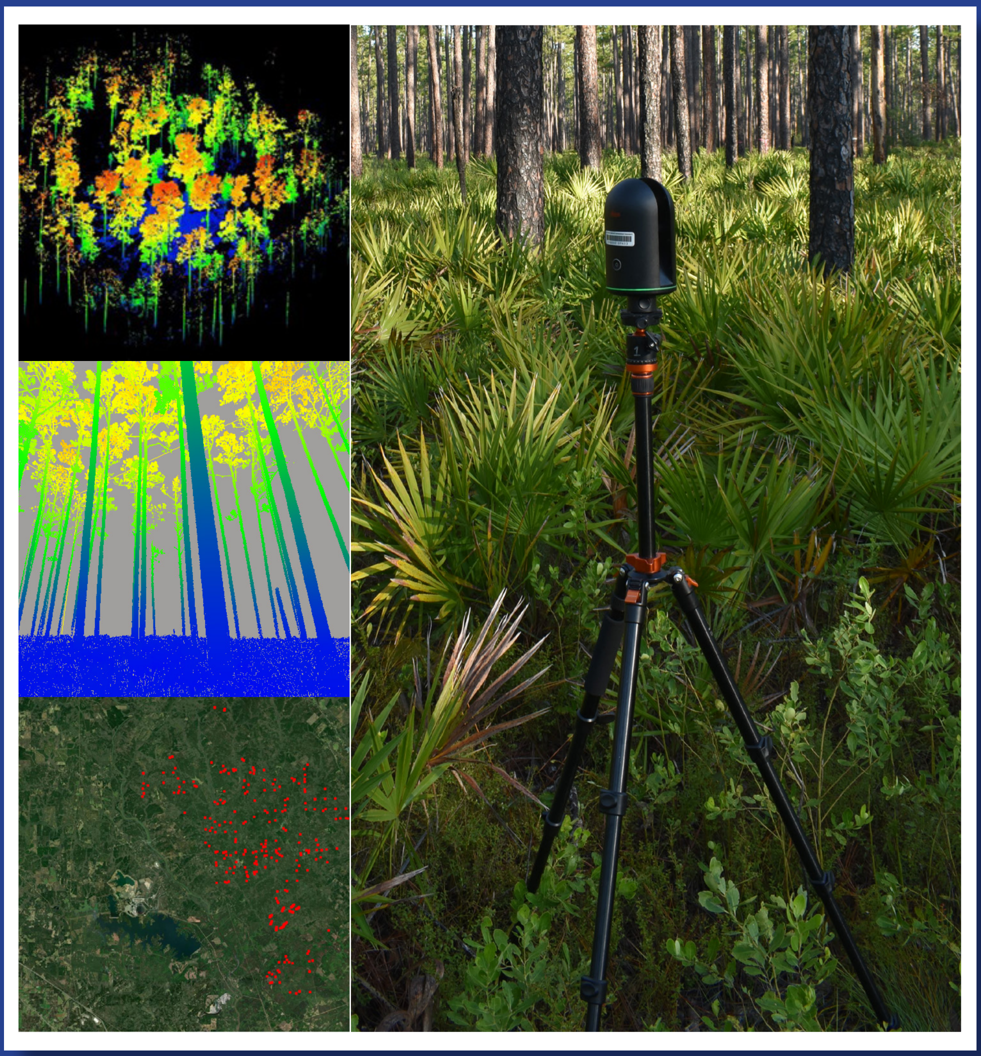
Forest Service
U.S. DEPARTMENT OF AGRICULTURE

Southern Research Station | General Technical Report SRS-277 | July 2024

Terrestrial 3D Laser Scanning for Ecosystem and Fire Effects Monitoring



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University of California-San Diego

U.S. Department of Defense

U.S. Department of the Interior U.S. Fish and Wildlife Service, National Park Service, Bureau of Indian Affairs, and U.S. Geological Survey

West Virginia University

July 2024

https://doi.org/10.2737/SRS-GTR-277

Forest Service
Research & Development
Southern Research Station
General Technical Report SRS-277

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Abstract

Long-term ecosystem monitoring documents land management actions and progress towards objectives through repeated observation and measurement. Traditional monitoring methods have evolved for specific applications across ecological disciplines and are often limited by data quality and repeatability. This report presents terrestrial laser scanning (TLS) as a sampling method that can complement and enhance existing monitoring methods. TLS captures in high resolution the 3D structure of a terrestrial ecosystem and, when integrated into monitoring, can standardize data collection, improve efficiency, and reduce bias and error. Streamlined data processing can rigorously analyze TLS data and incorporate constant improvements. The approach described in this report utilizes portable, push-button TLS equipment that, when calibrated with initial transect sampling, captures detailed forestry, fuels, and ecological features in <5 minutes per plot. We introduce an interagency automated processing pipeline and dashboard viewer for instant analysis and retrieval of hundreds of metrics. TLS metrics produced with these methods offer effective decision support for managers to quantify landscape-scale conditions. With continued improvement of scanner capabilities and affordability, these data will shape the future of terrestrial ecosystem monitoring and support natural resource managers in addressing the increasingly fast pace of ecological change.

Keywords: Terrestrial LiDAR, wildland fuels, forestry metrics, monitoring protocols, fire effects, remote sensing, forest inventory

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Acknowledgments

This project is a collaborative effort developed with partners from the U.S. Department of Agriculture, Forest Service; U.S. Department of the Interior; Northern Arizona University; University of California-San Diego; University of West Virginia; Los Alamos National Laboratory and the New Mexico Consortium. Funding was provided by the Department of Defense Strategic Environmental Research and Development Program (SERDP) and the Environmental Security Technology Certification Program (ESTCP) (RC-1119 and RC-2641). Authors thank Seth M. Munson and Kurtis Nelson of the U.S. Geological Survey, who contributed to the development of this monitoring protocol and LiDAR analysis methods.

Introduction

Monitoring, as the “intermittent recording of the condition of a feature of interest to detect or measure compliance with a predetermined standard,” is an often-mandated framework for the agencies tasked with stewarding our public lands and natural resources (Hellawell 1991). Monitoring is essential to ecosystem management (Christensen and others 1996) and for informing management goals under accelerating climate change (Hiers and others 2012). In this report, we describe the application of emerging technology to improve the utility and efficiency of monitoring within terrestrial ecosystems (e.g., forests and grasslands). Under the Forest and Rangeland Renewable Resources Planning Act of 1974, later amended by the National Forest Management Act of 1976, Congress formally directed the U.S. Department of Agriculture, Forest Service to monitor and assess the Nation’s natural resources (Morrison and Marcot 1995). At the national scale, the Forest Inventory and Analysis, Forest Health Monitoring, and FEAT/FIREMON Integrated programs conduct surveys or utilize remote sensing data to assess the status and trends of various forest and grassland conditions. Similarly, the Department of the Interior supports monitoring through the Bureau of Land Management Assessment, Inventory, and Monitoring, and National Park Service and U.S. Fish and Wildlife Service Inventory and Monitoring programs. Localized monitoring programs vary considerably by discipline, but can have multiple, concurrent sampling protocols for wildlife, forestry, and wildland fuels management programs. Programs such as these play a crucial role in adaptive resource management by evaluating management outcomes and the effects of natural disturbances to measure trends and departures from a predetermined desired state (Legg and Nagy 2006). Monitoring can ensure accountability by tracking the condition of valuable resources such as timber and endangered species habitat. It also documents the effects of land management activities, including timber harvesting, fuel treatments, and controlled burns. Effective monitoring data communicates management actions and goals and can be harnessed for public education as well as institutional or agency support.

Successful monitoring programs are goal-oriented, have rigorous sampling protocols, require trained expertise, and have a diligent remeasurement schedule (Lindenmayer and Likens 2010, Vos and others 2000). Furthermore, they require innovation to address the present and future challenges facing natural resource management, such as climate change and urbanization (Lovett and others 2007). Intensive, comprehensive, and detailed sampling protocols promote precision and accuracy, and minimize user bias and measurement error to create high-quality datasets that are useful for informing management and agency decisions as well as research and development. Challenges with monitoring that can contribute to poor data quality are associated with inconsistency in measurements among users, between plots, and through time, all increasing bias and error (Lindenmayer and Likens 2010, Pokswinski and others 2021). This is not withstanding potential changes in sampling protocols through time or across sites, which can reduce repeatability and compatibility between seemingly similar datasets. These issues can occur for various reasons, including but not limited to insufficient resources or time, personnel changes within a given monitoring program, and lack of trained personnel overall or with critical skill sets.

