Applications of Remote and Proximal Sensing for Improved Precision in Forest Operations

Bruce Talbot, Marek Pierzchała, Rasmus Astrup

Abstract

This paper provides an overview of recent developments in remote and proximal sensing technologies and their basic applicability to various aspects of forest operations. It categorises these applications according to the technologies used and considers their deployment platform in terms of their being space-, airborne or terrestrial. For each combination of technology and application, a brief review of the state-of-the-art has been described from the literature, ranging from the measurement of forests and single trees, the derivation of landscape scale terrain models down to micro-topographic soil disturbance modelling, through infrastructure planning, construction and maintenance, to forest accessibility with ground and cable based harvesting systems. The review then goes on to discuss how these technologies and applications contribute to reducing impacts on forest soils, cultural heritage sites and other areas of special value or interest, after which sensors and methods necessary in autonomous navigation and the use of computer vision on forest machines are discussed. The review concludes that despite the many promising or demonstrated applications of remotely or proximately sensed data in forest operations, almost all are still experimental and have a range of issues that need to be addressed or improved upon before widespread operationalization can take place.

Keywords: sensors, automation, operational efficiency, forest operations, precision forestry

1. Introduction

Technology is revolutionising our access to information about forest resources, landscapes, and individual forest machine performance (Ziesak et al. 2014). The improved information includes both higher spatial and temporal resolution of data and information, as well as access to previously unattainable information (Holopainen et al. 2014). In an economic sense, the forest sector is obliged to support developments that make management processes and operations more efficient. Forest operations management, therefore, needs to grasp these newly available technologies and knowledge in ensuring continual improvement.

Remote sensing is defined as the acquisition of information about an object without making physical contact with it, but there is an underlying understanding of ranges or technologies implied. During forest operations, nearby objects such as trees, stems, rocks, streams, and gullies also need to be measured from machine or human borne sensors, the so called proximal sensing (Mulla 2013). Proximal sensing is in the early stages of a potentially revolutionary change as cheap and robust sensors and technologies are increasingly applied in the collection, storage, and interpretation of data. Such data can be analysed and applied instantaneously or fed into Big Data systems that evaluate status and trends at local, regional or national levels (Lokers et al. 2016). For example, technologies inherent in smart phones and tablets today include distance ranging, orientation through inertial measurement units (IMUs) including magnetometers, gyroscopes and accelerometers, as well as Global Navigation Satellite Systems (GNSS's) and cameras (Tomaštík et al. 2016). In forestry, smartphone based sensors and apps have been demonstrated in a variety of uses ranging from the measurement of forest stands or log piles (Vastaranta et al. 2015) to distinguishing between work elements in cable yarding operations (Pierzchała 2017). Over the past two decades, airborne Light Detection and Ranging (LiDAR), commonly called airborne laser scanning (ALS), has become the standard practice for forest inventory in the Nordic countries (Næsset 2004). Spaceborne Radio Detection and Ranging (RADAR), ALS and airborne photogrammetry are now widely applied for estimating forest biomass, and a number of models exist for operational forest inventory (Rahlf et al. 2014, Gobakken et al. 2015). Developments in technology and the resulting improvements in forest inventories, in combination with better terrain information, have the potential to enable precision forestry (Holopainen et al. 2014), as well as improve the control and automation of forest harvesting systems (Ziesak et al. 2014).

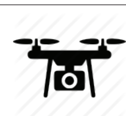
Mechanised systems account for a large and increasing share of timber harvesting, where they simultaneously provide stable platforms for the deployment of sensors with regard to power supply, protective housing, temperature regulation, lighting, as well as data storage, viewing and transmission (Talbot and Astrup 2014). In this way, forest machines can potentially serve as data collection platforms to help reduce field survey costs (Olivera and Visser 2014). Adding additional sensors to forestry machinery offers a multitude of potentially beneficial future applications (Ziesak et al. 2014). When it comes to applications in forest operations, the field places special demands on system ruggedness, compatibility, simplicity and robustness in terms of measurement accuracy and reliability. However, many sensors and technologies in the early stages of development are already being effectively applied in more rudimentary settings (Gallo et al. 2013, Visser et al. 2014).

This paper provides a brief overview of how different remote and proximal sensing technologies are being employed with respect to forest operations and how these are relevant for improving operational or environmental efficiency. The overview includes the most applicable remote sensing technologies for forest operations and their basic functionality, while a more categorical specification of these technologies might be found in e.g. Fardusi et al. (2017) or Holopainen et al. (2014). The existing literature is reviewed and discussed in terms of relevant research for terrain assessment applications, infrastructure planning and monitoring, and finally, ground and cable-based harvesting, including the avoidance or measurement of biological and environmental impacts. The paper concludes with a brief summary and outlook for the future.

1.1 Sensor deployment and its relevance for forest operations

The sensor platform refers to the sensor carrier, which could be a satellite, aeroplane, unmanned aerial vehicle UAV or a ground based vehicle or human. For example, Liang et al. (2015) distinguish between platforms for laser scanners as being Airborne Laser Scanning (ALS), Terrestrial Laser Scanning (TLS), Mobile Laser Scanners (MLS) and Personal Laser Scanning (PLS), while Bauwens et al. (2016) add the concept of Hand-Held Mobile Laser Scanning (HMLS). One of the main considerations in sensing the forest environment is the influence of the sensor deployment on the information gained. Each platform used offers a range of benefits and disadvantages, including the area of coverage per deployment, and the spatial and temporal resolution (Table 1).

