EVALUATING THE APPLICATION OF LIDAR TO MEASURE WILDLAND FIRE DEPTH OF BURN IN THE CANADIAN BOREAL FOREST

by

Josh Kelly

Faculty of Natural Resources Management

Lakehead University

04/15/24

EVALUATING THE APPLICATION OF LIDAR TO MEASURE WILDLAND FIRE DEPTH OF BURN IN THE CANADIAN BOREAL FOREST

by

Josh Kelly

An Undergraduate Thesis Submitted in
Partial Fulfillment of the Requirements for the
Degree of Honours Bachelor of Science in Forestry

Faculty of Natural Resources Management

Lakehead University

04/15/24

Dr. Jian Wang	Dr. Mark de Jong
Thesis Adviser	Second Reader

LIBRARY RIGHTS STATEMENT

Signature: ______________________________

Date: 04/15/24

A CAUTION TO THE READER

This HBScF thesis has been through a semi-formal process of review and comment by the thesis advisor and second reader. It is made available for loan by the Faculty of Natural Resources Management for the purpose of advancing the practice of professional and scientific forestry. The reader should be aware that opinions and conclusions expressed in this document are those of the student and do not necessarily reflect the opinions of the thesis supervisor, second reader, the faculty or Lakehead University.

ABSTRACT

Kelly, W.P. J. 2024. Evaluating The Application Of LiDAR To Measure Wildland Fire Depth Of Burn In The Canadian Boreal Forest. [47] pp.

This study evaluates the accuracy of Light Detection and Ranging (LiDAR) technology in measuring the depth of burn (DoB) resulting from wildland fires in the Canadian boreal forest. An analysis of the correlation between LiDAR and ground truth DoB measurements was conducted to determine the accuracy of the LiDAR measurements. Initial results revealed errors within the spatial alignment of the pre- and post-burn LiDAR data. Adjustments for spatial discrepancies using an offset approach were implemented; however, a poor correlation between measurements persisted. These findings indicate LiDAR is not an effective method for measuring the DoB in complex landscapes such as the boreal forest.

Despite these findings, the study strongly advocates for the continuation of research in this area to increase confidence in these results. Recommendations for future research include increasing the number and diversity of sampling locations and refining ground sampling and LiDAR data processing techniques to enhance measurement accuracy in complex forest landscapes.

Keywords: boreal, Canada, depth of burn, digital terrain model, fire management, forest fire, ground truthing, LiDAR, North America, remote sensing, wildland fire

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to the individuals who played critical roles in the completion of this research. Their unwavering support and encouragement pushed me to explore a topic that was outside of my comfort zone, ultimately leading to the development of many new skills. I am honored to have had the opportunity to learn from you, and I will carry your guidance with me as I navigate future challenges and opportunities.

Thank you to the following individuals:

Dr. Jian Wang, Professor, Lakehead University

Dr. Mark de Jong, Forest Fire Research Scientist, CFS

CONTENTS

TABLES

FIGURES

INTRODUCTION

The Canadian boreal forest spans approximately 552 million hectares (ha), constituting 55% of Canada's total land mass (NRCan 2024; Roi 2018). This forest region exerts significant influences on the social, economic, and environmental well-being of all Canadians. Environmentally, the boreal forest serves numerous functions, including air and water purification, carbon sequestration, climate regulation, and the provision of habitat to a diverse variety of wildlife species (Roi 2018). The tree species composition of the boreal forest varies considerably due to environmental conditions. The forest region is predominantly coniferous, consisting of species such as black spruce, jack pine, and balsam fir (Stanton & Bourchier 2015). Mixed wood and pure hardwood stands do occur within the boreal forest, including species such as white birch, trembling aspen, and balsam poplar (Stanton & Bourchier 2015). Throughout history, the flora and fauna species that comprise the boreal forest have adapted to periodic disturbance, given the frequent fire cycle within the ecosystem.

Fire plays an important role in the regeneration, succession, nutrient cycling, and species diversity of the boreal forest (Weber & Flannigan 1997). Since 1990, on average, wildfires have burned approximately 2.3 million ha of forest each year within Canada (NRCan 2020). Understanding the pivotal role of fire in maintaining the health of the boreal forest is crucial, as it should be viewed as beneficial from an ecological perspective. However, socially, forest fires can have numerous negative impacts. When a forest fire occurs near a community, it can lead to evacuations and property loss (Kulig et al. 2013). Additionally, forest fires can significantly impact the mental and physical health of affected individuals (Kulig et al. 2013). Due to these social impacts, the public, as well as governing bodies within Canada are growing extremely concerned about the increase in fire intensity, severity and frequency being observed (EPA 2024; NRCan 2022).

In Canada, the escalation can primarily be attributed to climate change and historical fire suppression, leading to the accumulation of extreme fuel loads (NRCan 2022). In 2023, Canada experienced its most destructive fire season recorded, resulting in the burning of 16.5 million hectares of land, which is 14 million hectares greater than the annual average (NRCan 2023a). With a substantial body of research consistently concluding that climate change will increase the intensity, severity, and frequency of forest fires, both federal and provincial governments are investing significantly in new technology to assist in the study of wildland fires (Ontario 2023; NRCan 2023b).

The primary objective of this study is to assess the accuracy of Light Detection and Ranging (LiDAR) technology in measuring depth of burn (DoB) within the Canadian boreal forest. LiDAR is a remote sensing method that utilizes high-frequency laser pulses to measure distances from a device to the Earth (Wandinger 2005). Today, LiDAR equipment is commonly attached to a variety of aircraft, including fixed-winged planes and drones to allow for aerial sampling over large areas. The data recorded from the pulses of light can be used to generate precise three-dimensional information about the surface of the Earth. Within forestry, LiDAR is growing in popularity. Many industry professionals believe it many become one of the most important methods for collecting forest resource management data (Carson et al. 2004). A multi-step process will be employed to answer this complex question. It will include analyzing pre- and post-fire LiDAR data to obtain DoB measurements. Field validation will then be incorporated in the results by ground-truthing the LiDAR DoB measurements. The correlation between the LiDAR and ground truth DoB values will indicate the accuracy of the LiDAR sampling method.

LITERATURE REVIEW

LiDAR TECHNOLOGY

Light Detection and Ranging (LiDAR) is a remote sensing method that utilizes high-frequency laser pulses to generate three-dimensional point clouds (Wandinger 2005). Each point in the cloud represents a single distance measurement calculated by the LiDAR system. The fundamental operation of a LiDAR sensor involves a transmitter, which projects a brief pulse of light, typically lasting only a fraction of a microsecond (Wandinger 2005). The system then measures the time it takes for the pulse of light to travel to an object, reflect off it, and return to the receiver (Wandinger 2005). The rate at which LiDAR can collect points varies greatly, ranging from tens of thousands to millions per second (Harrap & Lato 2010). The large quantity of points recorded are then compiled into a point cloud (Harrap & Lato 2010). The most common storage methods for LiDAR data are LAS and LAZ files (Béjar-Martos et al. 2022). The sampling method for LiDAR data collection varies based on the intended purpose of the data collection and the LiDAR system being implanted. It can be collected aerially, utilizing aircraft or drones, or ground-based, utilizing vehicles or stationary tripods (Harrap & Lato 2010).

AIRBORNE LIDAR DATA AND DIGITAL TERRAIN MODELING

Airborne LiDAR has revolutionized terrain mapping and three-dimensional modeling across many fields (Polat & Uysal 2015). Mounting LiDAR systems on aircraft allows for rapid sampling of large areas, resulting in significant time and cost savings compared to traditional methods (Höfle & Rutzinger 2011). For this reason, airborne LiDAR has become a widely used method for the collection of topographic data (Drosos & Farmakis 2006).

Digital terrain models (DTMs) are one of the primary applications for LiDAR data (Drosos & Farmakis 2006). A DTM is a representation of Earth's surface that is generated form LiDAR data (Polat & Uysal 2015). The creation of a DTM involves filtering and excluding non-ground points from the dataset, then interpolating the point cloud into a raster. Due to the large quantity of points within LiDAR datasets, various software have created algorithms that will filter the data, automating the process. DTM accuracy is influenced by various factors, including natural conditions as well as data processing procedures. Natural conditions that can negatively affect DTM accuracy include high surface variability, vegetation type, and the slope of the terrain (Hyyppä et al. 2005; Polat & Uysal 2015; Sterenczak et al. 2013). During data processing, the selection of algorithms for filtering and interpolation, along with the chosen grid size, have been identified as crucial factors affecting the accuracy of a DTM (Šiljeg et al. 2019; Sterenczak et al. 2013)

MEASURING DOB USING LIDAR

The literature on measuring DoB using LiDAR technology is quite limited. The application of LiDAR to measure DoB has been studied in peatland bogs. Specifically, Simpson et al. (2016), utilized LiDAR data to create pre- and post-burn DTMs in peatland environments to measure DoB. Their study demonstrated that LiDAR technology was able to accurately measure DoB, achieving results within 7-15 cm of ground truth values. Additionally, a minimum accuracy of 10 cm was achieved by Chasmer et al. (2017) during a similar study assessing depth of peat loss due to wildfires.

Accuracy values within this range are quite impressive, however, peatland environments have a significant lack of vegetation, especially tree species. As previously mentioned, complex landscapes significantly affect the accuracy of DTMs; however, Căţeanu & Ciubotaru, (2021) was able to prove accurate DTMs can be generated in complex forest landscapes.

While existing studies have explored the application of LiDAR in measuring the DoB within peat-land environments, the current literature suggests a gap in knowledge pertaining to the accuracy of DoB measurements in complex landscapes with high levels of surface variation. This gap highlights the necessity to continuously study the various applications and limitations of LiDAR.