Depending on the monitoring program’s objectives, sampling methods may include distance measures (Bitterlich 1952, Lindsey and others 1958, Picard and Bar-Hen 2007), line intercepts (Brown 1974, Canfield 1941), or quadrat methods (Lindsey and others 1958, Pound and Clements 1898), and standardized forest inventory protocols, such as fixed- or variable-radius plots. Each of these methods is tailored towards variables of interest. For example, Brown’s (1974) transects, an inventory method for sampling down, dead woody material, are commonly used for fire effects and fuels monitoring, but do not capture information on live or aerial fuels, herbaceous cover, and canopy structure, and may require high sampling intensities to reduce uncertainty (Sikkink and Keane 2008). Another example, the composite burn index, assigns a severity index based on assumed prefire conditions and visual estimates of fuel consumption, greenness, necrosis, and char following burning (Gallagher and others 2021). These sampling approaches provide quick general estimates of variables of interest and may benefit by incorporating more robust quantitative measurements that use advanced technology.

Advances in sampling tools and statistics can address many of these monitoring challenges through whole-plot remote sensing measurements (Loudermilk and others 2009, Rowell and others 2016, Skowronski and others 2007), and artificial intelligence/machine learning-driven analyses to reduce personnel bias (Ditria and others 2022, McClure and others 2020, Skowronski and others 2011). Terrestrial laser scanning (TLS) is one such tool to improve and enhance monitoring with output data that is not variable specific, but rather captures the entire structure of a plot and measures individual components (tree boles, shrubs, etc.) with high precision.

TERRESTRIAL LASER SCANNING FOR MONITORING

Light detection and ranging (LiDAR) is an active remote sensing tool used for recording discrete spatial positions in 3D. Numerous types of LiDAR instruments are operated via mobile (MLS), terrestrial (TLS), airborne (ALS), and unmanned aerial systems (UAS), among others. In each system, the scanners collect data by emitting lasers, which bounce off features and return to a sensor tens to hundreds of thousands of times per second (fig. 1), similar to sonar, but at a different electromagnetic wavelength. Scanners use two main techniques for calculating range measurements: phase-shift (or waveform) and time-of-flight (Liang and others 2016, Newnham and others 2015). Phase-shift scanners use a continuous laser to measure the intensity of reflected objects. In contrast, time-of-flight scanners record the time between laser pulses to determine distance with the speed of light. The resulting output of both techniques is a point cloud of data points displaying the 3D environment in x, y, and z coordinate space (fig. 2). Global positioning systems (GPS) can associate the

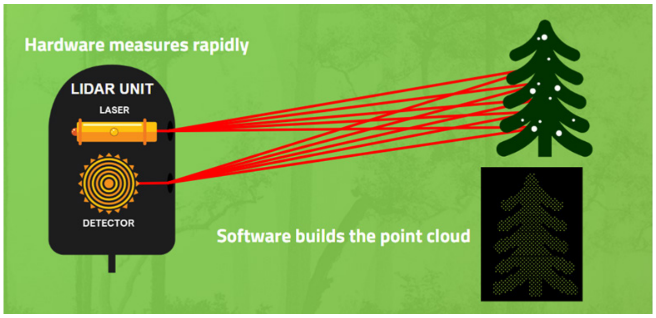

Figure 1—A terrestrial laser scanning (TLS) device sends out rapid laser pulses that bounce off objects and return to the device's detector, where distance is calculated with the speed of light. A point cloud image containing thousands of laser points is the output. (Courtesy photo by Jess Stetson)

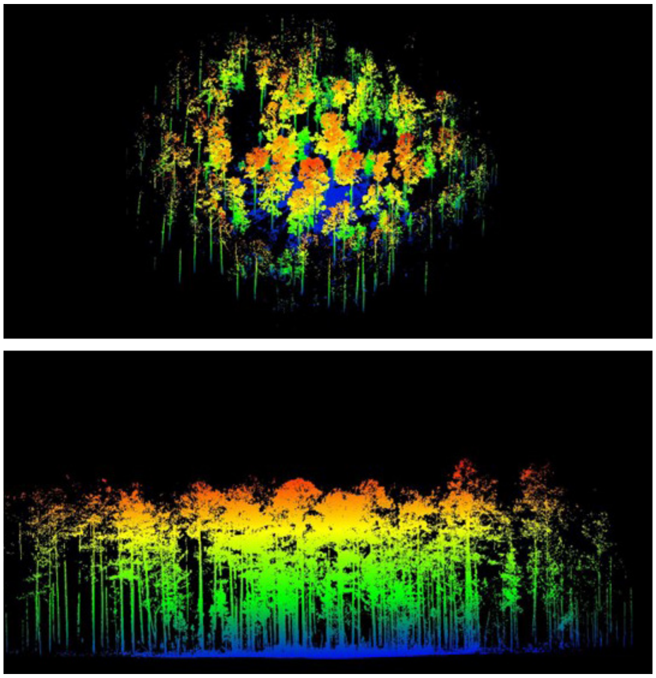

Figure 2—Raw 3D point cloud image output from a single 360° terrestrial laser scan of a southern pine forest: from (above) birds-eye view and (below) side view. For scale, the trees are approximately 25 m tall. (USDA Forest Service photo by Louise Loudermilk)

point cloud with real Earth coordinates relative to a map projection, and an inertial measurement unit (IMU) can allow for data collection from a moving platform. Many LiDAR systems are also equipped with cameras that capture RGB (true color) images to complement the 3D point cloud data. As a result, LiDAR technology is an increasingly relevant decision-support tool within the natural resource community (Hudak and others 2009). For example, ALS data produces wall-to-wall digital terrain models (DTM) and canopy height models (CHM), and locates, detects, and measures individual or close groups of trees across large landscapes or watersheds.

Of these various new approaches, TLS in particular has gained traction for wide natural resource applications. TLS-based monitoring is uniquely poised to standardize data collection with repeatable, quantitative data collection methods and instruments that are generally lightweight, portable, increasingly affordable, and easy to operate with minimal training (push button in many cases) (Gallagher and others 2021, Pokswinski and others 2021). This allows for rapid sampling of the 3D structure (<5 minutes per scan) of a typical forest plot (<0.1 ha) down to a centimeter resolution and hundreds of direct output metrics critical to habitat and fuel monitoring, such as basal area and canopy cover. Furthermore, these metrics can be used to predict nonmeasured attributes, such as surface fuel loading and fire severity. As a result, TLS can monitor large areas while producing a breadth of metrics, allowing for integrated monitoring across sites and disciplines. Repeated site visits are easily conducted with TLS monitoring, making it ideal for adaptive management and supplementing established monitoring plots with revisits. Additionally, 3D point clouds and RGB images derived from TLS instruments offer new visual tools for communicating management treatment effects or plot-level changes that occur through time.

There is a continuous need for rapid and accurate understanding of ecosystem dynamics. Amidst habitat loss, severe weather, increasing wildfire frequency, and climate change, landscapes are changing quickly, challenging adaptive management. This innovative TLS-based monitoring approach advances information for management by optimizing resource efficiency and effectiveness.

OBJECTIVES

This report introduces a novel TLS monitoring protocol for advanced ecosystem monitoring associated with the Interagency Ecosystem LiDAR Monitoring (IntELiMon) program. IntELiMon is an ever-evolving monitoring protocol and website (https://dmsdata.cr.usgs.gov/lidar-monitoring/) where processing, field protocols, and data products are continuously updated. This approach leverages tripod-based, push-button TLS technology to provide a fast, accurate, and consistent method for quantifying 3D plot structure and providing hundreds of forest and vegetation structural metrics. We provide a detailed guide on the protocol's technical background, field data collection, and processing options. We also highlight a state-of-the-art web portal for automated analysis and streamlined, interagency-compatible data storage and visualization. We summarize current and future research on the technology, including modeling techniques to monitor fuels and ecosystems, as well as linkages to fire modeling for land management decision support.

Field Data Collection Methods

TLS INSTRUMENT

For monitoring, a stationary TLS instrument is used to capture detailed (centimeter resolution), plot-level data with little to no instrument configuration and easy operation. Nonstationary options (mobile scanners on backpacks, vehicles, or UAS) can cover larger areas and are useful with trained expertise but are difficult to replicate consistently and efficiently. This monitoring protocol uses a stationary TLS instrument and includes an automated analysis and processing pipeline that presently supports data from the Leica BLK360 G1 and G2 (Leica Geosystems Inc., Heerbrugg, Canton St. Gallen, Switzerland). Many TLS instruments are available, however, and research and development into monitoring with other scanners (e.g., FARO and Trimble products) is underway. The Leica BLK360 series is currently being used for this TLS monitoring protocol; however, there is already promise in using other scanners (Stovall and Atkins 2021). As technology advances, new instruments will be tested. Considerations for instrument choice include instrument price, weight, portability, ease of use, field durability, data accessibility, laser specifications, and processing requirements.