Table 1 General characterisation of sensor deployment platform to spatial coverage and temporal resolution (adapted from Pierzchała (2017))

Sensor deployment platform	Coverage	Spatial resolution	Temporal resolution
	Global/National	Low	Medium to high
	Regional	Medium	Low
	Local	High	High
	Site	Ultra high	High

Furthermore, there are two main areas within which remote sensing technologies can be discussed:

⇒ those relating to the operating environment
⇒ those relating to forest operations themselves.

The operating environment determines the selection and use of machine systems, while the second area deals with issues influencing e.g. productivity or data capture during the actual operations.

Remote sensing technologies such as ALS, satellite and aerial photography, and satellite based radar enable large contiguous forest areas to be mapped in a uniform way (Rahlf et al. 2014), forming a basis for the development of efficient planning systems. The utility of using ALS forest and terrain data in harvest planning is discussed by Akay et al. (2009) and Heinimann and Breschan (2012), both of whom emphasize the benefits of the high resolution digital elevation models (DEMs) that have become available. These high resolution elevation models, with one or more point references per m^2, have revolutionised the basis for evaluating harvest system accessibility and performance analysis, enabling the use of high precision methods.

The proximal measurement of the forest operations environment (trees and terrain) commonly utilises LiDAR and/or photogrammetry, but the platforms used in deploying them differ and the data resolution is generally considerably higher due to the close proximity. Ground-based measurement provides vertical information on the stem that is not possible to obtain from the air. Examples of the use of terrestrial laser scanning (TLS) in doing pre-harvest tree and stand level assortment bucking have been demonstrated by e.g. Ducey et al. (2013) and Kankare et al. (2014). The stem proportions derived from TLS have been shown to correspond well with stem measurements obtained from the harvesting head (Astrup et al. 2014). Better information on stand-level assortments is useful in estimating the stumpage value of a stand and can be sourced in matching orders with harvest schedules in precision wood supply (Bergdahl et al. 2003).

Terrestrial platforms include the deployment of stationary sensors, sensors on manned or unmanned ground-based vehicles (UGVs), or on humans (Lauterbach et al. 2015, Bauwens et al. 2016, Rönnholm et al. 2016). Terrestrial deployment platforms often utilise the same sensors as aerial applications, but differ in terms of costs, payloads, energy sources, and resolution. The forest canopy poses a considerable challenge for terrestrial forest mapping (Blum et al. 2016). Ground-level surveying in forests with the use of GNSS is limited due to signal occlusion caused by dense crowns (Wing and Eklund 2007). This occlusion results in multipath error and discrete »jumps« in position estimates, making high accuracy positioning challenging, even with a differential global positioning system (DGPS) (Naesset and Jonmeister 2002, Sawaguchi et al. 2003).

Imaging sensors can be deployed on ground platforms either on vehicles intended for data capturing (mobile mapping) or on forestry equipment itself. An example is the sScale system from Dralle AS (Dralle and Tarp-Johansen 2010), which is an imaging system that can be mounted on a vehicle to measure timber piles, or the use of ATVs or UGVs for stand and tree-level measurement and inventory (Öhman et al. 2008, Miettinen et al. 2010, Liang et al. 2014). The harvester head itself is used as a sensor platform to measure tree sizes, and Kauhanen (2008) improved this functionality with image based data.

When properly calibrated, harvesting heads accurately measure diameter at 10 cm intervals along the entire stem length, and, with hundreds of millions of trees being harvested with CTL technology annually, harvesting heads represent a central data collection hub. Immediate uses of such data include local estimations of growth, and yield data at sub-stand level and the development of spatially explicit stem taper equations (Olivera and Visser 2016). Such data are automatically geo-referenced at the resolution achieved by the harvester GNSS. An area of great potential that remains to be fully solved is finding methods for matching single-tree data from ALS with that of the harvester head, as discussed by Lindroos et al. (2015) and Hauglin et al. (2017). Currently, certain harvester brands provide an estimate of the harvester head position relative to the base machine, calculated from hydraulic cylinder extension measurements and crane geometry. Improvements in absolute single-tree precision are, therefore, fully dependent on the accuracy of the GNSS data on the base machine. While this could be resolved with DGPS systems, the practical interim solution is likely to lie in the statistical segmentation of individual trees out of small groups identified in the immediate vicinity (Holmgren et al. 2012).

1.2 Infrastructure planning, construction and monitoring

Airborne LiDAR provides high-resolution ground terrain models that represent a considerable improvement on which to base estimations on something so detailed and costly as road planning, construction and maintenance. To this end, Aruga et al. (2005a) developed a forest road design programme based on a LiDAR digital elevation model (DEM) that could optimize the horizontal and vertical alignment of a road segment through the minimisation of construction and maintenance costs, using a tabu-search heuristic. Expanding on that, both Akay and Sessions (2005) and Aruga et al. (2005b) show how the addition of a model for predicting surface run-off from roads, which has important connotations both for environmental impact and for road maintenance, provide additional depth to the potential areas of application of the method. Contreras et al. (2012) demonstrate a model using a high resolution LiDAR derived DEM (1 m) to calculate the required earthwork on a number of hypothetical roads. The detailed DEM made it possible to use a higher number of cross sections in the evaluation than otherwise, resulting in differences in estimates of 2–21%, as compared with conventional planning.

