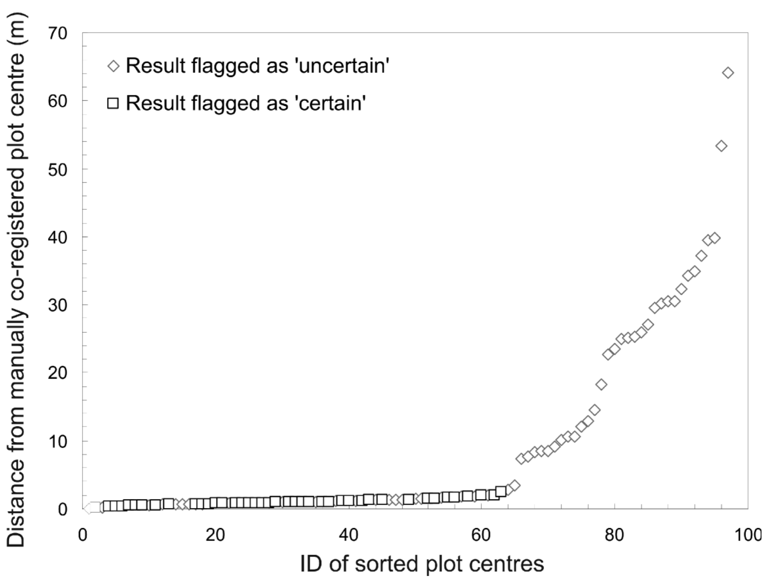

Figure 5. Distance between automatically and manually co-registered sample plot centre coordinates, sorted in ascending order. The squares indicate the points that were flagged ‘uncertain’ during co-registration while the diamonds were marked ‘certain’.

Table 4. Confusion matrix of suitability of quality flagging criteria for NFI data.

	Flagging result		
Reference	'Certain'	'Uncertain'	Total
Distance < 5.0 m	42	25	67
Distance > 5.0 m	0	31	31
Total	42	56	98
Commission error (%)	0	44.6	
Omission error (%)	37.3	0	
Overall accuracy (%)	74.5		

Table 5. Contribution of the different quality criteria that participated in marking a co-registration result as 'uncertain'. The total number of sample plots marked as 'uncertain' was 56.

Quality criterion	Participated in marking a solution as 'uncertain'	Participated in correctly marking a solution as 'uncertain'	Cases in which the criterion is decisive	Cases in which the criterion is decisive and the flagging result is correct
More than one cluster of minimum residuals	37 (66)	22 (39)	15 (27)	5 (9)
Slope sorted residuals < 0.001	25 (45)	9 (16)	15 (27)	4 (7)
Plot predominantly deciduous	4 (7)	3 (5)	2 (4)	1 (2)
Shift from original location > 20.0 m	19 (34)	19 (34)	5 (9)	5 (9)

Values given as *n* (%).

led to flagging of a correct solution. As a consequence, these 25 samples will be superfluously controlled by a data analyst during post-processing. Thus, the overall accuracy of the quality flagging rules amounts to 74.5%.

Table 5 gives an overview of the effectiveness of the four different quality criteria used for marking a solution as 'uncertain'. It shows that the criterion based on the occurrence of broad or multiple spatial clusters of minimum residuals is primarily responsible for marking a solution as 'uncertain'. Nevertheless, only in 22 cases out of 37 was this flagging result correct. The most reliable quality criterion appears to be the shift of more than 20.0 m from the original centre plot coordinate. All results marked as 'uncertain' by this criterion actually are found on a location that does not correspond to the optimum position. The least reliable quality measure is the slope of the sorted residuals: only nine out of 25 results marked as 'uncertain' by this criterion actually were located at an incorrect position. In 37 out of 56 (66%) cases only one quality criterion was responsible for marking a result as 'uncertain' (table 4, column 3). In the 19 other cases two or more criteria concurrently applied (e.g. a result was marked 'uncertain' both by the occurrence of two spatial clusters of minimum residuals and due to a shift of more than 20 m from the original location). The last column of table 5 shows the cases in which a criterion is decisive in marking a solution as 'uncertain' and this flagging result also marks a falsely located solution. In this respect, all criteria but the deciduous sample plot type criterion have more or less the same power of successfully identifying incorrectly co-registered sample plots. The contribution of the deciduous plot type criterion may appear very low compared to the 23.8% of deciduous forest cover present in Vorarlberg (section 2.1). This number is, however, somewhat distorted as most deciduous plots could not be unambiguously manually co-registered either and therefore were not included in the analysis. Thus, if all sample plots were used in the analysis this criterion would have had a significantly larger influence.