All details in this report pertain to the **Leica BLK360 G1** (hereafter referred to as BLK360 G1) and processing and analyzing its outputs.

The BLK360 G1 is a terrestrial laser system that is lightweight (1 kg), affordable (<$30,000), and splash resistant. The unit has an area of coverage that is 360° horizontally and 300° vertically, a range of accuracy of 4 mm at 10 m distance and 7 mm at 20 m distance, and a maximum range distance of 60 m (table 1, fig. 2). The unit has multiple sampling density settings to control the number of points collected, which can help manage data collection speed and file size (Loudermilk and others 2023). For this monitoring protocol, the medium density setting is required for compatibility with the automated analysis pipeline, which results in a scan time of <5 minutes.

Table 1—Specifications and performance of the Leica BLK360 G1 terrestrial laser scanner

Leica BLK360 G1	Specifications
Maximum range	60 m
Optimal plot range	10 m
Accuracy	6 mm @ 10 m
Point capture speed	360,000 points/s
Size	16 cm tall x 10 cm diameter
Weight	1 kg
Scan time	<5 minutes

The BLK360 G1 records only first returns of the laser, meaning that if a laser pulse intersects and bounces off multiple surfaces (split laser beam) to result in multiple laser returns, only the first one is kept. This is important when generating information about the density of porous materials, like leafy forest vegetation, because it allows for automated comparison of expected to actual laser returns and predicts where the density of objects is concentrated. These analyses are useful for predicting everything from fuel density to forestry metrics.

The BLK360 G1 is mounted on a camera tripod and operated by pressing a single button in the field. The simplicity of operation allows for efficient, repeated data collection with minimal training. In <5 minutes, the laser scans and collects a dense 3D point cloud (360,000 points per second) with a usable scan radius of 10 to 15 m. This monitoring protocol sets a usable scan radius to account for occlusion; although the scanner can capture data up to a 60 m distance, objects inherent to a forested environment (e.g., tree boles, foliage, debris) can occlude or block the scanner from capturing objects behind them, resulting in a shorter distance in which quality data can be captured. Experience and research show that a 10- to 15-m radius is ideal for plot monitoring purposes (Gallagher and others 2021, Loudermilk and others 2023, Pokswinski and others 2021). For example, one 10-m radius scan can result in a structural image with approximately 6 to 8 million 3D points (including RGB camera data) within an area similar to a one-tenth acre forestry plot (approximately 0.03 ha [0.07 acre]).

The BLK360 G1 battery life typically lasts for one day of scanning and exporting data, and can easily be supplemented with a battery change. Scan storage capacity is 32 GB or roughly 100 medium-resolution scans. The instrument is light enough to be carried by hand or in a backpack and operates within a temperature range of 5 to 40 °C (41 to 104 °F) as specified by the manufacturer. Wind and rain can affect scanner operability, potentially damaging the instrument as well as impacting point cloud accuracy. It is thus important to consider temperature and weather extremes during field sampling that may impact scanner functioning and plan accordingly.

BLK360 G1 APPLICATIONS

The BLK Data Manager Utility and Leica Cyclone Register 360 PLUS (BLK Edition) (Leica Geosystems Inc., Heerbrugg, Canton St. Gallen, Switzerland) are required for data offloading and file conversion for the BLK360 G1. These requirement guidelines may change over time. Please check with the company and instrument specifications and manuals. Refer to the latest methods manual for a list of suggested applications to complement TLS monitoring (USGS 2023b).

Digital data entry or paper datasheets?

Within the IntELiMon protocol, there is an option to use ArcGIS Survey123 (Esri, Redlands, CA) for digital data entry through a tablet or to use paper datasheets. Ultimately, the user can determine which option works best for their monitoring team and program. ArcGIS Survey123 provides automatic, offline digital datasheet entry that syncs with ArcGIS Online once connected to Wi-Fi. This method requires a field-durable mobile tablet and additional training for formatting and customization. Alternatively, one-page paper datasheets are handwritten, customizable, do not require additional hardware or technical formatting, yet require manual data entry after field sampling. If mobile tablets are the method of choice, it is suggested to always keep paper datasheets on hand during field sampling in case of technological mishaps or in environmental conditions that may limit mobile tablet use in the field.

BLK360 G1 HARDWARE PREPARATION

Prior to field sampling, check the BLK360 G1 for firmware updates and ensure the stand-alone/push-button functionality is engaged under the BLK360 G1 capture settings. Refer to the latest methods manual for instructions on updating the BLK360 G1 firmware, BLK license management, and setting the BLK360 G1 push-button behavior (USGS 2023b).

FIELD SAMPLING PROTOCOL

A tiered sampling protocol has been established for efficient and accurate TLS data collection that is customizable for monitoring needs (fig. 3). Following the protocol steps in order will ensure that scans are not visually obscured by the operator or equipment and that groundcover, tree structure, and fuels are not impacted by trampling during plot setup. Refer to the latest methods manual for a sample equipment list for TLS fuels and sampling ecological conditions (USGS 2023b).

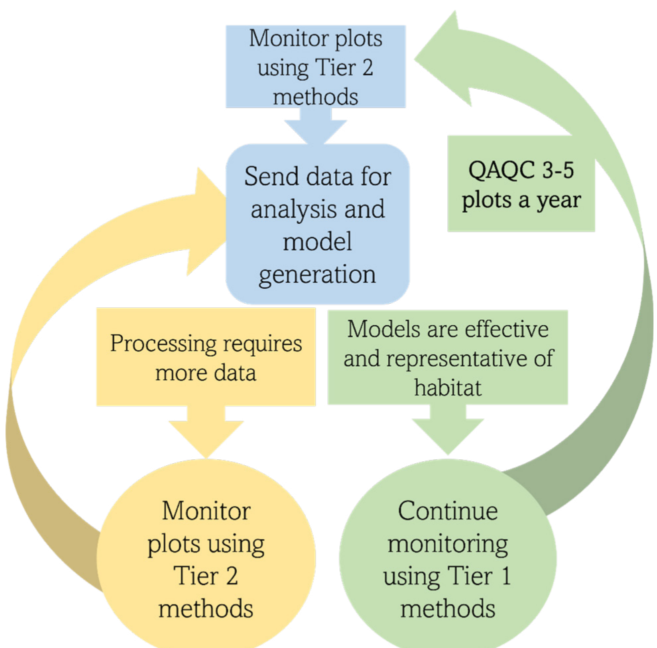

Figure 3—Conceptual diagram of the IntELiMon tiered terrestrial laser scanning monitoring protocol. QAQC = quality assurance quality control. (U.S. Fish and Wildlife Service diagram by Emily Link)

There are three tiers of data collection.

Tier 1 sampling occurs on all plots and includes a single 360° TLS scan and variable-radius sampling with a prism (hereafter referred to as prism pass) for hardwoods and conifers at designated plots.

Tier 2 sampling includes **Tier 1** plus additional (and often initial or intermittent) transect fuel sampling and overstory tree identification within each plot.

Tier 3 includes **Tier 2** plus any additional desired sampling, often for more site-specific, objective-driven, or research and development needs.

It is important to note that the goal of **Tier 2** sampling is to develop calibration datasets for specific monitoring sites, ensuring that models can accurately predict structural and surface fuel metrics with linear regression analyses. As such, areas that are first implementing TLS monitoring typically require, at a minimum, **Tier 2** sampling at as many plots as possible and, following model calibrations, are then able to step down to the simpler **Tier 1** in subsequent samplings at the same plots, or often within the same ecosystem with similar structural characteristics.

Plot Selection

Plot locations are chosen based on site-specific monitoring objectives, such as a goal to represent ecological variation, forest density, or fuel density conditions across a site. The number of plots can vary highly among sites, dependent on the range of conditions, access, size, burn history and frequency, and available resources. It is important to note that greater numbers of established plots contribute to better models built from **Tier 2** sampling as well as more consistent long-term data from **Tier 1** sampling. Random, grid, or stratified random plot sampling designs are commonly used at monitoring sites and consulting with a sampling expert can improve monitoring outcomes. Using existing monitoring plots is also suggested, from which legacy data sets may be linked to TLS data for incorporating past trends. If no monitoring program exists, or resources are limited, the user can start with a simple plot design (e.g., pick one ecosystem type of interest and assign a manageable number of randomly distributed plots). More plots can be added over time as resources become available and objectives are refined. Several trial plots may be performed to work out the details of plot navigation, setup, and execution for both **Tier 1** and **Tier 2** sampling. This allows for practice to minimize trampling, refine fuel categories (if needed), and download and process the TLS data. In this way, the user can ensure a comfortable working environment to practice the protocol and improve the quality of data collected in the actual plots.