METHODS

STUDY SETTING

The primary objective of this study is to assess the accuracy of LiDAR in measuring DoB within the Canadian boreal forest. To achieve this objective, ground-truthing was conducted by field researchers from the Canadian Forest Service (CFS) to evaluate the LiDAR-derived DoB measurements. This involved pre- and post-burn data collection on the ground and from the air, using a drone with an attached LiDAR system.

The research site chosen for this study is situated within Wabakimi Provincial Park in Ontario, Canada. There were multiple reasons this site was chosen. During the summer of 2023, a forest fire named SLK 033 started on June 12th. SLK 033 was classified as 'out of control' from June 12th to August 14th, after which its classification was changed to 'being held'. The classification of the fire changed from ‘being held’ to ‘under control’ on August 25th. Over this time, SLK 033 grew to 62, 378 hectares (ha). The research site was located within the fire perimeter in a 'green patch' unaffected by the initial fire. This ensured the experimental burn conducted for this research would not breach containment, as it was surrounded by an environment where the majority of fuels had already been consumed. However, during site selection, careful consideration was given to ensure that the chosen green patch was not a lowland area unaffected by the fire due to high moisture levels, but rather an area spared from the fire purely by chance. This was crucial to ensure that the site broadly represented the environmental conditions of the area naturally burned in SLK 033. Other factors that influenced the selection of this site were stand age and species composition. The mature stand exhibited characteristics typical of forests in the old-growth successional stage, as seen in Figure

1. This is advantageous because the irregular canopy gaps, commonly found in stands at this stage, will aid in the creation of accurate digital terrain models (DTMs). Additionally, the tree species composition at this site was representative of the boreal forest. It was conifer dominate and included tree species most commonly associated with the forest region. All trees with a height greater than 1.3 meters within the triangular plot were sampled. The resulting species composition was 84% black spruce (*Picea mariana*), 9% jack pine (*Pinus banksiana*), and 7% white birch (*Betula papyrifera*).

Figure 1. Image taken by a research team member to capture site characteristics from the ground.

DATA COLLECTION

The field sampling occurred in August 2024. Initially, sampling plots were established for the measurement of DoB, as seen in Figure 2. We opted for a triangular plot, following the methodology outlined in McRae et al. (1979). This method involved marking the vertices of an equilateral triangle with a side length of 30 meters by inserting three rebar stakes into the ground. After marking the vertices, we positioned DoB pins at 5-meter intervals, placing them 1 meter outside the triangle and 0.5 meters to the left. There were 5 DoB pins placed on each side of the triangle, totaling 15 DoB pins associated with this sampling method. Due to logistical limitations within the project, such as time and resource constraints, the team was unable to set up multiple triangular plots. To gather more information, three 30 m transects were established. This sampling method was chosen to gain additional information because it took significantly less time to set up. DoB pins were placed at 5 m intervals along the transects. There were 6 DoB pins placed on each transect, totaling 18 DoB pins associated with this sampling method. The location of all DoB pins and other relevant features were recorded using a differential GPS system.

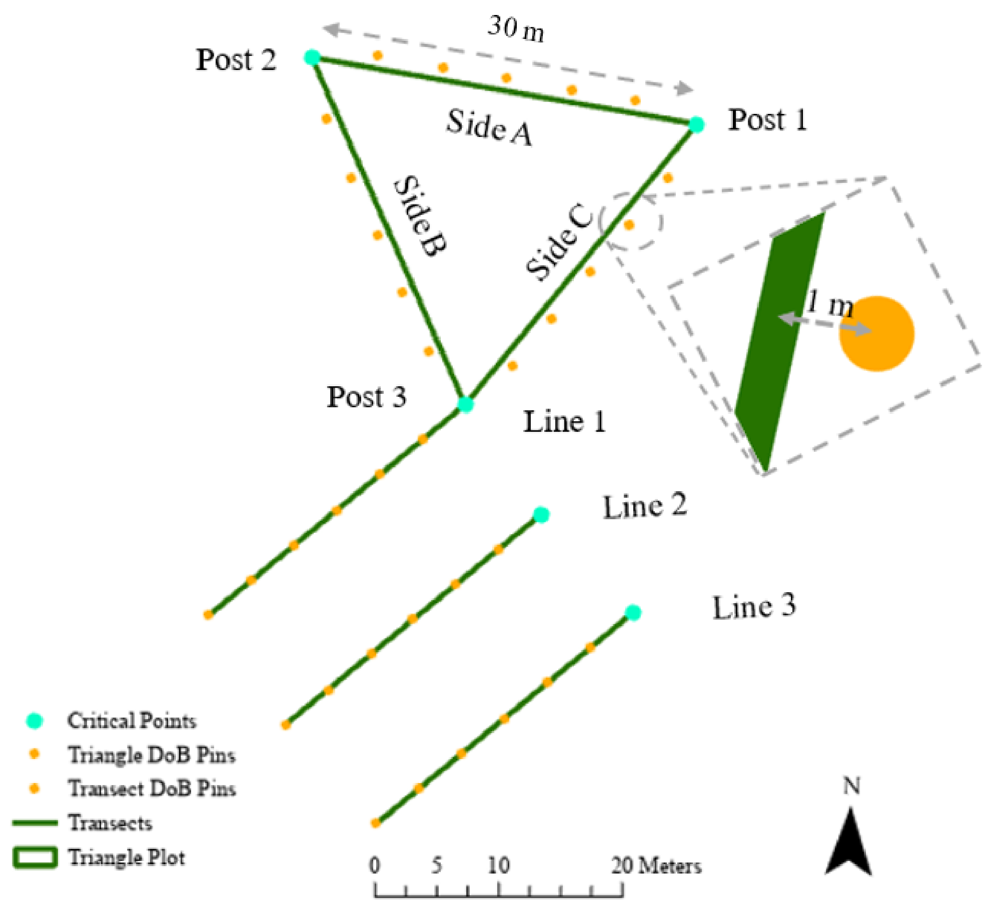

Figure 2. Sampling diagram, showing the triangular plot, transect lines, and DoB pin locations.

To obtain the "ground" DoB values, steel pins were inserted into the ground at the previously specified locations, and a baseline value was recorded. Following the experimental burn, shown in Figure 3, another measurement was taken on the DoB pin. The difference between these two values represented the depth to which the fire burned.

Figure 3. Image taken by a research team showing experimental burn blazing through the study site.

The LiDAR data was collected using a specialized DJI Matrice RTK drone equipped with a compact Zenmuse L1 LiDAR sensor. The drone was flown at an altitude of 60 meters above the ground, with the LiDAR sensor set to dual return mode, achieving a 240 kHz sampling rate. Additionally, it followed a pre-planned, systematic flight path, ensuring comprehensive coverage of the sampling area with 90% front and side overlap. Another drone, equipped with a RGB camera, followed a similar systematic flight path to capture aerial photos encompassing the entire sampling area. The data obtained from the differential GPS system was recorded on the ground to serve as points of reference during the LiDAR data analysis. GPS coordinates were recorded at posts 1 to 3 and at the location of each DoB pin along the three transect lines. Additionally, GPS data was collected along the path where the experimental burn ignition occurred. Following the experimental burn, the drone with the LiDAR sensor and the drone with the RGB camera were flown over the sampling area to obtain post-burn LiDAR data and aerial imagery.