Based on the last column of table 5, it can be stated that all four criteria are required to guarantee that all results with a distance of more than 5.0 m from the actual centre location are marked as 'uncertain'. It was shown in the previous section that this necessarily leads to commission errors in the quality flagging results.

4.3 *Model sensitivity to angle count sampling criterion and tree class parameter*

Not taking into account the minimum height criterion posed by the angle count method significantly reduced the number of samples that were correctly automatically co-registered: only 45 results out of 98 (i.e. 46%) had a distance of less than 5.0 m from the manually co-registered results (table 6). Overall accuracy of the quality flagging criteria is slightly superior to that obtained when taking into account the angle count tree selection criterion, which is explained by the reduced number of incorrect solutions that receive the quality flag 'uncertain'. Nevertheless, 10% of the results with a deviation of more 5.0 m from the actual location were not recognized by the adopted flagging rules as being 'uncertain'.

Omitting the tree class parameter in the cost function did not affect the number of correctly co-registered sample plots, i.e. 67 out of 98 sample plots were co-registered to a location at a distance of less than 5.0 m from the manually assigned optimum location (table 7). By contrast, the quality flagging rules performance is somewhat inferior, which is principally induced by marking two erroneously co-registered sample plots as 'certain'.

4.4 *Model robustness to changing input coordinates*

Table 8 shows that adding a random error to the measured coordinates hardly affects model performance, irrespective of the magnitude of the added error. The number and average error of correctly co-registered sample plots remain almost unchanged whereas there is only a slight decrease in performance of the quality flagging criteria. To analyse the results for which co-registration did not yield the same solution for all levels of random error, we calculated for every sample plot the average variation of the six different model run outcomes. Figure 6 shows this variation per sample plot

Table 6. Confusion matrix of suitability of quality flagging criteria for NFI data when angle count criteria are not taken into account.

	Flagging result		
Reference	'Certain'	'Uncertain'	Total
Distance < 5.0 m	27	18	45
Distance > 5.0 m	3	50	53
Total	30	68	98
Commission error (%)	10.0	26.5	
Omission error (%)	40.0	5.8	
Overall accuracy (%)	78.6		

Table 7. Confusion matrix of suitability of quality flagging criteria for NFI data when the tree class parameter is not considered.

	Flagging result		
Reference	'Certain'	'Uncertain'	Total
Distance < 5.0 m	41	26	67
Distance > 5.0 m	2	29	31
Total	43	55	98
Commission error (%)	4.7	47.3	
Omission error (%)	38.8	6.5	
Overall accuracy (%)	71.4		

Table 8. Summary statistics of the results after adding a random error to the original (measured) NFI locations ($n = 98$). The random error of 0.0 is equivalent to using the original, measured coordinates.

	Range of random error (m)					
	0.0	0.0–2.0	0.0–4.0	0.0–6.0	0.0–8.0	0.0–10.0
Number of correctly co-registered samples	67	67	67	67	67	67
Average error between reference centre locations and the automated co-registration result (m)	8.35	8.23	8.23	8.22	8.70	8.06
Overall accuracy flagging result (%)	74.5	73.5	72.4	72.4	72.4	70.4
Commission error 'uncertain' (%)	44.6	45.6	46.4	46.4	46.3	48.3
Omission error 'uncertain' (%)	0.0	0.0	3.2	3.2	6.5	3.2
Commission error 'certain' (%)	0.0	0.0	2.4	2.4	4.6	2.5
Omission error 'certain' (%)	37.3	38.8	38.8	38.8	37.3	41.8

(expressed as standard deviations) in combination with the accuracy and quality flagging results of the original, measured coordinates presented in figure 5. It can be clearly seen that those sample plots based on the original coordinates that were correctly co-registered were also accurately co-registered after adding random errors. By contrast, all sample plots with diverging co-registration results, as indicated by the larger standard deviations, were flagged as 'uncertain' in the different model runs, showing the successful performance of the quality flagging criteria.