Although the scanning range of the BLK360 G1 is extensive and dependent on vegetation density, we suggest using a 10-m radius (314.16 m^2/0.03 ha/0.078 acre) plot size to coincide with a 10-m radius transect sampling, to minimize occlusion within the single scan, and maximize detected ground points for height stratification. However, a larger plot size may be used, dependent on local conditions (e.g., 15-m radius in open forest conditions). Given a 10-m radius plot size, plots should be at least 15 m apart and at least 15 m from water, roads, or other built features. Frequent foot or mechanical traffic and safety concerns (e.g., tree snags) must be considered when selecting plots and throughout the continuous sampling of plots through time. Trampling or other soil and vegetation disturbance will impact the quality and consistency of data collected and models developed through time.

TLS Target Placard

The BLK360 G1 has no integrated GPS or compass, so 3D data points are not georeferenced or oriented. A GPS unit can be used to determine plot center, but not orientation. If orientation is desired, an optional target placard can be created and placed 2 m outside the plot radius (e.g., 10-m plot radius and the placard at 12 m due north) to orient each scan in cardinal space. Instructions for target placard construction can be found in the methods manual (USGS 2023b).

TLS DATA COLLECTION WITH THE BLK360 G1

Tier 1 Sampling

Navigate to plot center with ArcGIS Field Maps (Esri, Redlands, CA) or another mapping tool. If the designated plot center is close to a tree, adjust plot center so that the laser is not within an estimated distance of 3 times the diameter of the tree, if possible. Adjust plot location for any safety concerns. Record the site location, surveyor initials, date and time, and mark the location of plot center by using a GPS.

At plot center, raise a tripod to the maximum height (approximately 1.5 m) and situate it so the BLK360 G1 is directly over plot center. Secure the 2-m pole with the attached TLS target placard firmly in the ground 12 m north of plot center (i.e., 2 m outside the 10-m plot radius) (fig. 4). Before collecting TLS scans and any additional physical data, consider potential effects of trampling and disturbance of ground cover, tree structure, and fuels. For further instructions on scanning with the BLK360 G1, refer to the latest methods manual (USGS 2023b).

Once scanning is complete and the scanner is safely removed and stored, conduct a prism pass with a 10-factor prism over plot center and target 1.37 m (4.5 feet) above ground (at breast height). Categorize trees as “in” or “out” and record as either conifer or hardwood.

The prism pass can eventually become optional for **Tier 1** sampling after completing multiple iterations of **Tier 2** sampling and site-specific models have been established. Periodical **Tier 2** sampling, however, is optimal for crosschecking metrics.

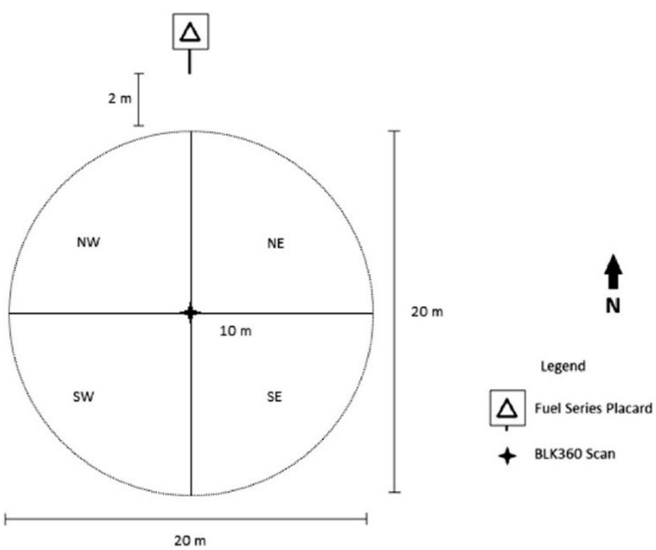

Figure 4—Plot layout for terrestrial laser scanning monitoring field data collection methods. (Courtesy diagram by Pokswinski and others [2021])

Tier 2 Sampling: Transect and Overstory Data Collection

Tier 2 sampling includes both a **Tier 1** scan and additional transect sampling. Once the TLS scanning is complete, fuel point intercept, coarse woody debris, fuelbed, litter and duff depth, and overstory data are collected, which requires establishing transects. Transects radiate 10 m out from plot center in each cardinal direction, resulting in two perpendicular 20-m transects that intersect at plot center (fig. 4). Place poles at the terminal end of each transect with a tape measure tautly stretched along the transect. When establishing the transects, take care not to trample the vegetation or litter, because this material will be sampled. Depending on the complexity of the site and proficiency of the data collector, fuels and ecological conditions data collection may take from 30 minutes to 1 hour. See the IntELiMon website (USGS 2023b) for example **Tier 2** datasheets with fuel categories that can be used in multiple ecosystem types.

FUEL SAMPLING:
fuel point-intercept sampling

Point intercept sampling methods similar to those developed by Goodall (1952) can be used to estimate percentage of vegetation cover accurately. An analogous approach is used here. Some fuel categories are standardized, such as live or fine fuels (graminoids, forbs, woody), leaf litter (conifer needles), and bare ground (no fuels) (Hiers and others 2007). Customizable categories can also be added, such as wiregrass, palmettos, bunch grasses, exotics, sagebrush, etc. (table 2).

Starting 0.5 m from a terminal end and repeating every meter thereafter (0.5, 1.5, 2.5, etc.), drop the fuel sampling rod vertically along the tape measure to avoid sample bias. Point-intercept tally vegetation that is <1.4 m in height and touching the fuel sampling rod. Tally the presence/absence of all live and dead vegetation by fuel categories on the datasheet at each sample point. Record each fuel category once per sample point, such that if two grass species are present at the sample point the graminoid category will receive one tally. No other materials beneath the object are counted if the fuel rod drops on a solid object (e.g., oak leaf, cone, twig, etc.). Bare ground is only counted when the fuel rod is touching bare mineral soil and is not covered by any other vegetation litter or live fuel. This point-intercept

Table 2—Example point-intercept fuel categories, rules, and exceptions for a southeastern longleaf pine (*Pinus palustris*) flatwoods ecosystem

	Fuel point-intercept categories
Graminoids	Live and dead grasses, sedges
Woody live	Live woody trees and shrubs <10 cm d.b.h.
Live saw palmetto[1]	Live saw palmetto (*Serenoa repens*) leaves and petioles
Vines[1]	Live and dead climbing or trailing woody-stemmed plants
Forbs	Live and dead, detached and attached, small herbs that do not fit in any of the above categories
Woody leaf litter	Dead and detached nonconifer leafy material
Pine needle leaf litter	Dead and detached conifer needles
Conifer litter[1]	Detached conifer material (bark flakes, catkins, etc.)
Dead saw palmetto[1]	Dead saw palmetto leaves and petioles
Bare ground	Only include dinner-plate-sized areas of bare ground, where no other fuel category is present or touching the fuel sampling rod

Fuel point-intercept sampling rules and exceptions
• A fuel category can only be marked once per meter point intercept. For example, if an *Andropogon* and *Dichanthelium* grass both touch the rod on point 1.5 m, only one tally would be marked for the graminoid group (even though both *Andropogon* and *Dichanthelium* are graminoids).
• If the fuel sampling rod drops on a solid object (oak leaf, pine cone, stick, etc.) or covers up other vegetation, no other vegetation or fuels beneath this object are included in the tally.
• Down woody debris (sticks, twigs, bark, stumps, logs, etc.), pine cones, top-killed shrubs, trunks of trees, mosses, lichens are not recorded here. Down woody debris, pine cones, and trees (>10 cm d.b.h.) are recorded elsewhere.
• If leaf litter is burned material, do not count as leaf litter if black and disintegrates when handled.
• Bare ground is only tallied when soil at that point is not covered by any other vegetative material in a dinner-plate-sized area or larger. If bare ground is tallied, then that is the only tally at that point.