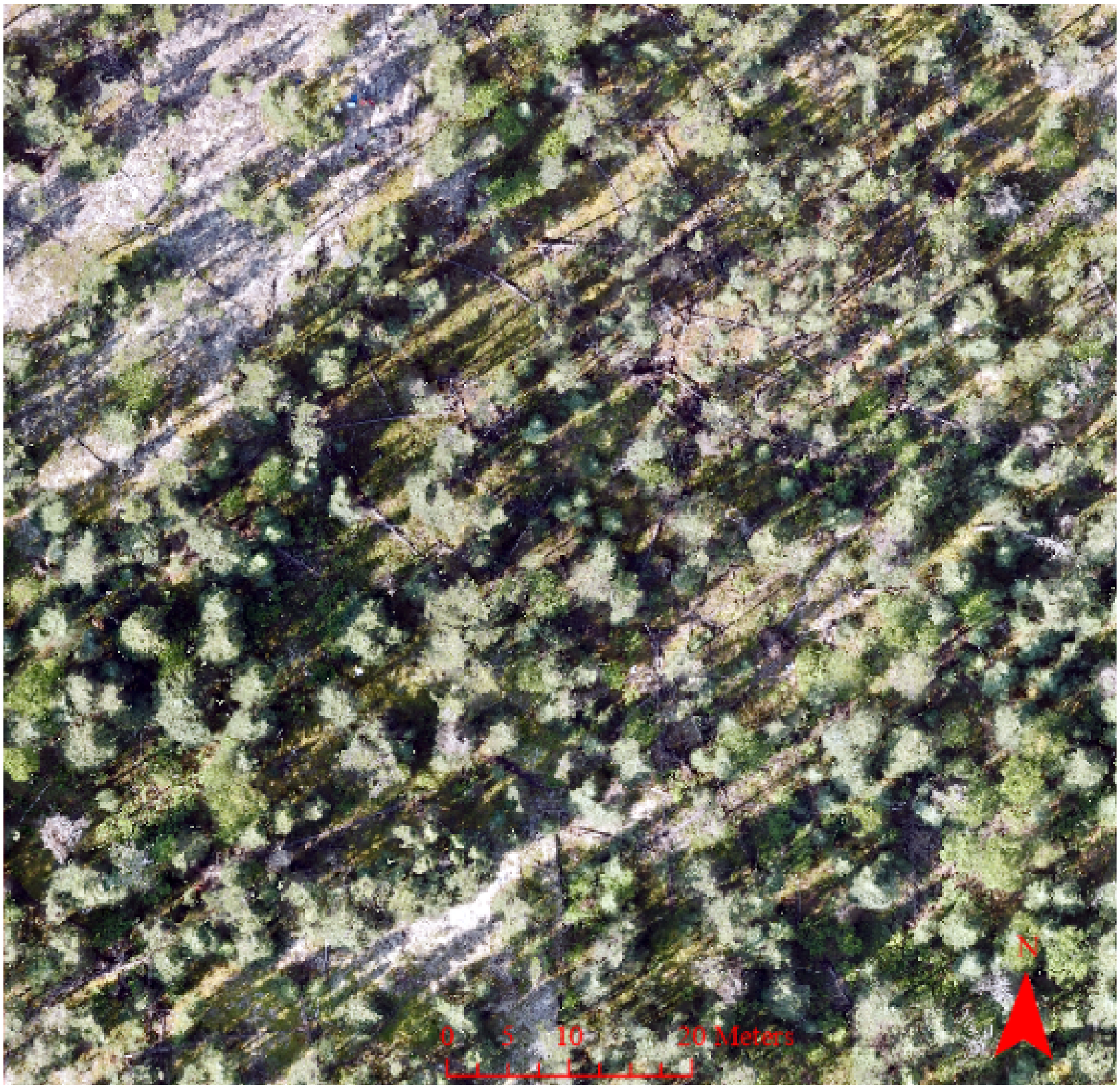

Figure 4. RGB aerial imagery of the study site before the fire, captured by a research team member.

Figure 5. RGB aerial imagery of the study site after the fire, captured by a research team member.

LIDAR DATA ANALYSIS

Upon the completion of field sampling, the pre- and post-burn LAS files were analyzed using ArcGIS Pro, Version 3.1.2 (Esri 2023). Firstly, the “Create LAS Dataset” tool was utilized to create a LAS dataset for the pre- and post-burn LAS files. The primary reason for this step was to compute statistics on the LAS files that would be utilized in later data analysis. Following this step, the ground points were classified. This was accomplished using the “Classify LAS Ground” tool. Within the tool, the “Standard Classification” ground detection method was implemented. Next, digital terrain models (DTMs) were generated for each dataset using the pre- and post-burn LAS datasets. These two DTMs allowed for the comparison of elevation values before and after the experimental burn.

To analyze the two DTMs, the “Minus” tool was used to subtract the post-burn elevation values from the pre-burn elevation values. The resulting ‘elevation change’ raster, represents how the experimental burn affected the elevation values of the two DTMs, thus indicating the DoB. The values from the elevation change raster at the location of each triangular and transect DoB pin were then extracted and compared to the ground truth DoB values.

Additionally, a second set of LiDAR DoB values with a 1.45 meter offset were generated. The offset value of 1.45 m was determined by sampling 9 constant locations within both DTMs, as illustrated in Figure 6. This value represents the average difference in elevation at these "constant" points. In this context, a constant point is defined as a location where there should be no elevation change between pre- and post-burn data due to being unaffected by the fire. Examples include rock faces and sections of the forest floor that remained unburned. The “offset” approach was taken to remediate an error that was occurring within the vertical alignment of the pre- and post-burn DTMs. To generate the DoB values with a 1.45m offset, the “Minus” tool was utilized to subtract 1.45m from the post-burn DTM elevation values. Subsequently, the “Minus” tool was once again utilized to subtract the post-burn DTM with a 1.45m offset from the pre-burn DTM. This produced the ‘1.45 m offset elevation change’ raster.

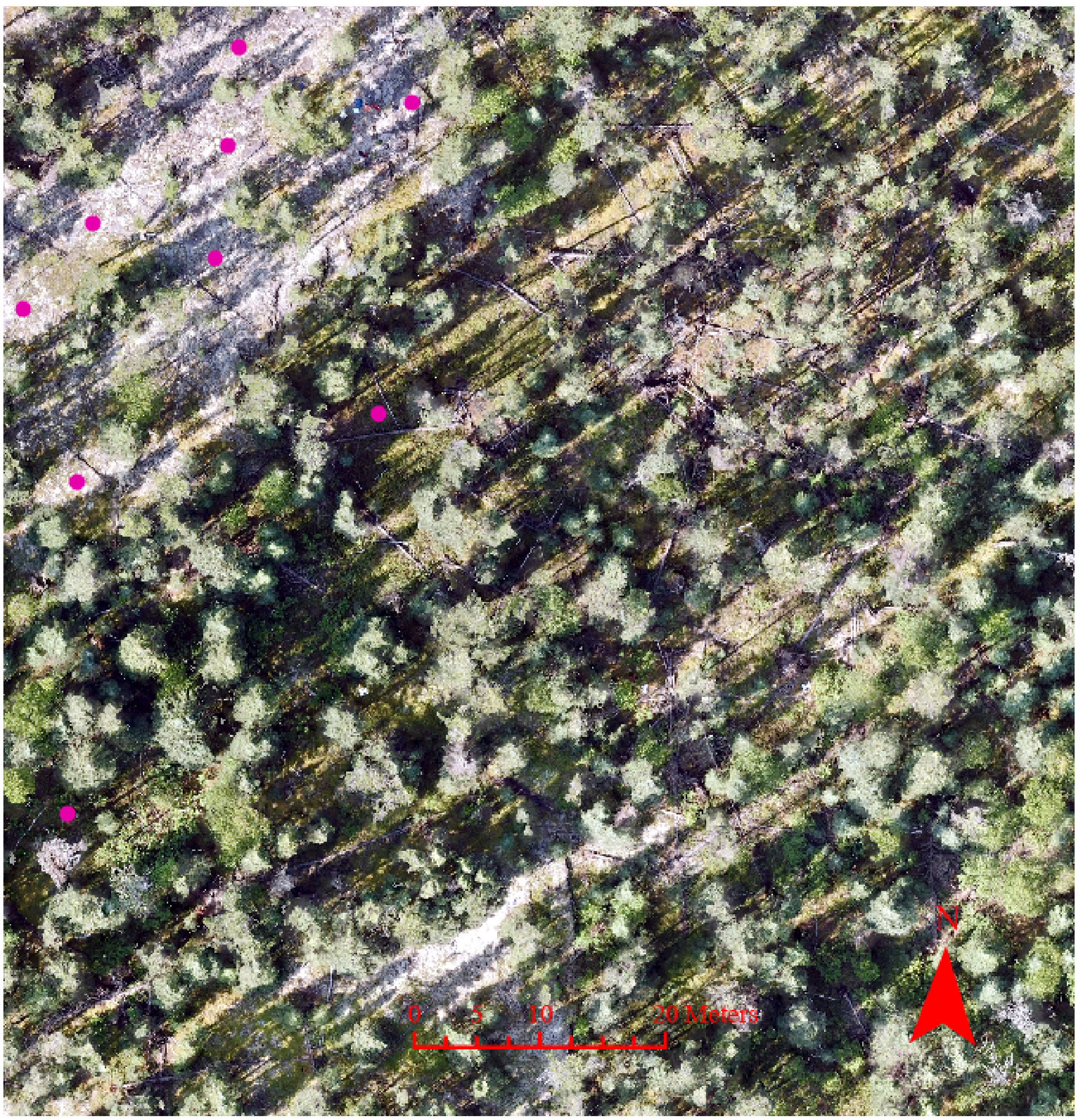

Figure 6. Sampling locations of the 9 constant points, represented in pink circles.

RESULTS

GROUND DOB VALUES

The DoB values obtained through the ground sampling method are presented in Tables 1 and 2, with Table 1 displaying values for the triangular plot and Table 2 for the three transect lines. Within the triangular plot, the DoB ranged from 0 cm to 12.5 cm, with a mean of 2.90 cm. In the three transects, the DoB ranged from 0 cm to 18 cm, with a mean of 6.61 cm. During the sampling process, some DoB pins fell over as the organic material supporting them was consumed by the fire. Consequently, no DoB value could be recorded for these pins, and they were assigned an "N/A" value. A total of 8 DoB pins fell over, 4 from the triangular plot and 4 from the transect lines.

Table 1. Ground DoB Values, Triangular Plot

Pin Number	Location	Distance (m)	DoB (cm)
1	Side A	5	0
2	Side A	10	7.55
3	Side A	15	N/A
4	Side A	20	0.9
5	Side A	25	1.05
6	Side B	5	0
7	Side B	10	1.45
8	Side B	15	N/A
9	Side B	20	5.6
10	Side B	25	0
11	Side C	5	0.5
12	Side C	10	1.9
13	Side C	15	N/A
14	Side C	20	N/A
15	Side C	25	12.5

Table 2. Ground DoB Values, Transect Lines

Pin Number	Location	Distance (m)	DoB (cm)
1	Line 1	5	18
2	Line 1	10	N/A
3	Line 1	15	0.8
4	Line 1	20	7.15
5	Line 1	25	1.9
6	Line 1	30	0
7	Line 2	5	0.3
8	Line 2	10	1.6
9	Line 2	15	18
10	Line 2	20	8
11	Line 2	25	2
12	Line 2	30	N/A
13	Line 3	5	1.7
14	Line 3	10	N/A
15	Line 3	15	14
16	Line 3	20	18
17	Line 3	25	1.25
18	Line 3	30	N/A

LIDAR RASTERS

Five critical rasters were generated as part of the LiDAR data analysis process. Figures 7 to 11 display the following: the pre-burn DTM, post-burn DTM, post-burn DTM with a -1.45 offset, elevation change raster and 1.45 m offset elevation change raster. Elevation values derived from these rasters were utilized to calculate the offset value and the LiDAR DoB measurements. The rasters are displayed using a greyscale ranging from black to white, where black represents the minimum elevation value and white represents the maximum elevation value. All values within this range will appear in various shades of grey, depending on their proximity to the minimum and maximum values.