4.5 *Transferability to LFI Stand Montafon*

The co-registration approach could correctly automatically co-register 342 of the 464 sample plots of the Stand Montafon LFI (i.e. 73.7% of the results had a distance < 5.0 m from the automatically co-registered centre coordinates). Despite the lack of a tree class parameter, this result even outperforms that obtained for the NFI, which was used for calibration of the model (table 9). In 238 cases the distance between automatically and manually obtained results was even less than the 1.0 m spatial resolution of the applied CHM.

Quality flagging criteria were very successful in identifying uncertain results (table 9). Only one out of 122 co-registration results with a distance > 5.0 m from the manually

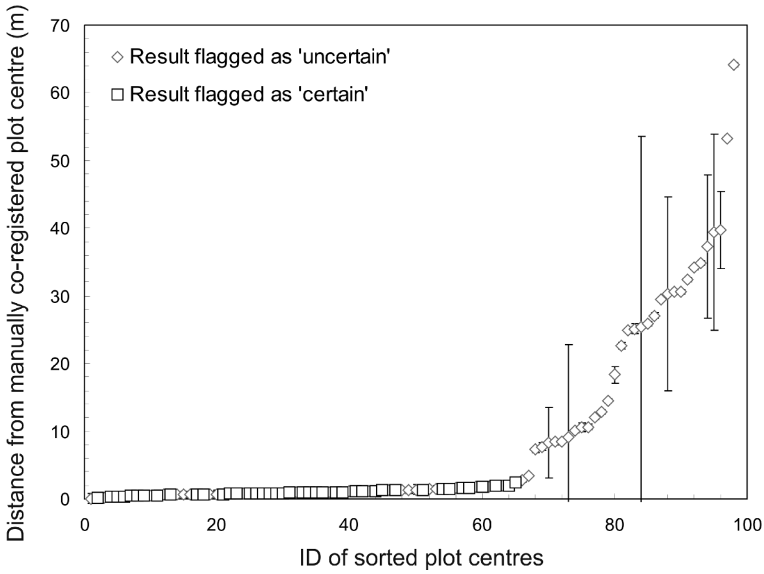

Figure 6. Distance between automatically and manually co-registered sample plot centre coordinates, sorted in ascending order. Automated co-registration was based on the measured sample plot centre coordinates. The squares indicate the solutions that were flagged 'uncertain' during co-registration while the diamonds were marked 'certain'. Error bars indicate the standard deviation of the six different model runs with different noise levels of the input coordinates as depicted in table 8.

Table 9. Confusion matrix of suitability of quality flagging criteria for LFI data.

	Flagging result		
Result	'Certain'	'Uncertain'	Total
Distance < 4 m	193	149	342
Distance > 4 m	1	121	122
Total	194	270	464
Commission error (%)	0.5	55.2	
Omission error (%)	43.3	0.8	
Overall accuracy (%)	67.7		

attributed reference location was marked as 'certain'. However, the commission error of the rules applied for flagging a result as 'uncertain' is relatively high at 55.2%.

4.6 *Influence of co-registration on stem volume estimations*

Testing the influence of co-registration quality on stem volume estimations was based on the 41 sample plots that during automated co-registration were marked 'certain'. Four sample plots were excluded from the model calibration because of the absence of growing stock measurements and another four samples were detected as outliers ($p < 0.05$) and were omitted. Figure 7 shows that using the automatically co-registered data yields a significant improvement (both in terms of R^2 and relative standard deviations obtained by cross-validation) compared to the original sample plot centre coordinates and even slightly outperforms the accuracy obtained when using the manually co-registered sample plot centre coordinates.

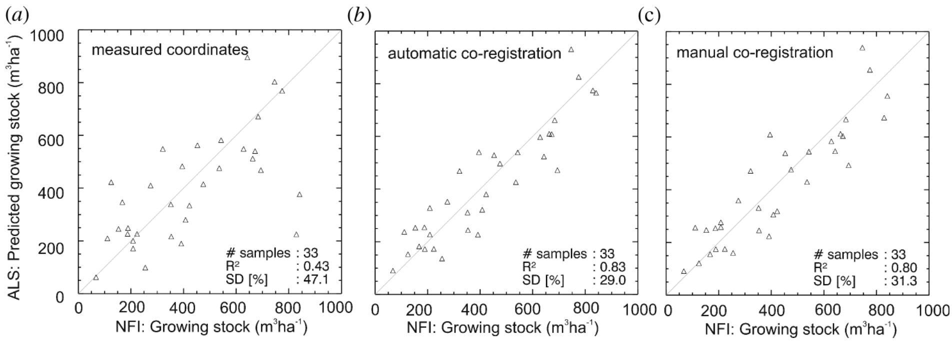

Figure 7. Effect of co-registration on calibration of the ALS-based stem volume model of Hollaus *et al.* (2009b): (*a*) when original sample centre coordinates measured by GPS are used, (*b*) when automatically co-registered coordinates are used, and (*c*) when manually co-registered coordinates are used.