Several applications of airborne LiDAR data in the monitoring and evaluation of existing forest roads have been demonstrated. Craven and Wing (2014) considered the influence of 4 different canopy conditions on the accuracy of estimation of road geometry based on LiDAR data, and showed mean vertical error of 0.28 m and horizontal error of 1.21 m, when considered against existing road centrelines. Road slopes were estimated to within 1% and error in horizontal curve radii was estimated with an absolute error of 3.17 m. The follow up work by Beck et al. (2015) used varying intensity values and return densities in classifying roads and demonstrated a high level of accuracy in doing so. In other applications, LiDAR has been used in detecting, monitoring or extracting the geometry of existing roads to evaluate whether they meet certain specifications. For instance White et al. (2010) extracted alignment and gradient data from a mountain forest road, showing deviations of 1.5 m in position, 0.5% in slope and 0.2% in terms of length when compared with field survey data. A similar approach applied by Azizi et al. (2014) resulted in more than 95% of the road length being classified within 1.3 m of the field surveyed normal. These developments represent considerable time and effort savings in providing detailed road geometry, providing essential complementary data to conventional field surveys. However, Krogstad and Scheiss (2004) list pitfalls of a blind adoption of these models including inconsistent data returns depending on canopy density and a resultant data smoothing that can provide a false basis for road design, as well as subsurface issues not reflected in the topography.

Beyond planning, construction and the retrieval of road geometry data, monitoring forest road conditions includes gathering information on their surface condition, the condition of the drainage system, the existence of vegetation, and seasonal damage. Existing roads represent partially open areas, which typically results in higher resolution LiDAR ground returns than under the forest canopy, which is the most common case for road planning. In their work on road quality control, Kiss et al. (2015) show the effect of resolutions ranging from 0.1 m to 2.0 m on the ability to correctly assess various parameters. Even at the lowest resolution, road surface was correctly classified in 66% of the cases, while ditches were correctly classified in 60% of the cases. Gaining an overview of the existence and condition of proper drainage is obviously of prime importance, although this is a dynamic factor and difficult to capture at the low temporal scale offered by airborne LiDAR.

There are also examples of higher resolution proximal road surface and road geometry modelling. Svenson and Fjeld (2016) applied a profilograph, a vehicle based system with LiDAR scanners, IMU and GPS, in extracting surface roughness and road geometry from a 320 km long stretch of mixed road classes. The derived information was used to predict fuel consumption and derive preferred routes during timber hauling (Svenson and Fjeld 2016). At a slightly lower resolution, Hrůza et al. (2016) demonstrated the use of a UAV and photogrammetry in assessing the condition of the wearing course of a forest road. Experiences gained in that study led the authors to recommend the use of mobile terrestrial systems as preferential for this type of work.

1.3 Machine access planning and layout

Machine access planning is largely about supporting decisions on which harvesting system to deploy and how best to go about doing that. Procedures for ground based harvesting and their potential for exploiting remotely sensed data are somewhat different than for cable harvesting, but both work toward maximising efficiency and minimising external impacts.

1.3.1 Ground based harvesting

Ground based harvesting is typically carried out with a cut-to-length (CTL) system (harvester and forwarder) or tree-length system (feller-buncher/skidder). Optimal planning of how the skid trails should be laid out is determined to a large degree by topography and soil bearing capacity. Examples of the use of LiDAR derived elevation models in doing this include Søvde et al. (2013), who used heuristics in finding extraction trails for a forwarder while restricting the degrees of pitch and roll through a cost penalty, and Strandgard et al. (2014), who assess the influence of slope on the productivity of a self-levelling processor. Sterenczak and Moskalik (2015) optimise a forest skid trail network through a novel combination of tree segmentation and terrain analysis, where the trees identified in the ALS dataset were used in estimating loads, while the gaps were used as potential nodes in the trail network. The model presented by Contreras et al. (2016) extends on these concepts, and includes the evaluation of a soil recovery cost in determining trail layout. However, despite the high resolution of LiDAR based terrain models as compared with their predecessors, and the detailed micro-slope maps they can produce, ALS data is not sufficient to provide estimates of surface unevenness. Surface unevenness remains one of the most critical factors determining accessibility and productivity of ground based harvesting systems and is currently more easily measurable in a post-harvest context.

Proximal scanning also shows strong potential in providing decision support during operations, for example in rapid detection of stand density and tree positions, assisting with thinning tree selection (Brunner and Gizachew 2014), allowing for data to be collected on individual tree selection by harvester operators (Brunner and Fredriksson 2012), or modelling which tree the operator might select beforehand (Fredriksson 2010). An overview of how remote sensing data can be used in improving the productivity of mechanised harvesting systems is provided by Alam et al. (2012).

1.3.2 Cable based harvesting

Planning of cable yarding corridor layout must maximise the utilisation of each machine setup while considering the suitability of load paths. Before the advent of LiDAR derived terrain models, desktop planning risked missing critical terrain points as it was not possible to discern the actual terrain form between contour lines, making it necessary to perform manual profile surveys in order to confirm the degree of deflection attainable in each span. Also, the surveyor needed to make an »a priori« listing of profiles to measure, as only a smaller sample of the site could be covered practically. Detailed LiDAR derived terrain models (1 pt.m^{-2}) now allow for complete analysis of harvesting sites to be made. Examples of such use have been demonstrated by Søvde et al. (2015), who search for the optimal location of landings, and Dupire et al. (2015), who use LiDAR DTMs to predict the load path in a given corridor.