Figure 7 displays the elevation values within the pre-burn DTM. The values ranged from 335.12 to 343.36 m, with a mean elevation value of 339.44 m.

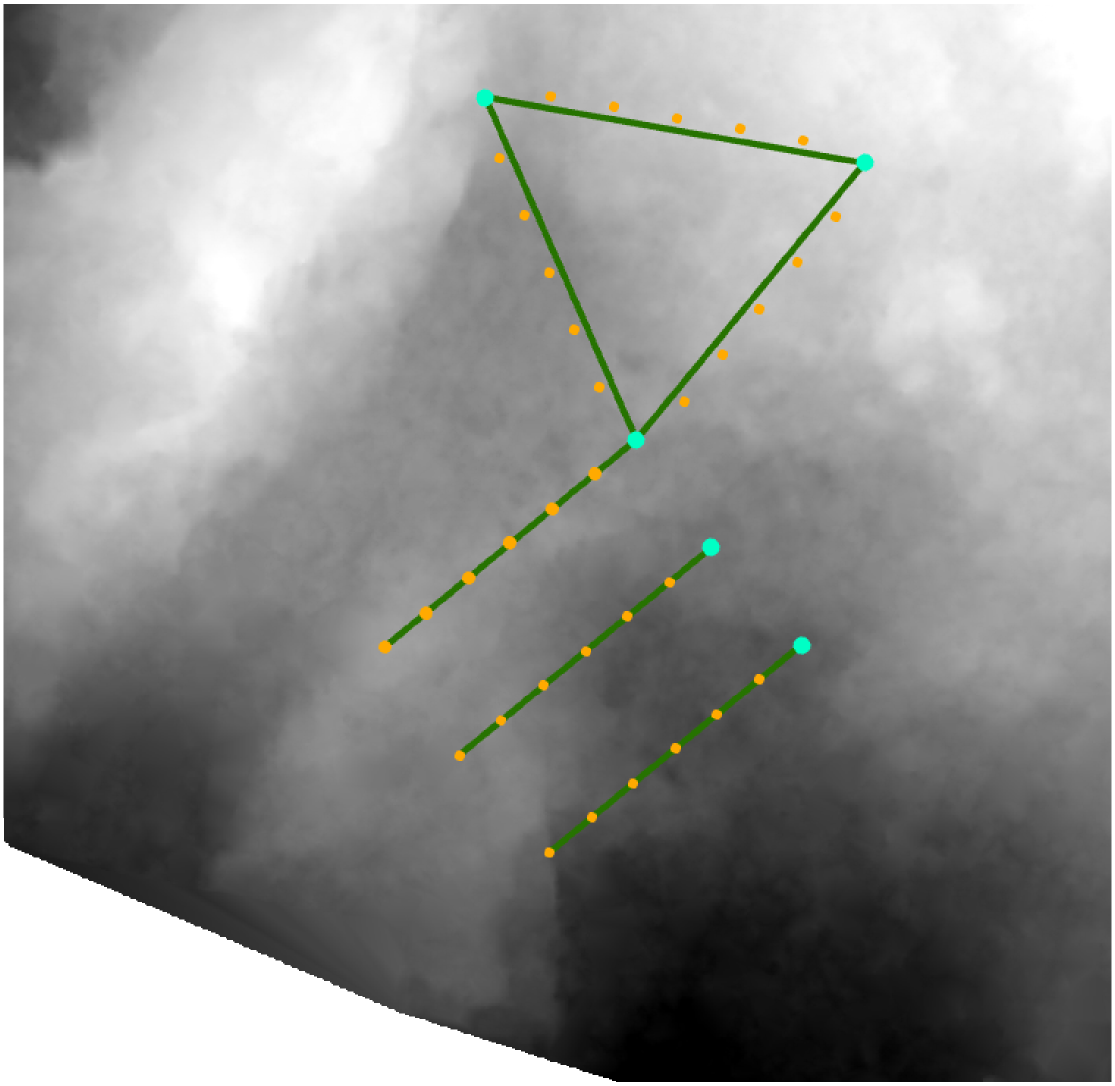

Figure 7. Pre-burn DTM.

Figure 8 displays the elevation values within the post-burn DTM. The values ranged from 336.62 to 344.6 m, with a mean elevation value of 340.89 m.

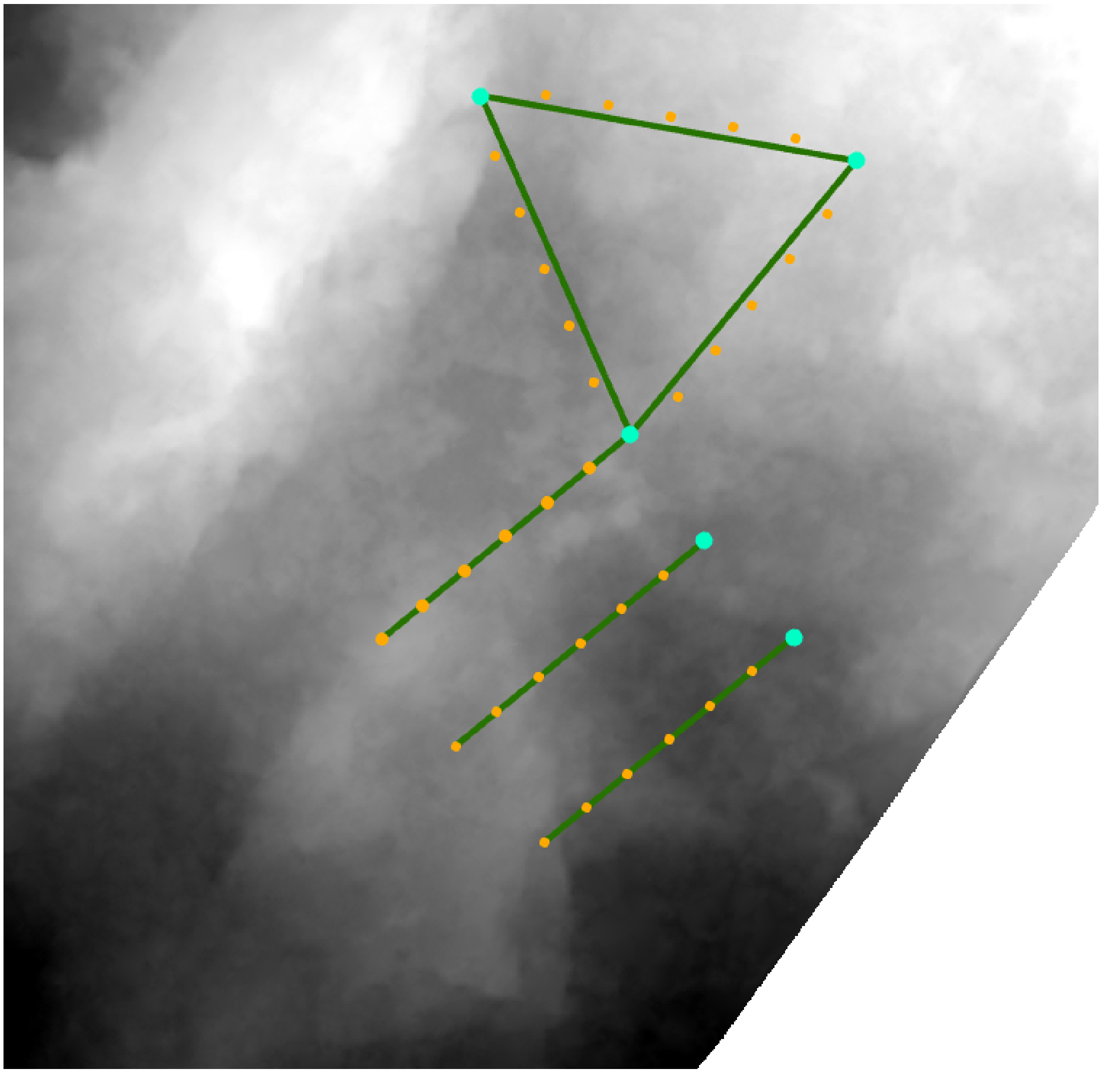

Figure 8. Post-burn DTM.

Figure 9 displays the elevation values within the post-burn DTM with a -1.45 m offset. The values ranged from 335.17 to 343.15 m, with a mean elevation value of 339.44 m.