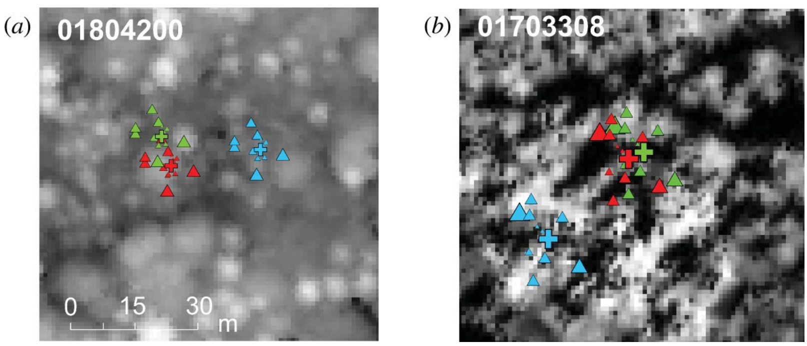

Figure 8. Examples of incorrectly co-registered sample plots. (*a*) Sample plot 01804200 is dominated by deciduous trees and lacks evident tree apices. Red triangles (crosses) show the original tree (centre) locations, blue the results of the automated co-registration, and green the results of the manual co-registration. (*b*) Sample plot 01703308 is characterized by an insufficient ALS point density for the applied spatial resolution of the CHM. The size of the triangles gives an indication of the relative height of the individual trees.

5. Discussion

The main objective of the proposed automated co-registration algorithm was to accurately co-register as many sample plots as possible, an objective that was achieved for 68% of the NFI sample plots (used for calibration) and for 74% of the LFI sample plots (used for validation). The threshold used to decide whether a result was correct or not was *a priori* set to 5.0 m based on the work of Gobakken and Næsset (2008). The appropriateness of this threshold was confirmed by the co-registration results, which for both the NFI (figure 5) and the LFI data set (not shown) show a sharp rise in co-registration errors around this threshold. A plausible explanation for this sharp rise is that, up to this point, deviations are mainly caused by small uncertainties in data and methods, causing the solution to potentially vary across the minimum cost function residuals around the optimum position. For an unambiguous solution these small-scale shifts can amount to several pixels (cf. figure 4(*b*)). By contrast, larger deviations are likely to be caused by solutions that are not located in the cluster of the minimum cost function residuals around the optimum position.

Taking into account the angle count criteria in the minimization function had a very significant influence on model performance; including the criteria in the way proposed in this study led to an increase in correctly co-registered samples of 49% (increase from 45 to 67). Weighting of the tree stand characteristics, another model component proposed in this study, had far less impact on the results. This justifies the transferability of the approach to FIs where the tree class parameter is not recorded, as in the case of the forest administration Stand Montafon Forstfonds LFI used in this study.

Based on the NFI data set, it was verified that 71% of the incorrectly co-registered results could be traced back to the occurrence of two or more spatially separable minima of the minimization function. This means that, even though an absolute minimum of the cost function exists, this may not necessarily be the most plausible result. In these cases, mostly the second or third smallest minimum residual indicated the correct location. Several other causes can be proposed for the rest of the discrepant results. Figure 8(*a*) shows a typical situation in which the algorithm fails to find a reliable optimum because of a very dense deciduous cover without clearly distinguishable tree apices. This is consistent with the findings of Olofsson *et al.* (2008), who reported significantly lower co-registration accuracies in dense plots. Difficulties were also encountered in cases where the inventory concerns solitary trees in open spaces. In two cases the manually established optimum solution was situated outside the search window of 61 m $\times$ 61 m around the original centre location. Enlarging the search window could overcome the latter problem, although as a consequence the number of possible solutions (minima) could increase too and give rise to additional ambiguities.