However, terrain alone does not determine the optimal layout of the cable corridor, as the location of suitable end trees (tail spars) and intermediate support trees also need to be verified. The pre-selection of these from LiDAR data has been shown to be both possible and effective (Scheiss 2005). Furthermore, Heinimann and Breschan (2012) describe how LiDAR can be used in gaining volume estimates for each planned cable corridor, a process which could ultimately feed back into the cable layout algorithms presented by (Dupire et al. 2015 and Søvde et al. 2015).

For both ground-based and cable harvesting, the identification of suitable landings is an important part of harvest planning. Complex spatial patterns can be determined from LiDAR data (Risbøl et al. 2014), and one related task is the detection and assessing of potential landings in terms of area, shape, and surface evenness (Søvde 2015). This makes it possible to estimate their proximity to forest roads, and their suitability in terms of wetness and other potentially detrimental factors.

1.4 Avoiding or measuring soil disturbance

Arguably one of the most significant applications of LiDAR derived terrain models has been in facilitating the mapping of areas of anticipated high moisture and, therewith, potentially high susceptibility to soil damage by vehicles. The topographic wetness index (TWI) essentially quantifies the influence of topography on hydrological processes on the basis of slope and upstream contributing area, and can be best visualised as representing flow accumulation. Cartographic Depth-To-Water (DTW) algorithms on the other hand basically indicate the anticipated vertical distance between ground water or open water surfaces at any given point in the surrounding terrain. Both have shown to be robust in delineating soil, vegetation and drainage type (Murphy et al. 2011) and are increasingly used in applications of high relevance to forest operations, such as assessing accessibility and the risk of causing rutting and compaction (Murphy et al. 2008). Ågren et al. (2014) found that both provided useful soil wetness predictors but that TWI delineations are sensitive to scale and landscape variations, while DTW produces a resolution-consistent wet-area delineation. Campbell et al. (2013) evaluated the use of DTW in predicting rut depth on a high resolution DEM and found good consistency although this has not yet been effectively demonstrated in forestry. Challenges remain in determining the scale of analysis, satisfactorily including effects of soil texture and geology and handling seasonal conditions (Ågren et al. 2015) or even daily variations in machine-specific forest soil trafficability (Vega-Nieva et al. 2009). For example, Niemi et al. (2017) achieved soil damage prediction accuracies of over 85% when including an existing soil map in their wetness index calculations. These indices constitute a considerable improvement to forest management data, especially when combined with mathematical programming based decision support systems such as BeST Way in showing the optimal layout of main access trails, as shown by Westlund et al. (2015). In a further step, Pohjankukka et al. (2016) demonstrate the use of machine learning in avoiding soft areas, as bearing capacity known at given control points is used in training a model in estimating bearing capacity in other parts of the stand. This study represents the early phases of what is likely to become a rapidly growing application of the autonomous utilisation of remote and proximally sourced data in forest machines. The notion of machines sharing such information for a given site has already been put forward by Ala-Ilomäki et al. (2012).

The measurement of wheel rut depth after forwarding has been shown to be feasible with photogrammetry (Haas et al. 2016, Pierzchała et al. 2016), however, there remain a number of challenges to using the method effectively. If not measured iteratively, the original soil surface needs to be estimated and interpolated from the adjacent margin, which may not always be accurate. Also, photogrammetry generates a surface model and not a terrain model, which can result in problems in distinguishing between e.g. a brash mat, surface water, and the real soil surface.

1.5 Improving information on key cultural and biological features in avoiding damage

A central part of planning and executing forest operations lies in avoiding change or damage to cultural remnants, special habitats, or the transgression of property borders. Remote sensing and especially airborne LiDAR has the potential for providing better geographic information on the key features of importance in forest operations planning and execution. LiDAR has been used in the detection of cultural heritage sites (Risbøl et al. 2014). The use of LiDAR has also shown to have some success in habitat characterization (Vierling et al. 2008, Sverdrup-Thygeson et al. 2016), where, with improvements in predictability, the segmentation and the delineation of boundaries indicating areas to avoid or treat differently, may yet become a mainstream part of harvest planning. By providing such polygons on high resolution DEMs, methods can be developed to calculate the operations cost taking regard of special biotopes (Søvde et al. 2014), in providing forest managers and society at large with a quantitative tool on which decisions can be based.

1.6 Autonomous machines, machine navigation and vision

The use of autonomous or remotely operated machines has gained a solid foothold in applications from agriculture to open-cast mining (Mousazadeh 2013). Forestry brings a special set of challenges, most notably a complex operating environment with poor GNSS coverage, and operation in an environment that is open to the public, and therefore subject to demanding safety requirements. Nevertheless, there are good reasons for pursuing the development of autonomous machines, not least the social (isolated work environment) and economic (one operator can control multiple machines) benefits offered (Hellström et al. 2009). Given the limited GNSS coverage available under tree canopies, other localization approaches such as Simultaneous Localization and Mapping (SLAM), which attempts to locate the machine with reference to its surroundings, while simultaneously mapping its surroundings, offer some potential for the future. These concepts have been demonstrated on forest machines (Miettinen et al. 2007, Öhman et al. 2008, Tang et al. 2015). Onboard sensors, such as 2D LiDAR scanners, radars and stereo-cameras, are essential in providing navigational support for autonomous machines. In a step toward fully autonomous forwarding, Ringdahl et al. (2011) were able to demonstrate accurate path tracking in repeating a route already traversed, although this did include a significant GNSS component. With regard to application of machine vision and sensor fusion in forest operations, Pierzchała (2017) demonstrated the use of cameras, an accelerometer, IMU and GNSS unit in identifying work phases in a cable logging operation, Lideskog and Karlberg (2016) used machine vision techniques to develop strategies for efficient mound positioning in connection with soil scarification, while Matej (2014) used computer vision in determining the tilt angle of a forest machine, based on the assumption that tree stems it was imaging were vertically orientated.