This is an example of how fuel categories can be designed for a particular ecosystem type, by using general (e.g., graminoids, woody live) and more custom (e.g., saw palmetto) fuel categories.
d.b.h. = diameter at breast height.
[1] A custom category, created for the monitoring needs of the site and ecosystem type.

sampling is unique in that, though a fuel category is only marked once per sample point, vegetation can fit into multiple fuel categories and be recorded as such on the datasheet. For example, suppose one indicator grass and one generic grass touches the fuel rod. In that case, one tally is given to the indicator group and only one tally for the graminoid group (even though both grasses are graminoids). In all cases, indicator groups are optional categories specific to the region or habitat being monitored. Continue in this manner every meter (i.e., 0.5, 1.5, 2.5, etc.).

Upon completion, each transect will have 20 sample points for a total of 40 sample points. Each tally in a category will represent 2.5 percent of the cover for that particular category. The following are disregarded when using the sampling rod because they are accounted for elsewhere in the protocol: down woody debris (sticks, twigs, bark, stumps, logs), cones, and tree trunks. Mosses and lichens are not counted unless added as a custom category indicator. See table 2 for an example of point-intercept fuel categories used in sandhill longleaf pine forests.

Point-intercept fuel categories can be designed for a particular ecosystem type, such as the example in table 2 for a longleaf pine (*Pinus palustris*) flatwoods ecosystem. General (e.g., graminoids, woody live) and more custom (e.g., saw palmetto) fuel categories were used in table 2. In this example, live saw palmetto is only marked under that category and not under woody live; woody live accounts for all other live woody plants except saw palmetto. Users can start with the default fuel categories provided by the IntELiMon protocol and optionally expand upon them with customized fuel categories as desired or according to monitoring needs.

FUEL SAMPLING: coarse woody debris and down and dead woody sampling

Coarse woody debris sampling uses the planar intercept method (Brown 1974) to tally down and dead woody fuels that intersect the entire 40 m of transects. These fuels are broken out into standard fuel time lag categories (1-hour, 10-hour, 100-hour, and 1000-hour) and female conifer cones. A wildland fire fuel sizing gauge with a 6-mm slot for 1-hour fuels, a 2.5-cm slot for 10-hour fuels, and a 7.5-cm slot for 100-hour fuels can be used to determine the debris diameter. Make a tally along the two perpendicular 20-m transects in the corresponding category each time one of these fuels crosses the plane of the transects. Note that one branch can be counted multiple times if it crosses the transect plane in multiple places. For example, one large branch with several small branches crossing the line, several small branches crossing the line, or the same large branch crossing the line more than once. For this sampling, decay status is disregarded and does not affect count or diameter. Standing dead material attached to the ground (i.e., top-killed shrubs) is tallied if it is <1.5 m in height. Tally and note the species of each individual female conifer cone that crosses the transect plane.

FUEL SAMPLING: fuelbed, litter, and duff depth sampling

Collect fuelbed, litter, and duff depths at 0.5, 3.5, 6.5, 13.5, 16.5, and 19.5 m along each transect for a total of 12 measurements. The fuelbed depth is defined as the top of the litter layer (Oi) to the tallest live or dead vegetation. Sample the fuelbed depth within a plane 30.5 cm (12 inches) on each side of the measurement point, perpendicular to the tape, with a maximum fuelbed depth of 1.4 m. At this same sample point, record the litter depth as the greatest height where litter touches the rod. Note that litter can either be defined as leaf litter, fine litter, or dead fine vegetation, depending on the ecosystem type and monitoring needs. Also measure the duff layer depth, containing partially to highly decomposed vegetation, ending at the top of the mineral soil. Take care when measuring this layer to avoid compressing the material. Measurement increments are 0.0, 0.1 cm (for trace), 1.0 cm, and by the centimeter thereafter.

Overstory sampling

Characterize overstory trees >10 cm in diameter at breast height (d.b.h.) within the four quadrants 10 m of plot center (delineated by perpendicular transects). Tally trees by quadrant (NW, NE, SE, and SW), species/taxa, and abundance.

Tier 3 Sampling: Additional Data Collection

Tier 3 sampling can be performed as needed, or with specific objectives in mind; for instance, to measure surface fuel mass in clip plots (e.g., Loudermilk and others 2023), burn severity (e.g., Gallagher and others 2021), or woodland/rangeland woody cover via line intercept methods (e.g., Herrick and others 2005) to relate to the TLS output metrics. Other examples include additional tree measurements, biodiversity sampling, destructive harvesting, or qualitative information such as habitat quality.

DATA OFFLOADING

At the end of each collection day, export scans and delete them from the BLK360's internal storage. Using a fully charged battery can prevent the BLK360 G1 from shutting off during data export. Refer to the latest methods manual (USGS 2023b) for step-by-step instructions for using BLK Data Manager Utility and Cyclone Register to export, delete, and convert scans from the proprietary .blk format to more widely usable .ptx format.

Outputs and Metrics

AUTOMATED PROCESSING AND DATA ANALYSIS

The TLS data collected through this protocol can be processed and analyzed automatically through the IntELiMon viewer, a streamlined processing pipeline maintained by the USGS Earth Resources Observation and Science (EROS) Center (USGS 2023a) (fig. 5). TLS scans can be directly uploaded to IntELiMon, on the EROS server, where they are processed through carefully developed scripts and archived with explicit metadata for each dataset. Scan file and plot identification preparations are described in the methods manual (USGS 2023b). This initial data flow generates hundreds of structural metrics calculated from each TLS 3D point cloud and, when coupled with initial field transect data, is used in a machine learning environment to predict tree and fuels data for forestry and ecological monitoring. EROS is capable of processing 100 TLS scans per day and results can be accessed via the IntELiMon viewer, an interactive data dashboard for users to access and download processed TLS data and metadata. Quality control/quality assurance and metadata management are built into the data workflow.

Metrics derived from TLS scans capture the complex ecological structure of a plot. Given the millions of data points within each point cloud, multiple ways exist to measure and characterize portions of the scan. When processed with the EROS scripts, scans are clipped to a 15-m radius, normalized (elevation measurements are converted to height above ground), and, depending on the metric, are analyzed in their entirety, within designated height strata, or within 2 cm by 2 cm by 2 cm voxels (3D pixels) (i.e., within cubic space). Surface vegetation is defined in stratums of 0.5, 1.0, 1.5, 2.0, and >2.0 m, and forest stratum types include groundcover (0–1 m), understory (1–3 m), midstory (3–9 m), and overstory (>9 m). Using a spherical neighborhood, the point cloud is rasterized and analyzed for summary metrics, including the proportion of returned and unreturned pulses and occluded space. Here, the x,y,z coordinates are converted to spherical coordinates. This allows points to be tracked along their flight path and for estimation of the proportion of pulses that return to the scanner from a particular distance, those that continue further away from the scanner, and those that never return (i.e., never hit an object and return). This method can be used to differentiate between true gaps (i.e., space without vegetation) and occluded space (i.e., not measured because no pulses passed through the volume). The input .ptx point cloud is also converted to .las format for basic LiDAR outputs, including a DTM, CHM, summary statistics, and height bin metrics. A tree classification identifies individual boles via a segmentation algorithm

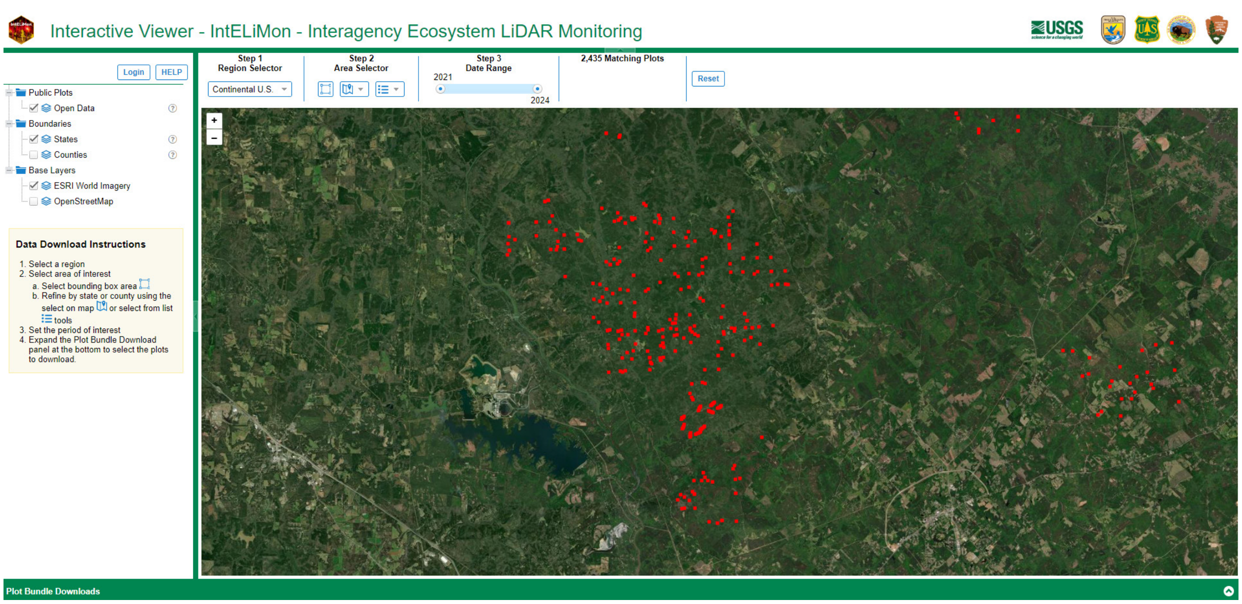

Figure 5—IntELiMon interactive viewer dashboard, March 2024. (USGS image)