Measurement errors in the FI data (tree height, DBH and position) and the raw ALS data (e.g. instrument noise, orthorectification errors) and inaccuracies in the CHM resulting from interpolation of the DSMs and DTMs additionally provided potential sources for a non-optimal fit between FI data and the CHM. At this point it should be recalled that the objective of this study was to develop an automated co-registration method that is robust for data captured under operational conditions and suited for large area applications. This entails that both the FI and ALS data were not optimized for the scope of the current study. Concerning the commercial ALS terrain mapping campaigns, acquisition times were chosen such that influences of vegetation were minimized as much as possible, that is during leaf-off conditions. As a consequence, the heights of deciduous trees may have been significantly underestimated by the CHM. Another consequence of using commercially available ALS data sets is depicted in figure 8(*b*); because of the relatively low point density of the large-area terrain mapping campaigns and the complex topography of the area, at several sample plot locations numerous data gaps occur in the CHM. However, in densely forested areas the limited number of ground hits led to an inaccurate reconstruction of the terrain. The availability of higher point densities is expected to significantly reduce ambiguities resulting from this error source. In addition, the time lag of up to 2–3 years between FI and ALS data acquisition may have introduced additional uncertainties.

A major limitation of using national and local FI data is the lack of high-precision GPS measurements of the centre coordinates that could serve as a reference for quality assessments. This forced us to base the accuracy assessments on a reference data set that had been manually co-registered by visual interpretation. Although the accuracy of this method is thought to be high, several problematic plots had to be excluded from the analysis as no evident manual solution could be found for these. Thus, the inclusion of all sample plots could to some degree have modified the statistics presented in this work.

Quality flagging appeared an indispensable premise for the practicability of the approach in an operational environment by giving an indication of the quality of the result and by potentially reducing post-processing efforts. The proposed combination of measures used to flag a result as 'uncertain' is very powerful and only in one case out of 153 (i.e. the sum of NFI and LFI) failed to mark a solution with a distance of more than 5.0 m from the reference location as 'uncertain'. As a consequence, this plot would not be suggested to the data analyst as a potential candidate for manual post-processing. A consequence of laying out the quality flagging rules to achieve the lowest possible omission errors for the result 'uncertain' is the relatively high commission errors. Approximately half of the results marked as 'uncertain' in fact have a solution very close to the reference centre coordinate, and would be unnecessarily verified during post-processing. Nevertheless, in terms of the effects on data quality of subsequent thematic applications, identification of all uncertain results has a higher importance than low commission errors.

Model robustness is a key element for the applicability of the proposed method in an operational environment where data from different data campaigns and with variable accuracy levels are combined. The approach appeared to be relatively insensitive to the accuracy of the measured centre coordinates; for deviating coordinates of the input centre locations, in most cases the algorithm converged to one and the same solution. For the sample plots where this was not the case, quality flagging criteria led to the appropriate flagging result 'uncertain'.

The example stem volume model calibrations based on three different levels of co-registration results, presented in §4.6, illustrate the practical relevance of adequate co-registration between FI and ALS data in general and the potential of the automated algorithm in performing this task in particular. The improved stem volume estimates when using more accurate sample plot locations are also in accordance with the findings of Gobakken and Næsset (2008).

6. Conclusions

The current study shows that a robust approach can be developed for the co-registration of FI data based on the angle count method and ALS data acquired under operational conditions. Even though the ALS data were far from optimal for vegetation analyses, accurate results could be obtained for 68% and 74% of the sample plots, for Austrian NFI and local FI data, respectively. It is expected that increasing the point density of the ALS campaigns and optimizing the acquisition times for vegetation studies will further increase the accuracies obtained. In addition, in the near future the approach will be validated in more detail for an area that is dominated by deciduous and mixed forests.

The sample plots that could not be co-registered adequately with the proposed approach were efficiently detected by quality flagging criteria. The quality flagging in combination with images showing the spatial distribution of the minimization function residuals are of great importance when the approach is applied operationally to large data sets, as these outputs can be effectively used to manually identify and attribute the correct locations of the sample plots that could not be adequately co-registered by the automated approach. As the algorithm developed will be part of an operational processing chain for Austrian NFI data, it has a high practical relevance.

Acknowledgements
We thank the Landesvermessungsamt Feldkirch for granting the use of the ALS data. Parts of this study were funded by the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management (BMLFUW) in the framework of the project ÖWI-Regio.

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