2. Conclusions

This review presented a range of current applications of remote and proximal sensing techniques and their relevance to forest operations. Forest inventory is now routinely carried out with LiDAR in an operational setting, and in this way directly impacts the planning and implementation of forest operations. A fundamental issue identified throughout the review was that, while many papers demonstrate new methods or applications for utilising remotely and proximally sensed data, these methods were not necessarily mature or used in an optimal combination, and there remains a series of challenges to realising almost all the applications discussed. In the same light, the review shows that the potential for making improvements and operationalizing some of the developed approaches and techniques is considerable and should be a focus of forest operations research in the years to come.

The development of remote and proximal sensing technology and techniques will provide a previously inconceivable amount of data. Especially the machine-mounted sensors that unceasingly collect vast amounts of data will provide the forest operations researcher with a large and continually increasing basis from which to extract useful information. These data can, with the application of sensible analytical approaches, provide significant opportunities for decision support as well as operations monitoring and evaluation.

At the same time, these possibilities will challenge the forest operations researcher with demands on exceptional skills related to data analysis. The approach to answering new research questions will change from one of gathering data to one of how to use the vast amounts of freely generated data effectively. The forest operations researcher of the future will, in addition, be required to have a certain degree of expertise related to sensors and connectivity of such sensors, described as the internet-of-things. Also, together with remotely and proximally measured big-data come special demands with regards to ethics and data security. Detailed forest and personal information related to land owners, managers, forest contractors, machine operators, forest workers and researchers will be instantaneously accessible via the internet, and protocols for the generation and handling of this data will require continuous modernisation.

Finally, it is anticipated that procedures for incorporating remotely sensed cultural heritage, environmental, and biological data will be continually developed as they become a central part of harvesting planning in the future.

Acknowledgements

This paper was written with financial support from the Norwegian Research Council through the project Sustainable Utilization of Forest Resources in Norway (225329/E40) and the H2020 Bio-Based Industries supported project, TECH4EFFECT (Grant Agreement No. 720757).

3. References

Akay, A.E., Oğuz, H., Karas, I.R., Aruga, K., 2009: Using LiDAR technology in forestry activities. Environmental Monitoring and Assessment 151(1): 117–125.

Akay, A.E., Sessions, J., 2005: Applying the Decision Support System, TRACER, to Forest Road Design. Western Journal of Applied Forestry 20(3): 184–191.

Ala-Ilomäki, J., Lamminen, S., Sirén, M., Väätäinen, K., Asikainen, A., 2012: Using harvester CAN-bus data for mobility mapping. Proceedings of the Nordic Baltic conference on forest operations – OSCAR. Lazdina, D., Jansons A., Konstantinova, I. Riga, Latvia, LSFRI Silava 25(58): 85–87.

Alam, M.M., Strandgard, M.N., Brown, M.W., Fox, J.C., 2012: Improving the productivity of mechanised harvesting systems using remote sensing. Australian Forestry 75(4): 238–245.

Aruga, K., Sessions, J., Akay, A.E., 2005a: Application of an airborne laser scanner to forest road design with accurate earthwork volumes. Journal of Forest Research 10(2): 113–123.

Aruga, K., Sessions, J., Miyata, E.S., 2005b: Forest road design with soil sediment evaluation using a high-resolution DEM. Journal of Forest Research 10(6): 471–479.

Astrup, R., Ducey, M.J., Granhus, A., Ritter, T., von Lüpke, N., 2014: Approaches for estimating stand-level volume using terrestrial laser scanning in a single-scan mode. Canadian Journal of Forest Research 44(6): 666–676.

Azizi, Z., Najafi, A., Sadeghian, S., 2014: Forest road detection using LiDAR data. Journal of Forestry Research 25(4): 975–980.

Bauwens, S., Bartholomeus, H., Calders, K., Lejeune, P., 2016: Forest inventory with terrestrial LiDAR: A comparison of static and hand-held mobile laser scanning. Forests 7(6), 127.

Beck, S.J., Olsen, M.J., Sessions, J., Wing, M.G., 2015: Automated Extraction of Forest Road Network Geometry from Aerial LiDAR. European Journal of Forest Engineering 1(1): 21–33.

Bergdahl, A., Örtendahl, A., Fjeld, D., 2003: The economic potential for optimal destination of roundwood in North Sweden–Effects of planning Horizon and delivery precision. International Journal of Forest Engineering 14(1): 81–88.

Blum, R., Bischof, R., Sauter, U.H., Foeller, J., 2016: Tests of reception of the combination of GPS and GLONASS signals under and above forest canopy in the Black Forest, Germany, using choke ring antennas. International Journal of Forest Engineering 27(1): 2–14.

Brunner, A., Fredriksson, C., 2012: A thinning model describing individual tree selection by harvester operators. Manuscript.

Brunner, A., Gizachew, B., 2014: Rapid detection of stand density, tree positions, and tree diameter with a 2D terrestrial laser scanner. European Journal of Forest Research 133(5): 819–831.

Campbell, D.M.H., White, B., Arp, P.A., 2013: Modeling and mapping soil resistance to penetration and rutting using LiDAR-derived digital elevation data. Journal of Soil and Water Conservation 68(6): 460–473.