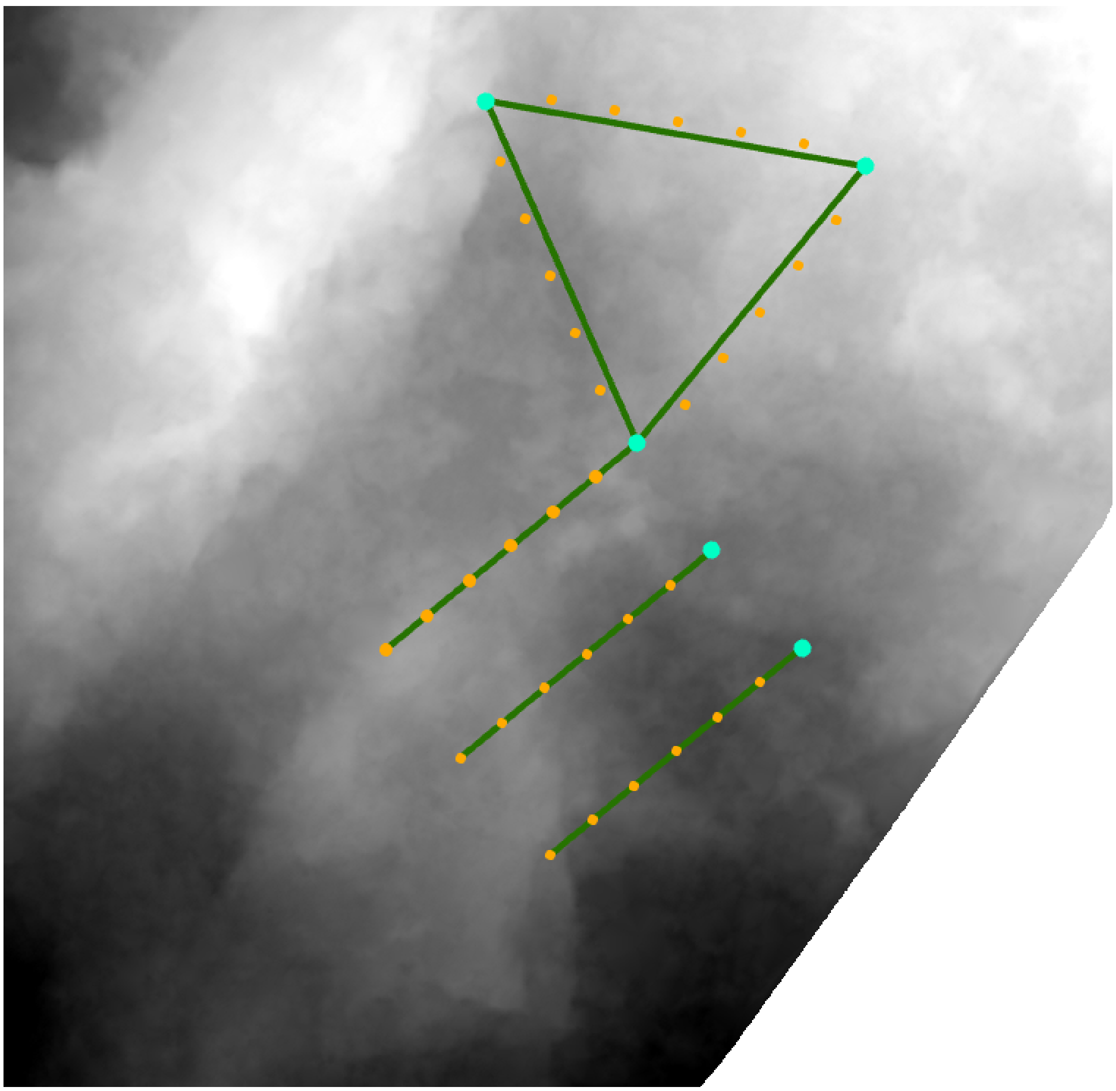

Figure 9. Post-burn DTM with -1.45 m offset.

Figure 10 displays the elevation values within elevation change raster. The values ranged from -2.74 to 0.27 m, with a mean elevation value of -1.43 m.

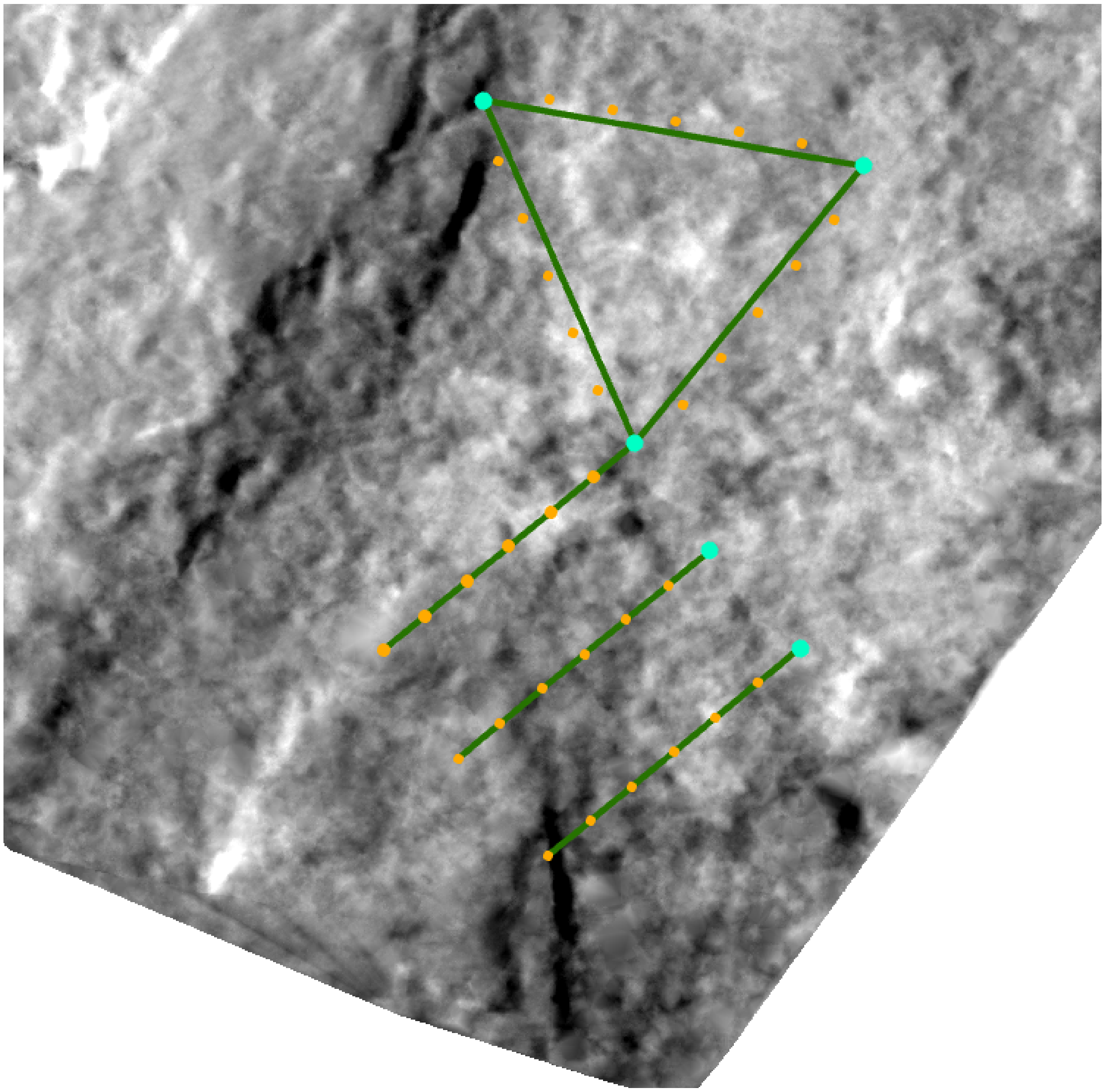

Figure 10. Elevation change raster.

Figure 11 displays the elevation values within offset elevation change raster. The values ranged from -1.74 to 1.27 m, with a mean elevation value of 0.43 m.