(de Conto and others 2017), providing a tree inventory and metrics that include corrected basal area, tree descriptive statistics, and foliage diversity metrics. Fuels are filtered out to create a stemless 0- to 3-m point cloud, allowing for shrub classification and output shrub inventory and summary statistics. Fine fuels and coarse woody debris are further defined from the fuels point cloud. This results in over 200 forestry metrics and structural characteristics, tree and shrub inventories, and raster grids, including a DTM, CHM, and 10-m^2 shrub tile (table 3 and figs. 6, 7, and 8). These metrics range from vegetation distribution, density, tree and fuel heights, and d.b.h. to forest structural characteristics including differences between true forest gaps and space created by occlusion. Note that metric improvement and development is continuous. As metrics are updated, previously collected TLS scans and field data can be reanalyzed for metric and data updates and consistency. Details on processing and early metric development are in Gallagher and others (2021), Maxwell and others (2023), and Loudermilk and others (2023).

Table 3—Examples of directly measured (Tier 1) or predicted (Tier 2 or Tier 3[1]) metrics from the terrestrial laser scanning monitoring protocol

Category	Direct measurements	Predicted/calibrated measurements
Trees	Tree density, percentage of canopy cover, height, d.b.h., c.b.h.	Conifer versus broadleaved
Shrubs	Shrub density, heights	Percentage of cover
Graminoids	TBD	Percentage of cover
Leaf debris	TBD	Percentage of cover
Woody debris	Estimates of 1,10,100,1000 fuels	Percentage of cover
Duff	TBD	Depth
Fuelbed	<3 m height estimates	Depth
Surface fuel loading (<1 m height)	N/A	Surface fuel biomass (tons per acre)[1]
Vegetation/fuel volume	Volume of canopy, ladder, and surface fuels	Volume of canopy, ladder, and surface fuels
New category (as developed)	TBD	TBD
Other nuanced categories		
Height statistics	Height estimates in various portions of the TLS point cloud	TBD
Space and occlusion	Percentage of space in various portions of the TLS point cloud	TBD

New category represents the ability to add new categories/metrics/predictors as they are developed. Other nuanced categories represent the multitude of categories that are not necessarily related to a known vegetative feature but quantify various portions of the point cloud by using statistical measures. These measures quantify the structure of the vegetation, space between vegetation, and occlusion behind vegetation.

d.b.h. = diameter at breast height; c.b.h. = canopy base height; TBD = measurements or estimates could still be developed; N/A = not applicable; TLS = terrestrial laser scanning.

[1] Tier 3 predicted metrics are calculated with additional field sampled data. Colocated scans and physical biomass measurements were used to predict surface fuel biomass and consumption (Loudermilk and others 2023).

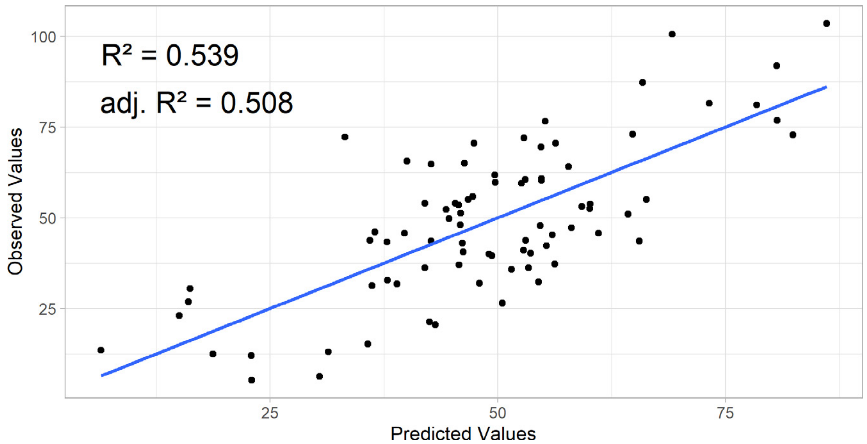

Figure 6—Linear regression analysis of mean fuelbed depth. Terrestrial laser scanning metrics (from Tier 1) were used to predict the observed field-sampled, plot-level data (from Tier 2). Units are centimeters.

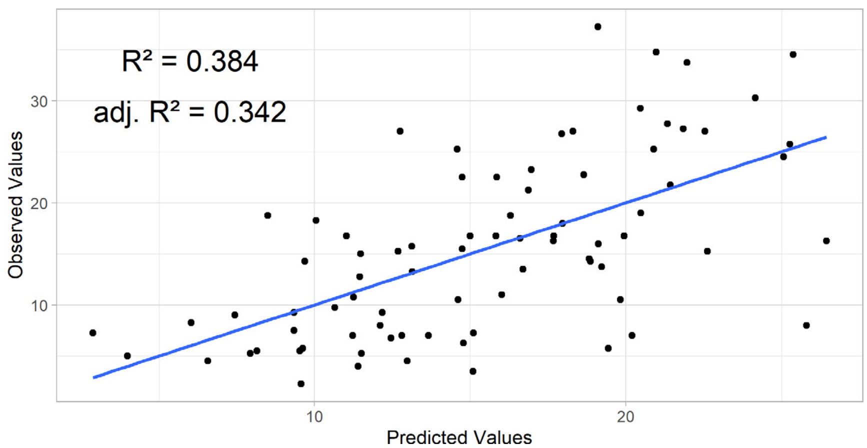

Figure 7—Linear regression analysis of mean litter depth. Terrestrial laser scanning metrics (from Tier 1) were used to predict the observed field-sampled, plot-level data (from Tier 2). Units are centimeters.

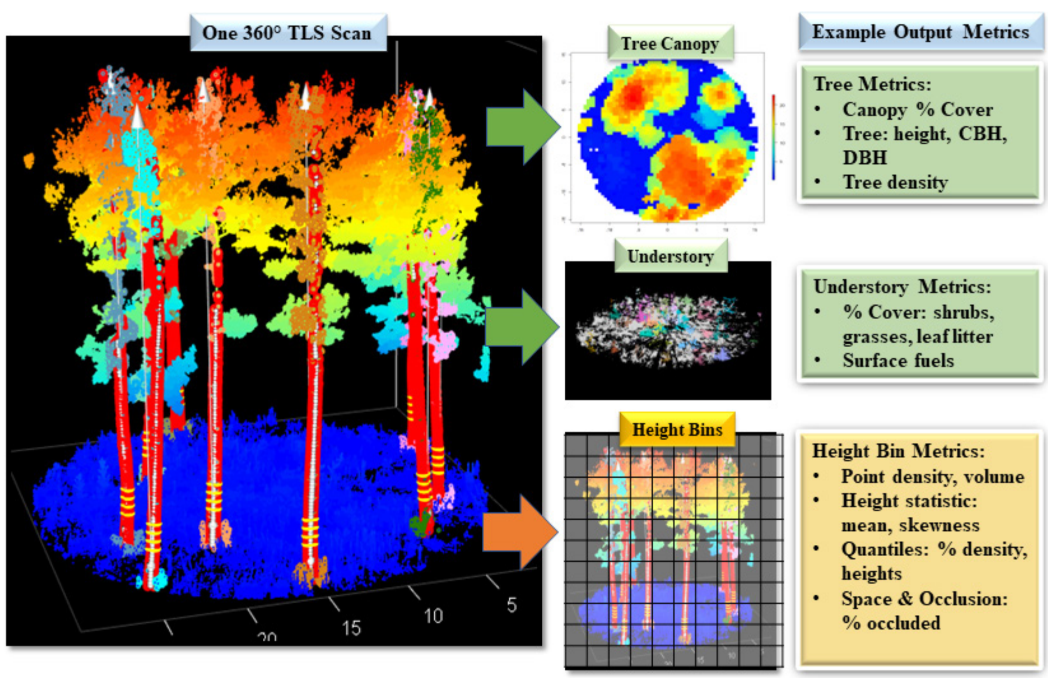

Figure 8—Processing flow example of one 360° terrestrial laser scan as output by the IntELiMon system. Trees were located, identified, and measured for diameter, height, and overall canopy cover, then removed to estimate understory or percentage of surface cover vegetation and fuels (green boxes). Then the entire 3D dataset (point cloud) was segmented into height bins (or 3D boxes) and hundreds of metrics were calculated (yellow box) for use in predictive modeling (e.g., surface biomass, burn severity). (USDA Forest Service image by Louise Loudermilk)