Contreras, M., Aracena, P., Chung, W., 2012: Improving Accuracy in Earthwork Volume Estimation for Proposed Forest Roads Using a High-Resolution Digital Elevation Model. Croatian Journal of Forest Engineering 33(1): 125–142.

Contreras, M.A., Parrott, D.L., Chung, W., 2016: Designing Skid-Trail Networks to Reduce Skidding Cost and Soil Disturbance for Ground-Based Timber Harvesting Operations. Forest Science 62(1): 48–58.

Craven, M., Wing, M.G., 2014: Applying airborne LiDAR for forested road geomatics. Scandinavian Journal of Forest Research 29(2): 174–182.

Dralle, K., Tarp-Johansen, M.J., 2010: Method and a system for automatic measurement and tracking of logs, industrial wood and boards, Google Patents.

Ducey, M.J., Astrup, R., Seifert, S., Pretzsch, H., Larson, B.C., Coates, K.D., 2013: Comparison of forest attributes derived from two terrestrial LiDAR systems. Photogrammetric Engineering & Remote Sensing 79(3): 245–257.

Dupire, S., Bourrier, F., Berger, F., 2015: Predicting load path and tensile forces during cable yarding operations on steep terrain. Journal of Forest Research 21(1): 1–14.

Fardusi, M.J., Chianucci, F., Barbati, A., 2017: Concept to Practice of Geospatial-Information Tools to Assist Forest Management and Planning under Precision Forestry Framework: a review. Annals of Silvicultural Research 41(1): 3–14.

Fredriksson, C., 2010: Modellering av skördarförarens trädval vid gallring. Master, Universitet for miljø- og biovitenskap.

Gallo, R., Grigolato, S., Cavalli, R., Mazzetto, F., 2013: GNSS-based operational monitoring devices for forest logging operation chains. Journal of Agricultural Engineering 44(2s): 140–144.

Gobakken, T., Bollandsås, O.M., Næsset, E., 2015: Comparing biophysical forest characteristics estimated from photogrammetric matching of aerial images and airborne laser scanning data. Scandinavian Journal of Forest Research 30(1): 73–86.

Haas, J., Ellhöft, K.H., Schack-Kirchner, H., Lang, F., 2016: Using photogrammetry to assess rutting caused by a forwarder–A comparison of different tires and bogie tracks. Soil and Tillage Research 163: 14–20.

Hauglin, M., Hansen, E.H., Næsset, E., Busterud, B.E., Gjevestad, J.G.O., Gobakken, T., 2017: Accurate single-tree positions from a harvester: a test of two global satellite-based positioning systems. Scandinavian Journal of Forest Research: 1–8.

Heinimann, H.R., Breschan, J., 2012: Pre-harvest assessment based on LiDAR data. Croatian Journal of Forest Engineering 33(2): 169–180.

Hellström, T., Lärkeryd, P., Nordfjell, T., Ringdahl, O., 2009: Autonomous Forest Vehicles: Historic, envisioned, and state-of-the-art. International Journal of Forest Engineering 20(1): 31–38.

Holmgren, J., Barth, A., Larsson, H., Olsson, H., 2012: Prediction of stem attributes by combining airborne laser scanning and measurements from harvesters. Silva Fenn 46(2): 227–239.

Holopainen, M., Vastaranta, M., Hyyppä, J., 2014: Outlook for the Next Generation's Precision Forestry in Finland. Forests 5(7): 1682–1694.

Hrůza, P., Mikita, T., Janata, P., 2016: Monitoring of Forest Hauling Roads Wearing Course Damage using Unmanned Aerial Systems. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis 64(5): 1537–1546.

Kankare, V., Vauhkonen, J., Tanhuanpää, T., Holopainen, M., Vastaranta, M., Joensuu, M., Krooks, A., Hyyppä, J., Hyyppä, H., Alho, P.,Viitala, R., 2014: Accuracy in estimation of timber assortments and stem distribution – A comparison of airborne and terrestrial laser scanning techniques. ISPRS Journal of Photogrammetry and Remote Sensing 97(1): 89–97.

Kauhanen, H., 2008: Close Range Photogrammetry-Structured Light Approach for Machine Vision Aided Harvesting. Proc. ISPRS XXI Congress, Beijing, China.

Kiss, K., Malinen, J., Tokola, T., 2015: Forest road quality control using ALS data. Canadian Journal of Forest Research 45(11): 1636–1642.

Krogstad, F., Scheiss, P., 2004: The allure and pitfalls of using LiDAR topography in harvest and road design. Joint Conference of IUFRO 3.06 Forest Operations under Mountainous Conditions and the 12th International Mountain Logging Conference Vancouver, B.C.: 1–10.

Lauterbach, H.A., Borrmann, D., Heß, R., Eck, D., Schilling, K., Nüchter, A., 2015: Evaluation of a backpack-mounted 3D mobile scanning system. Remote Sensing 7(10): 13753–13781.

Liang, X., Jaakkola, A., Wang, Y., Hyyppä, Y., Honkavaara, E., Liu, J., Kaartinen, H., 2014: The Use of a Hand-Held Camera for Individual Tree 3D Mapping in Forest Sample Plots. Remote Sensing 6(7): 6587–6603.

Liang, X., Wang, Y., Jaakkola, A., Kukko, A., Kaartinen, H., Hyyppä, J., Honkavaara, E., Liu, J., 2015: Forest Data Collection Using Terrestrial Image-Based Point Clouds From a Handheld Camera Compared to Terrestrial and Personal Laser Scanning. IEEE Transactions on Geoscience and Remote Sensing 53(9): 5117–5132.

