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Can global navigation satellite system signals reveal the ecological attributes of forests?

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ABSTRACT

Forests have important impacts on the global carbon cycle and climate, and they are also related to a wide range of industrial sectors. Currently, one of the biggest challenges in forestry research is effectively and accurately measuring and monitoring forest variables, as the exploitation potential of forest inventory products largely depends on the accuracy of estimates and on the cost of data collection. A low-cost crowdsourcing solution is needed for forest inventory to collect forest variables. Here, we propose global navigation satellite system (GNSS) signals as a novel type of observables for predicting forest attributes and show the feasibility of utilizing GNSS signals for estimating important attributes of forest plots, including mean tree height, mean diameter at breast height, basal area, stem volume and tree biomass. The prediction accuracies of the proposed technique were better in boreal forest conditions than those of the conventional techniques of 2D remote sensing. More importantly, this technique provides a novel, cost-effective way of collecting large-scale forest measurements in the crowdsourcing context. This technique can be applied by, for example, harvesters or persons hiking or working in forests because GNSS devices are widely used, and the field operation of this technique is simple and does not require professional forestry skills.

1. Introduction

The total global forest area exceeds 4 billion hectares, and it covers 31% of the total land surface (FAO, 2010). Additionally, forests contain more than half of all terrestrial species and account for 75% of terrestrial gross primary production (GPP), which represents carbon assimilation from photosynthesis by vegetation per unit area and time (Beer et al., 2010; Pan et al., 2013), and 80% of Earth's total plant biomass (Kindermann et al., 2008). All of these reflect the high ecological and economic importance of forests. The conversion of solar energy into biomass through photosynthesis makes forest ecosystems a key component of the global carbon cycle and climate. A major portion of the total forest carbon storage comprises the growing stock of carbon reserves (Kindermann et al., 2008). Thus, one of the biggest current challenges in forest inventory research is effectively and accurately measuring and monitoring forest biomass (Holopainen et al., 2014; Hyyppä et al., 2008; Liang et al., 2014). The recent knowledge regarding forest biomass is based on ground measurements and coarse- or medium-resolution satellite images (Hyyppä et al., 2008; Liang et al., 2014; Thenkabail 2015). The exploitation potential in the field of biomass and stem volume mapping is largely dependent on the accuracy of what can be obtained and the cost of data collection. Optimally, when forest inventory data are more accurate and updated in time, the storages of the forest industry will move from real storages to forests (Holopainen et al., 2014; Liang et al., 2014).

There is also growing interest for citizens to participate in the data collection of geospatial information (Heipke, 2010). More commonly, crowdsourcing is understood as geospatial data collection by voluntary citizens who are untrained in the disciplines of geography, cartography or related fields (Thenkabail, 2015). In the field of forestry, crowdsourcing has been used to assess the condition of city trees. For example, PhillyTreeMap is a web-based application that allows citizens to input tree information of city forests; today, data on over 179,000 Philadelphian trees are stored in the database.

A variety of field measurement and remote sensing technologies have been studied in the prediction of forest biophysical attributes and their changes (Koch, 2010; Rahlf et al., 2014; Hyyppä et al.,

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Table 1
Correlations (R) between GNSS signal strength losses and forest attributes.

Forest attributes	GPS	GLONASS
Mean tree height	0.75	0.71
Mean DBH	0.73	0.69
Basal area	0.85	0.78
Stem volume	0.84	0.76
Biomass	0.85	0.77

2008; Liang et al., 2012, 2014, 2015; Karila et al., 2015; Solberg et al., 2015; Nilsson, 1996; Yu et al., 2010; Nelson et al., 1988). Reference data for sample plots are conventionally collected through manual measurements, which are expensive, time consuming and labor intensive (Holopainen et al., 2014; Heipke, 2010). Consequently, trees are typically measured by sampling criteria already at the plot-level, and tree attributes are often retrieved using allometric models instead of actual measurements, which introduce inaccuracies that propagate to the stand- and national-scale estimation of forest resources(Holopainen et al., 2014; Karila et al., 2015; Solberg et al., 2015).

Previous studies also show that GNSS (global navigation satellite system) positioning does not work well in forests (Sigrist et al., 1999; Kaartinen et al., 2015; Alonso et al., 2014). The denser the canopy is, the less accuracy the positioning solution possesses (Meng et al., 2009; COST235, 1996). Therefore, it is surprising that GNSS signals have not yet been studied as an observable source to measure forest attributes. In this study, we asked, "Can GNSS signals be used as an informative indicator to reveal the physical properties of forests?" This is not only a scientific question; it also may have remarkable societal and industrial impacts.

2. Material and methods

2.1. Test site and reference dataset of forest inventory

The proposed technique was studied using field experiments conducted at our established test site located in Evo, southern Finland (61.19°N, 25.11°E), where a reference dataset of forest inventory has been established. The test site is part of the southern Boreal Forest Zone, and it mainly comprises approximately 2000 ha of managed boreal forest. The topography of the area varies from 125 m to 185 m above sea level. Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*) are the dominant tree species in the study area, contributing 40% and 35% of the total volume, respectively (Yu et al., 2010).