TLS-BASED MONITORING CHALLENGES

The most notable limitation to TLS-based monitoring is the obscuration caused by objects, such as large trees or dense vegetation close to the scanner. This occlusion blocks the laser pulse from collecting data behind a given object. Occlusion is accounted for in this monitoring protocol with several methods. First, occlusion is calculated from the point cloud, where all laser pulses (regardless of whether they intercept an object) are accounted for. This allows for the differentiation between true empty space (e.g., open canopy space) and obscured space (e.g., space behind a tree bole). This also applies to the differentiation between true and unknown vegetation structures. Second, there is ongoing research to predict what is being occluded given the existing plot structure captured by the scan. Although there are well-known approaches to merge (stitch) multiple adjacent scans together to provide a complete 3D point cloud of all the vegetation (for examples, see Cheng and others 2018, Guan and others 2020, and Tremblay and Beland 2018), the loss of efficiency needed to merge multiple scans currently outweighs the potential gain in information. Merging multiple scans is further complicated by vegetation movement during and between scans, causing errors in the merging process and output metrics. The dense structural information in a single scan, even given obstruction issues, ultimately provides millions of structural 3D data points to work from. This point-based monitoring approach is more straightforward than attempting to merge multiple scans, increasing efficiency of data collection and processing, notwithstanding standardization of sampling.

Ground-level data, including compact leaf litter, organic soil layer (duff), or microtopography are not as well characterized as larger objects (trees, shrubs) in the scans. The **Tier 2** sampling data (e.g., transect sampling) are used to overcome this bottleneck by building site-level models to predict these lower strata data from field data as calibration. Fine or coarse woody debris can be captured given the high point density of the scans and distinct structural patterns of the wood, but is dependent on location within the scan, vegetation density, and size of the debris. Again, the **Tier 2** sampling data are well-suited to build site-level models of this information. Standing dead tree or snag identification is currently a limitation, although they can be differentiated in leaf-on or strictly evergreen conditions. Leaf-on versus leaf-off scans of the same plots also provide information on snags.

Recent Research and Applications

RECENT RESEARCH

Extensive research has contributed to the development of this TLS monitoring protocol, including metric analyses and methodologies blending TLS and field sampled data. Here we review the most recent publications that use the BLK360 G1 scanner for measuring complex structural characteristics (metrics) of terrestrial ecosystems at the plot level and prediction modeling of other structural and nonstructural aspects of the system.

BLK360 G1-derived metrics were initially developed by Anderson and others (2021) and Gallagher and others (2021). Both studies collected field measurements to relate to the metrics calculated from each individual scan with a BLK360 G1. The metrics were similar in measuring trees, shrub and herbaceous cover, as well as calculating density and height statistics within height classes. They differed in how they divided the scan point clouds into height bins and calculated percentage of various types of vegetation cover. Anderson and others (2021) used a combination of TLS and traditional field-based sampling methods to predict groundcover species richness in southern pine flatwoods. Vegetation structure, assessed as vertical and horizontal openness and variability, was used as a proxy for richness in the TLS data in addition to intensity, or the strength of each return. TLS metrics were found to accurately predict species richness in groundcover plant communities where structure and richness are tightly coupled. They found that herbaceous richness was generally more accurate than shrub richness. Gallagher and others (2021) used the single-scan TLS approach for monitoring wildland fire burn severity in the New Jersey Pinelands National Reserve. They found that TLS-based methods for quantifying plot-level burn severity offered significant improvements compared to the Composite Burn Index (CBI), which is the most widely used field-based method. The authors found that TLS overcame CBI's limitations of subjectivity and repeatability and excelled at characterizing understory vegetation where prescribed fire effects are most pronounced, where both CBI and ALS are weakest due to qualitative estimates and canopy occlusion, respectively. That same year, Pokswinski and others (2021) published the first methods paper using the BLK360 G1 for terrestrial ecosystem monitoring and introduced the initial plot-based, transect methods featured in this report.

Loudermilk and others (2023) demonstrated TLS capabilities for predicting understory vegetation and fuel biomass as well as consumption by fire in frequently burned Southeastern U.S. pinelands. They describe 162 of the TLS metrics in detail, and illustrate how various fuel mass classes, such as fine fuels, fine woody debris, or simply total surface biomass pre and postburn, can be predicted by using TLS metrics. Finally, Maxwell and others (2023) assessed shrub height predictions from TLS metrics (in the New Jersey Pinelands National Reserve) when (1) varying the number of randomly selected shrub height measurements and (2) by using metrics from leaf-off versus leaf-on TLS data. They found that at least 10 random shrub heights (20 being ideal) were needed for accurate predictions and that leaf-on TLS data generally provided more precise predictions. Their work highlights the importance of reference data sampling density, design, and data characteristics when training empirical models for extrapolating to new sites or plots.

Other notable references are related to single or multiscan analyses that use other TLS instruments. Batchelor and others (2023) illustrate the use of single scans of the FARO® Focus 3D S120 terrestrial laser scanner (FARO Technologies Inc., Lake Mary, FL) for estimating new structural complexity metrics in Pacific Northwest forests. Many studies have used multiple merged scans to predict grass, shrub, tree, or fuel attributes at various scales and by using a variety of metrics of interest (e.g., Alonso-Rego and others 2020, Cooper and others 2017, Loudermilk and others 2009, Olsoy and others 2014, Wallace and others 2022). Merged FARO® Focus scans were used to relate structural complexity of mixed pine-hardwoods forests of the southern Appalachian Mountains to vascular plant biodiversity (Walter and others 2021). Stovall and Atkins (2021) compared merged predictions of tree metrics output and modeled from the BLK360 G1 and the FARO® Focus 3D S120. They concluded that although metrics were comparable between instruments, laser technology (BLK360 G1: time-of-flight versus FARO® Focus: phase-shift) impacts each scanner's range and point noise output. Generally, the BLK360 G1 had less noise and required less filtering than the FARO® Focus.

These advances drive the operational adoption of TLS for long-term monitoring and management by continuously improving point cloud metric measurement and interpretation. It should be noted that these are the most recent examples that use BLK360 G1 scanners and that technology and methods are continuously advancing. Many other TLS and LiDAR applications in ecosystem and forestry research were not included here because they are beyond the scope of this report.

FUTURE DIRECTIONS OF RESEARCH

Research informing this monitoring protocol continues to advance with the development of new methods and applications for 3D forest structure characterization. LiDAR technology is also advancing quickly and instruments well-suited for this type of monitoring continue to be developed. Therefore, understanding how these instruments sample the environment will be vital for TLS-based monitoring to maintain consistency and value in the future. Future research in this area will include direct comparisons of new and old sensors to set a standard that can be maintained. This includes comparing the precision of the BLK360 G1 scanner with other low-cost alternatives (Stovall and Atkins 2021). Such comparisons can assist in addressing current limitations of TLS monitoring and tailor scanner instruments for unique ecosystems and monitoring needs.

Metrics derived from the 3D point cloud are continually improving in detail and accuracy. This includes predicting occluded areas given the existing plot structure captured by the scan. There is ongoing research with promising results on segmenting point clouds into different types of fuels (e.g., coarse woody debris versus leaf litter) or mapping shorter vegetation such as tree seedlings, shrubs, or bunchgrasses. There is also an effort to create 3D tree, shrub, and grass models in an inventory or 3D library to generate virtual vegetation or forested stands to simulate and quantify a desired or representative fuel environment. Quantitative structure models (QSMs) are particularly useful for such segmentation work (Brede and others 2019, Stovall and Atkins 2021). QSMs and other advancements can distinguish between plant species or plant functional types based on their relative structural characteristics (e.g., broadleaved versus needleleaved trees). QSM approaches can also provide unique insights related to species identification (Åkerblom and others 2017, Krooks and others 2014) and plant physiology and structure (Hackenberg and Bontemps 2022). There is a need for understanding fine-scale complexities, such as further characterization or prediction of groundcover plant diversity or soil organic layer development and consumption by fire. Other structural characteristics captured by the 3D point cloud, such as canopy density, canopy gaps, ground substrate, and soil surface characterization have additional applications, including erosion models.