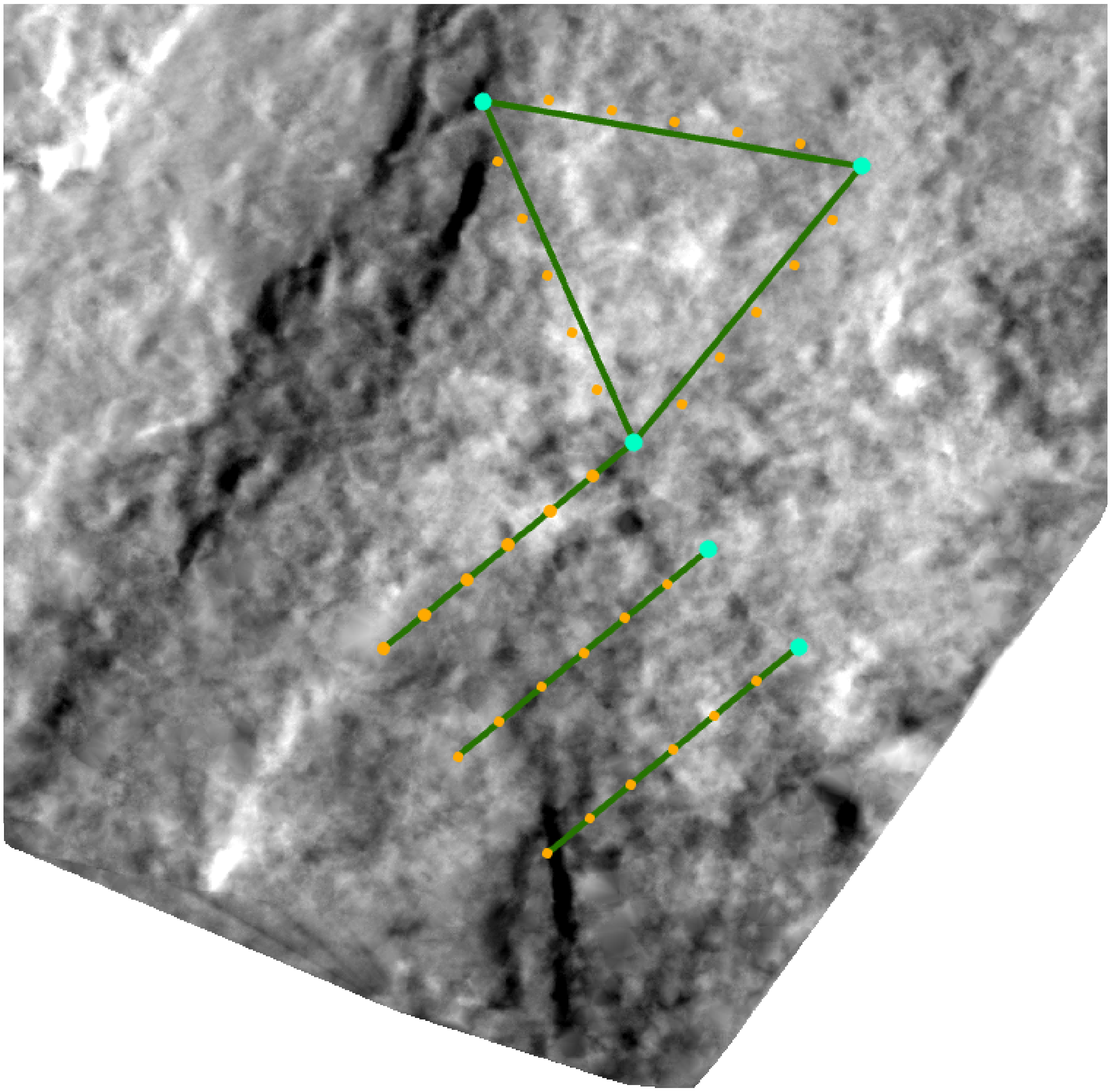

Figure 11. Offset elevation change raster.

OFFSET VALUE

The difference between pre- and post-burn elevation values, at the 9 constant locations, are presented in Table 3. The largest difference between the two DTMs was 1.92 m and the mean difference across the 9 locations is equal to 1.45 m.

Table 3. Difference Between Pre- and Post-Burn DTMs.

Location	Pre-burn Elevation (m)	Post-burn Elevation (m)	Differnce (m)
1	342.59	343.83	-1.24
2	341.02	342.30	-1.28
3	336.75	338.26	-1.51
4	339.51	341.43	-1.92
5	341.95	343.27	-1.32
6	340.97	342.35	-1.38
7	340.09	341.37	-1.27
8	341.55	342.93	-1.38
9	342.24	343.97	-1.73

LIDAR DOB VALUES

The DoB values obtained through the LiDAR sampling method are presented in Tables 4 and 5. Table 4 displays values for the triangular plot, while Table 5 presents values for the three transect lines. Both tables include DoB values derived from the elevation change raster and the 1.45 m offset elevation change raster. In the triangular plot, the 'no offset' DoB values range from -148.6 cm to -90 cm, with a mean of -128.4 cm. The '1.45 m offset' DoB values range from -12.2 cm to 38.5 cm, with a mean of 14.8 cm. For the three transect lines, the 'no offset' DoB values range from -213.8 cm to -104.9 cm, with a mean of -147.3 cm. The '1.45 m offset' DoB values range from -66.6 cm to 39.4 cm, with a mean of -2.4 cm.

Table 4. LiDAR DoB Values, Triangular Plot

Pin Number	Location	Distance (m)	DoB (cm)	
			No Offset	1.45 m Offset
1	Side A	5	-143.44	-10.04
2	Side A	10	-126.35	21.57
3	Side A	15	-145.11	4.96
4	Side A	20	-112.03	26.10
5	Side A	25	-113.72	25.16
6	Side B	5	-145.99	-12.21
7	Side B	10	-145.35	9.87
8	Side B	15	-123.97	9.69
9	Side B	20	-89.99	37.68
10	Side B	25	-120.33	38.50
11	Side C	5	-148.57	24.02
12	Side C	10	-122.49	11.63
13	Side C	15	-120.84	18.39
14	Side C	20	-129.59	4.67
15	Side C	25	-138.73	11.91

Table 5. LiDAR DoB Values, Transect Lines

Pin Number	Location	Distance (m)	DoB (cm)	
			No Offset	1.45 m Offset
1	Line 1	5	-140.55	4.40
2	Line 1	10	-104.87	39.35
3	Line 1	15	-131.17	14.71
4	Line 1	20	-143.24	1.51
5	Line 1	25	-141.32	3.50
6	Line 1	30	-137.94	6.53
7	Line 2	5	-146.06	-0.13
8	Line 2	10	-146.69	-2.46
9	Line 2	15	-166.23	-22.08
10	Line 2	20	-164.84	-20.15
11	Line 2	25	-141.42	3.82
12	Line 2	30	-149.82	-6.79
13	Line 3	5	-151.45	-6.71
14	Line 3	10	-136.72	9.43
15	Line 3	15	-140.05	4.46
16	Line 3	20	-138.15	6.41
17	Line 3	25	-213.82	-66.58
18	Line 3	30	-157.18	-12.58

COMPARISON OF LIDAR AND GROUND DOB VALUES

Figures 12 to 15 present a comparison of LiDAR and ground truth measurements using line charts, illustrating DoB trends along the sides of the triangular plot and transect lines. The LiDAR-derived values are represented in green, and the ground values are represented in reddish-brown. Any 'Pin Number' for which ground data was lost, as indicated by 'N/A' in Tables 1 and 2, has been omitted from the charts, as an accurate comparison cannot be made.

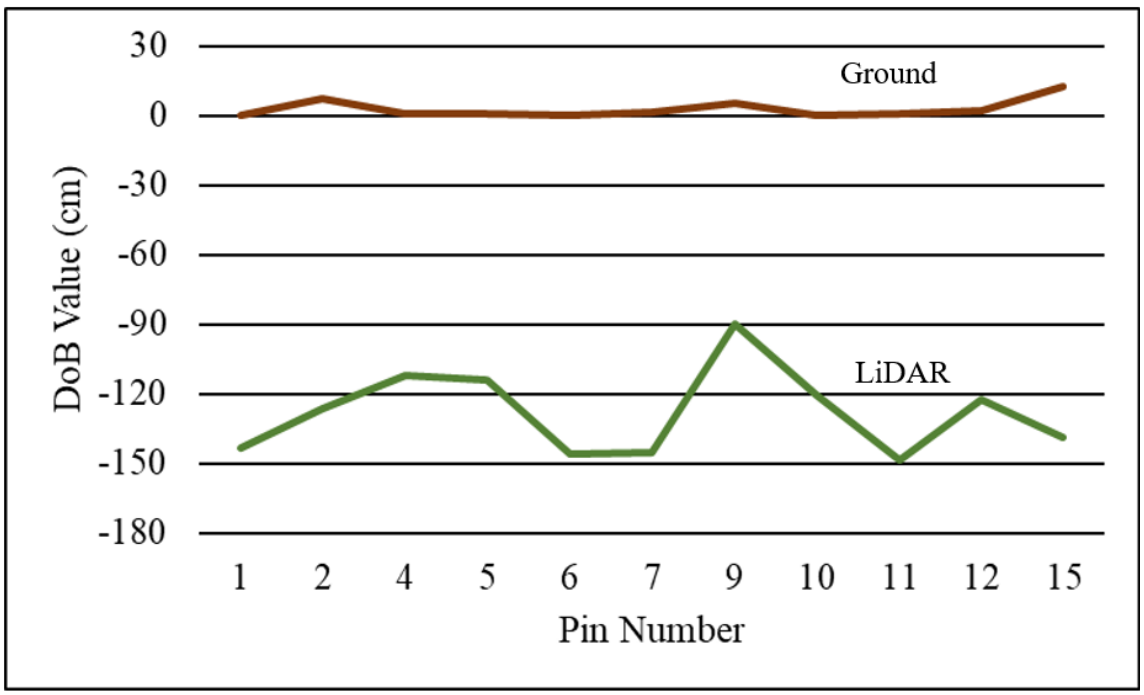

Figure 12. Comparison of triangular plot DoB values derived from the elevation change raster and ground truth measurements.

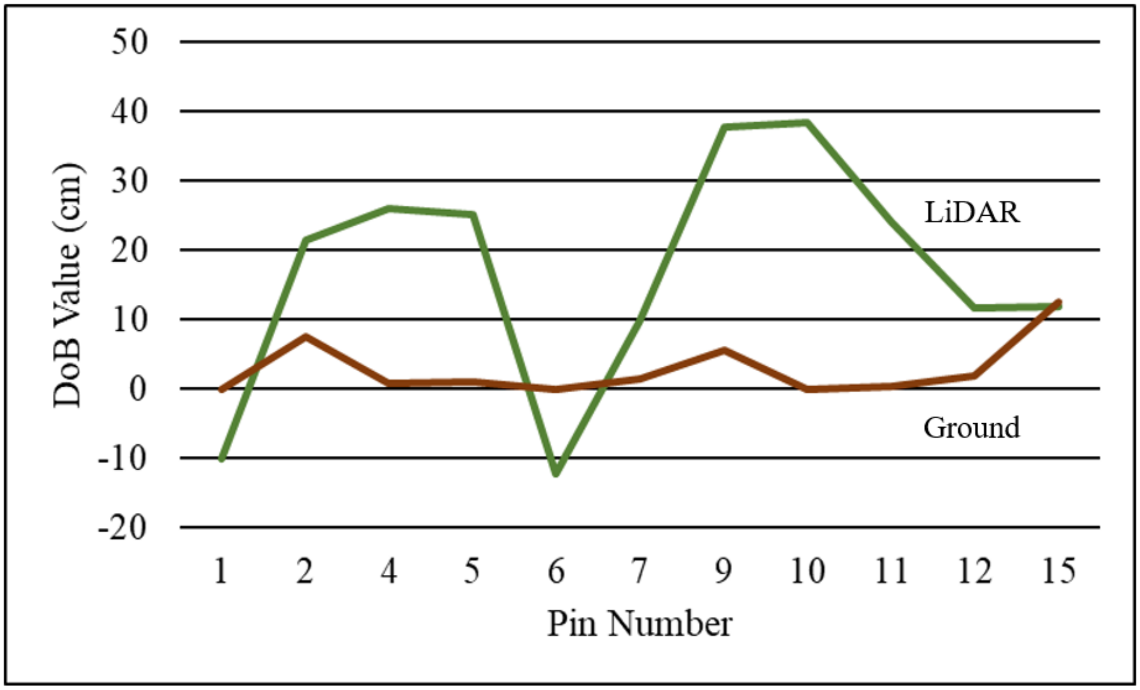

Figure 13. Comparison of triangular plot DoB values derived from the offset elevation change raster and ground truth measurements.