The reference dataset of forest attributes included mean tree height, mean diameter at breast height (DBH), basal area, stem volume, and biomass of trees. These data were generated with airborne laser-scanning data (acquisition date July 25th 2009, point density 10 points per m^2) and field measurements in 292 sample plots (10 m radius circular area distributed over the same area as the study area) using an area-based approach (Hyyppä et al., 2008; Yu et al., 2010) and Random forests (RF) technique (Breiman, 2001; Hastie et al., 2009; Yu et al., 2011). Finally, plots of circular areas of 10 m radius were created along the trajectory with the center point of the circle following the trajectory, and they were utilized as reference plots. In this study, the reference datasets of these plots were used as sample set in the RF regression algorithm to establish the proposed GNSS-based nonparametric regression model for predicting forest attributes.

2.2. GNSS data collection

As illustrated by Supplementary Fig. S1, two Trimble GNSS receivers were used to collect GNSS observables in parallel in the test site, including ranging measurements, navigation data, and signal strength indicators. One was placed on top of a tripod under open-sky conditions (Supplementary Fig. S2), and it was the benchmark for calculating the signal strength loss (SSL), which is the primary observable of estimating forest attributes in this study; the other, called the rover receiver, was carried on an all-terrain vehicle (Supplementary Fig. S3), which was driven around the test site for collecting GNSS data. Both GNSS receivers were able to track the US Navstar GPS (Global Positioning System) and the Russian GLONASS (GLObalnaja NAvigatsionnaja Sputnikovaja Sistema) satellites.

Table 2
Accuracy of plot-based forest attribute predictions using the features of different GNSS combinations.

Features	Forest attributes	Bias	Bias (%)	RMSE	RMSE (%)	R
GPS	Mean height (m)	0.00	0.00	4.05	18.77	0.83
	Mean DBH (cm)	−0.06	−0.25	4.25	19.54	0.79
	BA (m^2/ha)	−0.01	−0.07	6.03	30.78	0.83
	Volume (m^3/ha)	0.70	0.32	77.94	35.81	0.82
	Biomass (Mg/ha)	−0.37	−0.37	34.04	33.51	0.83
GLONASS	Mean height (m)	−0.10	−0.47	4.34	19.92	0.80
	Mean DBH (cm)	−0.11	−0.51	4.74	21.49	0.74
	BA (m^2/ha)	−0.12	−0.64	6.56	33.53	0.79
	Volume (m^3/ha)	−1.38	−0.63	89.40	40.79	0.75
	Biomass (Mg/ha)	−0.44	−0.43	39.07	38.38	0.77
GPS + GLONASS	Mean height (m)	−0.08	−0.38	3.61	16.95	0.87
	Mean DBH (cm)	−0.05	−0.22	4.13	19.24	0.80
	BA (m^2/ha)	−0.08	−0.44	5.57	29.22	0.86
	Volume (m^3/ha)	−0.39	−0.18	72.78	34.39	0.85
	Biomass (Mg/ha)	−0.65	−0.66	32.14	32.53	0.85

3. Derivation of GNSS features

The distributions of the received signal powers of both receivers were compared in terms of carrier-to-noise ratio (C/N_0) as shown in Supplementary Fig. S4 and evidently showed lower signal strengths with the in-forest receiver overall. Due to the presence of forest canopies, the signal strengths received by the in-forest receiver were less stable than those of the out-forest one, as shown in Supplementary Fig.S5, which compares the variations between two adjacent epochs of the observed signal strengths of both receivers. It shows that the in-forest receiver at 9.4% epochs was subject to C/N_0 fluctuations greater than 3 dB, while this value was 1.3% epochs for the out-forest receiver. The out-forest receiver was utilized as the benchmark of the signals in space, and the signal strength loss was defined by the difference between the two receivers in C/N_0 observables at each corresponding epoch (t) for each satellite (sv), i.e.,$SSL_{(sv,t)} = [C/N_{0in-forest} - C/N_{0out-forest}]_{(sv,t)}$.

SSL measurements were calculated for every satellite and epoch, and the satellites of low elevations were excluded by a cut-off elevation of 30° because they have higher noise levels in the measurements (Wu et al., 2010). As a function of satellite elevations, the slant penetration paths of the satellite signals caused larger signal strength losses than the vertical path. A mapping function was utilized for compensating the effect of satellite elevations and normalizing SSL measurements to the vertical direction, $SSL_{\perp} = SSL \times \sin(\theta)$, where θ is the satellite elevation and $SSL_{\perp}$ is the adjusted signal strength loss. Every SSL measurement was associated with a specific sample plot of forest reference data to which the rover receiver's position of current epoch belonged. Thus, there were a number of SSL measurements within the range of each sample plot. For each sample plot and each GNSS system (GPS and GLONASS in this study), six features of SSL measurements were derived, as indicated below, for the prediction of forest attributes:

- number of SSL measurements