Future integration of TLS with ALS and spectral reflectance datasets could provide full vegetation distribution datasets for more complete landscape analyses. Work is underway to automate processing of multiple overlapping TLS scans and overlapping TLS and ALS scans to expand coverage of TLS fine-scale data to the extent of ALS through imputation and interpolation techniques. There is potential to integrate a spectral reflectance index with the 3D data for even further improvements to fine-scale burn severity mapping as well as identifying species, plant functional types, or fuel types. Another major research avenue is to apply TLS vegetation and fuels data, including 3D libraries, as onramps for next generation wildland fire and smoke simulation models (Linn and others 2020, Loudermilk and others 2023, Peterson and others 2022), such as WFDSS (Pence and Zimmerman 2011), FIRETEC (Furman and Linn 2018), and QUIC-Fire (Linn and others 2020, USDA Forest Service 2022). By providing detailed wildland fuel parameters and forest structure, particularly in 3D, TLS monitoring data can be used as a direct input, or coupled with ALS for full coverage of canopy and understory vegetation characterization. As such, 3D point clouds can be used to develop 3D fuels inputs to advance fire models (Mueller and others 2021). The high detail from TLS is uniquely suited to laboratory scale experiments and comparisons with such models, where point cloud-derived vegetation structure can identify thresholds in fuel mapping detail and help inform better understanding of fine scale fire spread (Marcozzi 2022).

MANAGEMENT APPLICATIONS AND DEMONSTRATION

Numerous land management agencies, including the Forest Service, the Department of the Interior's U.S. Fish and Wildlife Service, National Park Service, and Bureau of Indian Affairs, among others, currently implement TLS monitoring, with other groups expressing interest in its use. The U.S. Fish and Wildlife Service Southeast Fire Program first unveiled this protocol for fire effects monitoring of hazardous fuel treatments on national wildlife refuges in collaboration with Forest Service and university research partners. Although the effort began in the Southeastern United States, it is quickly gaining national interest, and operational training and testing has occurred across additional national wildlife refuges, national forests, national parks, tribal lands, and Department of Defense installations, among others (USDA Forest Service 2024). More training events are planned at national training centers (see next section on Training, Coproduction, Technology Transfer).

The protocol arose out of a need to improve the accuracy and precision of fire effects monitoring and is thus well-suited for capturing changes in understory vegetation structure and volume due to both natural disturbances and management treatments. Pre and postfire TLS monitoring can be used for surface biomass change detection to estimate fuel consumption and assess maintenance of target surface fuel characteristics over time (Loudermilk and others 2023). Other demonstrated applications of the TLS protocol include critical habitat evaluation, documentation of restoration projects or disturbance events, and for determining habitat suitability for potential use in wildlife translocation. For example, on St. Marks National Wildlife Refuge, TLS monitoring is used to assess habitat of threatened and endangered species such as the frosted flatwoods salamander (*Ambystoma cingulatum*), black rail (*Laterallus jamaicensis*), and red-cockaded woodpecker (*Dryobates borealis*) and quantify response efforts to bark beetle disturbances (Link 2023). Other applications include, but are not limited to, assessing changes through time, such as forest succession, mortality or regeneration patterns, fire effects including fuel consumption, invasive species encroachment, or management treatment response.

In addition to its monitoring applications, TLS has substantial potential to inform next generation national fuels maps, which would benefit fire models and decision-support systems that rely on such data. Current national fuels maps such as LANDFIRE (USDA Forest Service and USDOI 2024) and decision-support systems such as WFDSS (Pence and Zimmerman 2011) primarily use data derived from 30-m satellite imagery, but are limited in their ability to use detailed 3D fuels data. In contrast, new prototype fuel mapping systems such as FastFuels (USDA Forest Service 2023), fire models such as QUIC-Fire (Linn and others 2020, USDA Forest Service 2022), and decision-support systems that integrate them, such as the BurnPro3D platform developed by WIFIRE (UC-San Diego 2023), all represent fuels in high detail 3D, and can thus leverage 3D data not only from TLS but from ALS or UAS as well. Each of these 3D mapping technologies has its own strengths and limitations and next-generation fuels maps could likely integrate all of them. Although TLS is not wall-to-wall in coverage, its below-canopy detail will greatly enhance fine-scale surface fuel characterization. Integration of detailed 3D fuels data and fire models could lead to a wide range of management applications outside of current capabilities, including simulation-based assessments of fuel treatments, testing prescribed burn ignition patterns, and evaluating risk in the context of prescribed burns. Natural resource managers in many landscapes are demonstrating this technology for use in monitoring and working with scientists and practitioners for additional innovation and research. These new technologies could serve to advance decision-support tools needed for prescribed fire or fuel treatment planning, silviculture prescription design, assessments of fire risk and fire effects, and other natural resource management needs.

Beyond the valuable ecological metrics provided by TLS monitoring, RGB panoramic photos captured by the BLK360 G1 scanner serve as an incredible visual communication tool. They can be collected from the scanner alongside the point cloud and give a detailed look at a given plot from a human perspective. Flat images are notably lighter weight than point clouds, consuming at least two orders of magnitude less disk space per file. As such, panoramic imagery is a more viable option for sharing between colleagues, especially from the field over a cellular network. WIFIRE, a University of California-San Diego-based program specializing in data integration and visualization of wildland fire behavior, has created immersive visualizations of TLS monitoring plots by reprojecting the TLS point clouds to an RGB panoramic image (UC-San Diego 2023). These immersive forest experiences allow the user to virtually revisit monitoring plots, witness the effects of management treatments, and easily recollect structural attributes. In addition to displaying the RGB colors collected from the BLK360 G1, ecological metrics can be embedded and displayed in the immersive experience, giving the user the opportunity to see their metadata in context.

TRAINING, COPRODUCTION, TECHNOLOGY TRANSFER

Training, coproduction, and technology transfer opportunities for utilizing this TLS monitoring protocol are well underway across the United States. Although training is currently a collaborative grassroots effort among Federal agencies and research consortia, more formalized training curricula are in development. Check with each agency's training or technology transfer liaison for upcoming opportunities. Courses range from technical training on field data collection and initial data processing to data analysis and modeling for advancing the application of TLS monitoring in land management decision support.

To accelerate technology transfer for innovative land management tools, the Department of Defense and USGS, in partnership with a host of other Federal partners including the Forest Service, have established the National Innovation Landscape Network (DOD 2024). Currently, the Innovation Landscape Networks formed in both the Southwestern and Eastern United States have made TLS monitoring and fuels characterization a focal area for innovation and technology transfer (USDA Forest Service 2024). Coproduction is recognized as the key to success for this type of innovation, where technology and management needs hit a crossroad, but can efficiently and effectively advance with continuous feedback and involvement between researchers and resource managers. As these innovation landscapes develop and mature, opportunities for scaling up training, technology transfer, and novel uses for TLS will likely grow and expand over time.

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Long-term ecosystem monitoring documents land management actions and progress towards objectives through repeated observation and measurement. Traditional monitoring methods have evolved for specific applications across ecological disciplines and are often limited by data quality and repeatability. This report presents terrestrial laser scanning (TLS) as a sampling method that can complement and enhance existing monitoring methods. TLS captures in high resolution the 3D structure of a terrestrial ecosystem and, when integrated into monitoring, can standardize data collection, improve efficiency, and reduce bias and error. Streamlined data processing can rigorously analyze TLS data and incorporate constant improvements. The approach described in this report utilizes portable, push-button TLS equipment that, when calibrated with initial transect sampling, captures detailed forestry, fuels, and ecological features in <5 minutes per plot. We introduce an interagency automated processing pipeline and dashboard viewer for instant analysis and retrieval of hundreds of metrics. TLS metrics produced with these methods offer effective decision support for managers to quantify landscape-scale conditions. With continued improvement of scanner capabilities and affordability, these data will shape the future of terrestrial ecosystem monitoring and support natural resource managers in addressing the increasingly fast pace of ecological change.

Keywords: Terrestrial LiDAR, wildland fuels, forestry metrics, monitoring protocols, fire effects, remote sensing, forest inventory

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