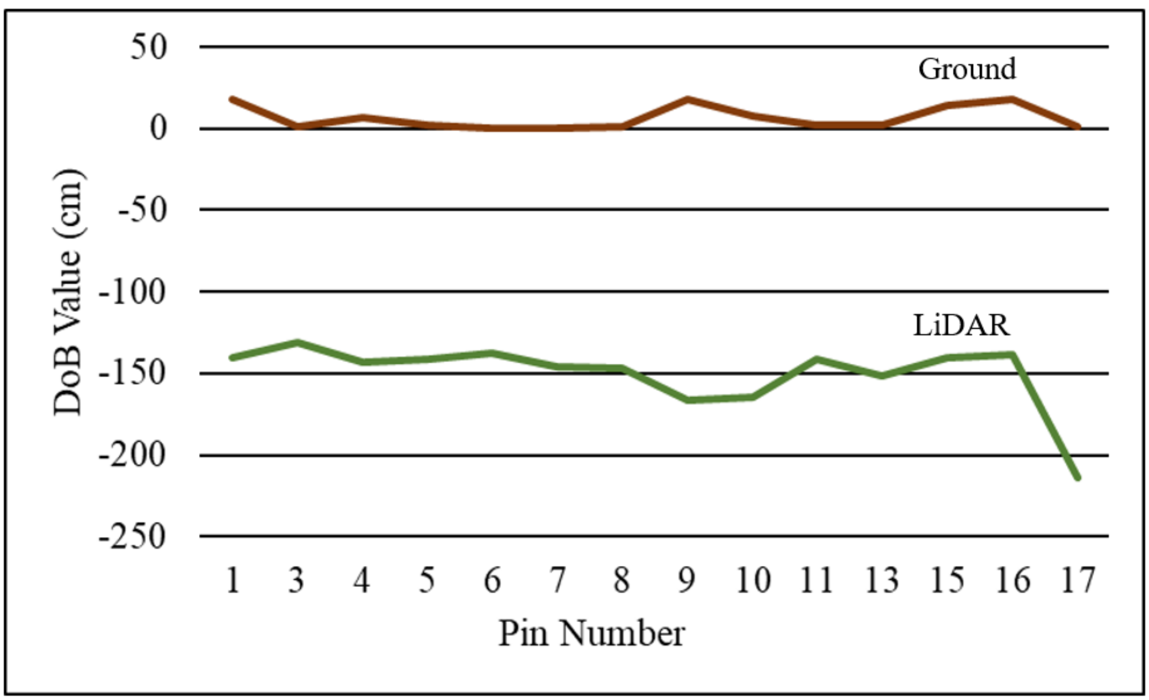

Figure 14. Comparison of transect DoB values derived from the elevation change raster and ground truth measurements.

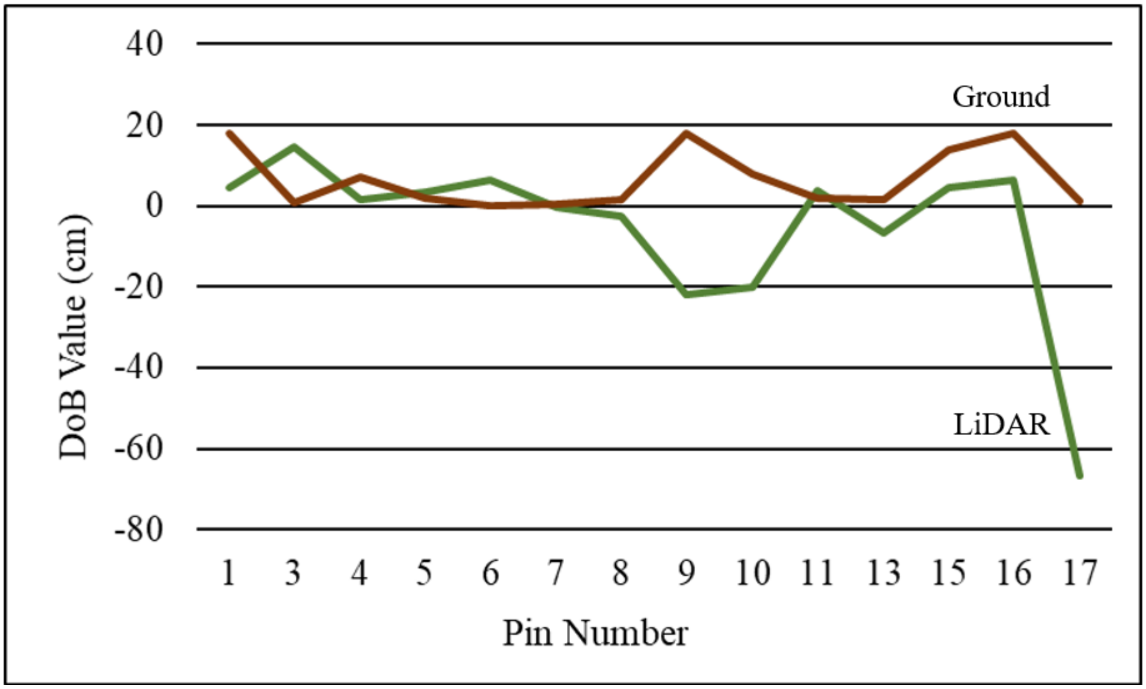

Figure 15. Comparison of transect DoB values derived from the offset elevation change raster and ground truth measurements.

CORRELATION BETWEEN DOB MEASUREMENTS

Figures 16 to 19 display the correlation between LiDAR and ground DoB values. The scatter plots generated show that the DoB values for the triangular plot with 'no offset' have an R^2 value of 0.0156. After applying the 1.45 m offset, the R^2 value slightly increases to 0.0196. Similarly, for the transect lines, the R^2 values are 0.0061 for the 'no offset' values and 0.0038 for the '1.45 m offset' values.

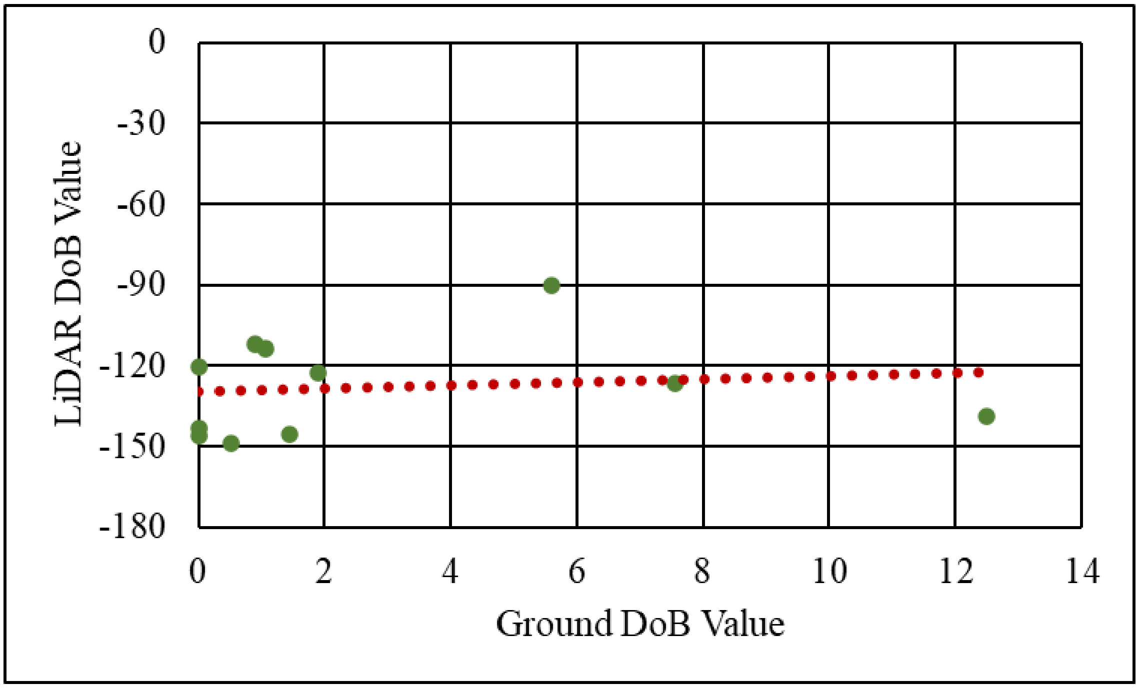

Figure 16. Correlation between triangular plot DoB values derived from the elevation change raster and ground truth measurements.