Lideskog, H., Karlberg, M., 2016: Simulated continuous mounding improvements through ideal machine vision and control. Silva Fennica 50(2): article id 1386.

Lindroos, O., Ringdahl, O., La Hera, P., Hohnloser, P., Hellström, T.H., 2015: Estimating the Position of the Harvester Head–a Key Step towards the Precision Forestry of the Future? Croatian Journal of Forest Engineering 36(2): 147–164.

Lokers, R., Knapen, R., Janssen, S., van Randen, Y., Jansen, J., 2016: Analysis of Big Data technologies for use in agro-environmental science. Environmental Modelling & Software 84: 494–504.

Matej, J., 2014: Determination of forestry machine's tilt angle using camera and image processing. Computers and Electronics in Agriculture 109: 134–140.

Miettinen, M., Kulovesi, J., Kalmari, J., Visala, A., 2010: New measurement concept for forest harvester head. Field and service robotics. Springer Berlin Heidelberg: 35–44.

Miettinen, M., Ohman, M., Visala, A., Forsman, P., 2007: Simultaneous Localization and Mapping for Forest Harvesters. Robotics and Automation, 2007 IEEE International Conference on. IEEE: 517–522.

Mousazadeh, H., 2013: A technical review on navigation systems of agricultural autonomous off-road vehicles. Journal of Terramechanics 50(3): 211–232.

Mulla, D.J., 2013: Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems engineering 114(4): 358–371.

Murphy, P.N., Ogilvie, J., Meng, F.-R., White, B., Bhatti, J.S., Arp, P.A., 2011: Modelling and mapping topographic variations in forest soils at high resolution: A case study. Ecological Modelling 222(14): 2314–2332.

Murphy, P.N.C., Ogilvie, J., Castonguay, M., Zhang, C.-F., Meng, F.-R., Arp, P.A., 2008: Improving forest operations planning through high-resolution flow-channel and wet-areas mapping. The Forestry Chronicle 84(4): 568–574.

Naesset, E., Jonmeister, T., 2002: Assessing point accuracy of DGPS under forest canopy before data acquisition, in the field and after postprocessing. Scandinavian Journal of Forest Research 17(4): 351–358.

Niemi, M.T., Vastaranta, M., Vauhkonen, J., Melkas, T., Holopainen, M., 2017: Airborne LiDAR-derived elevation data in terrain trafficability mapping. Scandinavian Journal of Forest Research: 1–12.

Næsset, E., 2004: Accuracy of forest inventory using airborne laser scanning: evaluating the first nordic full-scale operational project. Scandinavian Journal of Forest Research 19(6): 554–557.

Olivera, A., Visser, R., 2014: Integration of harvester data and geospatial information. Harvesting technical note HTN07-03. Future Forest Research Ltd. Rotorua, New Zealand.

Olivera, A., Visser, R., 2016: Development of forest-yield maps generated from Global Navigation Satellite System (GNSS)-enabled harvester StanForD files: preliminary concepts. New Zealand Journal of Forestry Science 46(1): 3.

Pierzchała, M., 2017: Developing the use of imaging technology for forest operations. PhD, Norwegian University of Life Sciences.

Pierzchała, M., Talbot, B., Astrup, R., 2016: Measuring wheel ruts with close-range photogrammetry. Forestry 89(4): 383–391.

Pohjankukka, J., Riihimäki, H., Nevalainen, P., Pahikkala, T., Ala-Ilomäki, J., Hyvönen, E., Varjo, J., Heikkonen, J., 2016: Predictability of boreal forest soil bearing capacity by machine learning. Journal of Terramechanics 68: 1–8.

Rahlf, J., Breidenbach, J., Solberg, S., Næsset, E., Astrup, R., 2014: Comparison of four types of 3D data for timber volume estimation. Remote Sensing of Environment 155: 325–333.

Ringdahl, O., Lindroos, O., Hellström, T., Bergström, D., Athanassiadis, D., Nordfjell, T., 2011: Path tracking in forest terrain by an autonomous forwarder. Scandinavian Journal of Forest Research 26(4): 350–359.

Risbøl, O., Briese, C., Doneus, M., Nesbakken, A., 2014: Monitoring cultural heritage by comparing DEMs derived from historical aerial photographs and airborne laser scanning. Journal of Cultural Heritage 16(2): 202–209.

Rönnholm, P., Liang, X., Kukko, A., Jaakkola, A., Hyyppä, J., 2016: Quality analysis and correction of mobile backpack laser scanning data. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences: 41–47.

Sawaguchi, I., Nishida, K., Shishiuchi, M., Tatsukawa, S., 2003: Positioning precision and sampling number of DGPS under forest canopies. Journal of Forest Research 8(2): 133–137.

Scheiss, P., 2005: The application of spatially explicit digital elevation and canopy surface data for harvest planning: moving from coarse digital elevation models and stand averages to detailed ground and canopy surface models in the design of forest transportation systems. Scientific cooperation for forest technology improvement – FORMEC. Ed. B., Košir, Ljubljana, Slovenia: 52–65.

Sterenczak, K., Moskalik, T., 2015: Use of LIDAR-based digital terrain model and single tree segmentation data for optimal forest skid trail network. iForest – Biogeosciences and Forestry 8(5): 661–667.

Strandgard, M., Alam, M., Mitchell, R., 2014: Impact of Slope on Productivity of a Self-levelling Processor. Croatian Journal of Forest Engineering 35(2): 193–200.

Svenson, G., Fjeld, D., 2016: The impact of road geometry and surface roughness on fuel consumption of logging trucks. Scandinavian Journal of Forest Research 31(5): 526–536.

Sverdrup-Thygeson, A., Ørka, H.O., Gobakken, T., Næsset, E., 2016: Can airborne laser scanning assist in mapping and monitoring natural forests? Forest Ecology and Management 369: 116–125.

Søvde, N., Løkketangen, A., Church, R., Oppen, J., 2015: A semi-greedy metaheuristic for the European cableway location problem. Journal of Heuristics 21(5): 641–622.

Søvde, N., Sætersdal, M., Løkketangen, A., 2014: A Scenario-Based Method for Assessing the Impact of Suggested Woodland Key Habitats on Forest Harvesting Costs. Forests 5(9): 2327–2344.

Søvde, N.E., 2015: Algorithm for estimating the suitability of potential landing sites. Mathematical and Computational Forestry & Natural Resource Sciences 7(1): 1–8.

Søvde, N.E., Løkketangen, A., Talbot, B., 2013: Applicability of the GRASP metaheuristic method in designing machine trail layout. Forest Science and Technology 9(4): 187–194.

Talbot, B. Astrup, R., 2014: Forest Operations and Ecosystems Services in Norway – a review of the issues at hand and the opportunities offered through new technologies. Journal of Green Engineering 4(4): 271–290.

Tang, J., Chen, Y., Kukko, A., Kaartinen, H., Jaakkola, A., Khoramshahi, E., Hakala, T., Hyyppä, J., Holopainen, M., Hyyppä, H., 2015: SLAM-Aided Stem Mapping for Forest Inventory with Small-Footprint Mobile LiDAR. Forests 6(12): 4588–4606.

Tomaštík, J.J., Tomaštík, S.J., Saloň, Š., Piroh, R., 2016: Horizontal accuracy and applicability of smartphone GNSS positioning in forests. Forestry: An International Journal of Forest Research 90(2): 187–198.

Vastaranta, M., Latorre, E., Luoma, V., Saarinen, N., Holopainen, M., Hyyppä, J., 2015: Evaluation of a Smartphone App for Forest Sample Plot Measurements. Forests 6(4): 1179.

Vega-Nieva, D.J., Murphy, P.N.C., Castonguay, M., Ogilvie, J., Arp, P.A. 2009: A modular terrain model for daily variations in machine-specific forest soil trafficability. Canadian Journal of Soil Science 89(1): 93–109.

Vierling, K.T., Vierling, L.A., Gould, W.A., Martinuzzi, S., Clawges, R.M., 2008: Lidar: shedding new light on habitat characterization and modeling. Frontiers in Ecology and the Environment 6(2): 90–98.

Visser, R., Raymond, K., Harrill, H., 2014: Mechanising steep terrain harvesting options. NZ Journal of Forestry 59(3): 3–8.

Westlund, K., Rönnqvist, M., Flisberg, P., Friberg, G., 2015: BeST Way – The next generation of forwarding planning 16th Symposium for systems analysis in forest resources (SSAFR). L.O., Eriksson. Uppsala, Sweden, SLU, Skogforsk.

White, R.A., Dietterick, B.C., Mastin, T., Strohman, R., 2010: Forest Roads Mapped Using LiDAR in Steep Forested Terrain. Remote Sensing 2(4): 1120.

Wing, M.G., Eklund, A., 2007: Performance comparison of a low-cost mapping grade global positioning systems (GPS) receiver and consumer grade GPS receiver under dense forest canopy. Journal of Forestry 105(1): 9–14.

Ziesak, M., Marques, A.F., Rasinmaki, J., Rosset, C., Nummila, K., Scholz, J., Mittlboeck, M., Pinho de Sousa, J., Häkli, J., Rommel, D., 2014: Advances in forestry control and automation systems i Europe – FOCUS: the concept idea in a multinational EU research project. Proceedings of the 6th Precision Forestry Symposium: The anchor of your value chain. P., Ackerman, E., Gleasure and H., Ham. Stellenbosch, South Africa, Faculty of AgriSciences, Stellenbosch University: 114 p.

Öhman, M., Miettinen, M., Kannas, I., Jutila, J., Visala, A., Forsman, P., 2008: Tree measurement and simultaneous localization and mapping system for forest harvesters. Field and Service Robotics: Results of the 6th International Conference. C., Laugier, R., Siegwart 42: 369–378.

Ågren, A., Lidberg, W., Ring, E., 2015: Mapping Temporal Dynamics in a Forest Stream Network—Implications for Riparian Forest Management. Forests 6(9): 2982.

Ågren, A., Lidberg, W., Strömgren, M., Ogilvie, J., Arp, P., 2014: Evaluating digital terrain indices for soil wetness mapping–a Swedish case study. Hydrology and Earth System Sciences 18(9): 3623–3634.

Received: March 19, 2017
Accepted: June 08, 2017

Authors' addresses:

Bruce Talbot, PhD. *
e-mail: bta@nibio.no
Marek Pierzchała, PhD.
e-mail: map@nibio.no
Rasmus Astrup, PhD.
e-mail: raa@nibio.no
Norwegian Institute for Bioeconomy Research
Department of Forestry and Forest Resources
Hoegskoleveien 7
1430 Ås
NORWAY

* Corresponding author