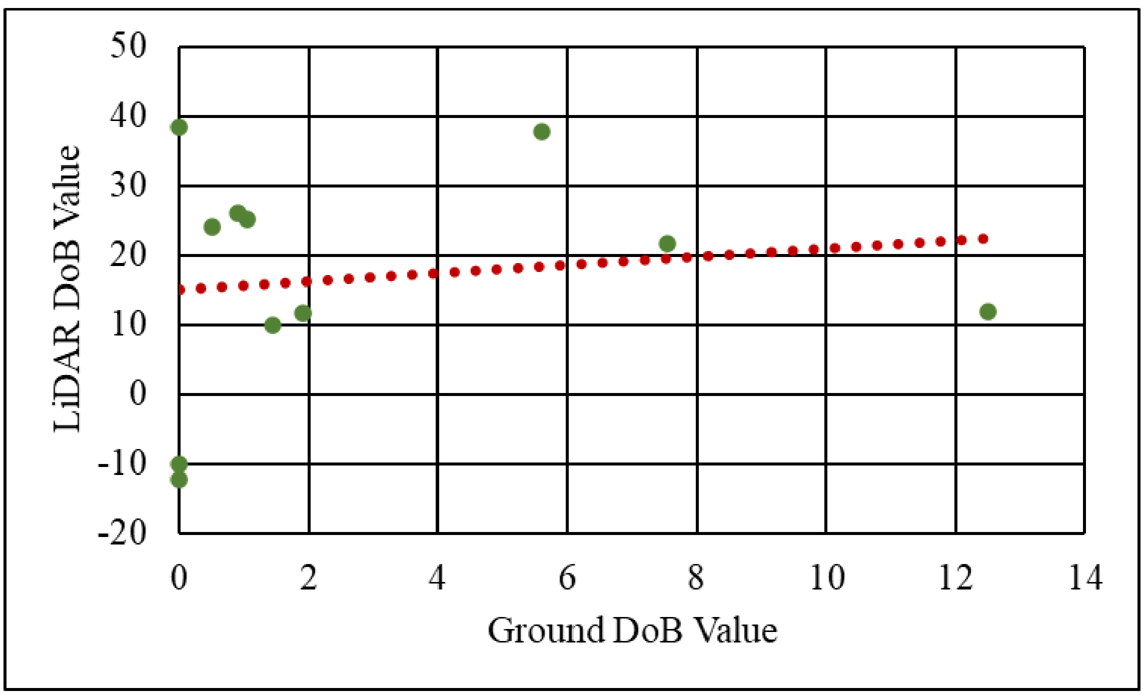

Figure 17. Correlation between triangular plot DoB values derived from the offset elevation change raster and ground truth measurements.

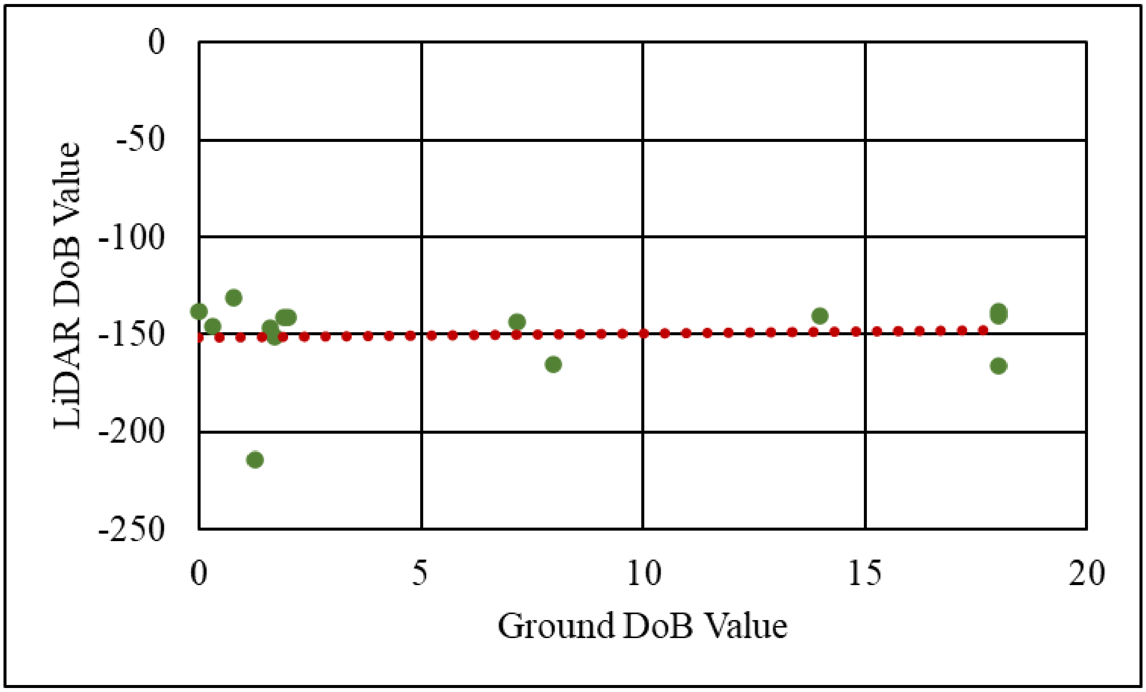

Figure 18. Correlation between transect DoB values derived from the elevation change raster and ground truth measurements.

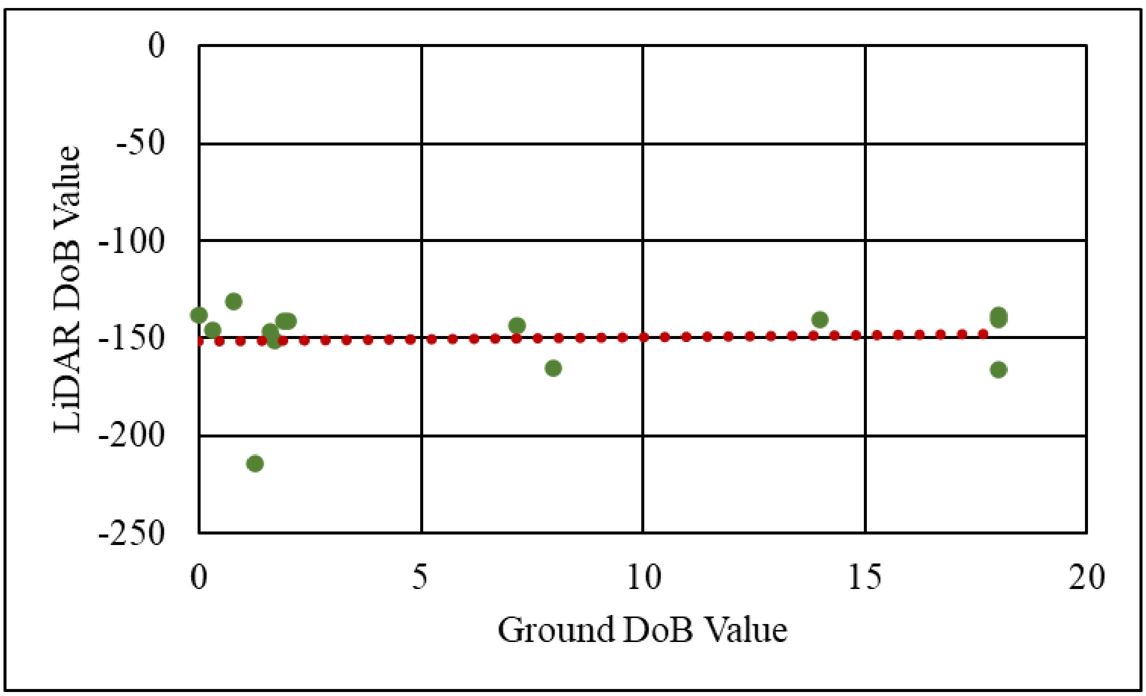

Figure 19. Correlation between transect DoB values derived from the offset elevation change raster and ground truth measurements.

DISCUSSION

The accuracy assessment conducted in this study indicates LiDAR is not effective for measuring DoB produced by forest fires in the Canadian boreal forest using the current methodology. This was indicated by the extremely low R^2 values representing the correlation between the LiDAR and ground truth measurements in Figures 16 to 19.

When comparing the pre- and post-burn DTMs, it became evident that there was an error in the spatial alignment of the two rasters, which likely had a significant influence on the accuracy of the LiDAR DoB measurements. According to the post-burn DTM, the majority of the study area increased in elevation after the fire. To address this issue, it was hypothesized that utilizing an offset based on 'constant' points within the study area may improve the spatial alignment of the two rasters, thereby enhancing the correlation between LiDAR and ground DoB measurements. However, despite the application of the offset, the correlation between the LiDAR and ground truth DoB measurements remained extremely weak.

Additionally, the trends observed between the LiDAR and ground truth DoB measurements in Figures 13 and 15 do not suggest any correlation between the two sampling methods. In Figure 13, the LiDAR values significantly over- or under-estimate the DoB. While in Figure 15, the LiDAR values do not appear to over- or under-estimate the DoB values as dramatically as in Figure 13, the data seems to exhibit an inverse relationship with the ground data. The primary cause for the poor correlation can likely be attributed to the underlying issues with the spatial alignment of the pre- and post-burn DTMs.

The primary limitations of this study included the small number of plots, loss of ground truth data, and issues with the spatial alignment of the pre- and post-burn DTMs. Unfortunately, due to temporal, resource, and weather constraints, the study could only include one triangular plot and three transect lines. To enhance the confidence in the results and their generalizability, it is recommended that the number of plots and the diversity of sampling locations be significantly increased. Furthermore, the loss of 8 DoB pins further reduced the available data for the accuracy assessment. To mitigate this issue in future studies, increasing the depth at which the pins are inserted into the ground is recommended to prevent data loss. Lastly, the difference in spatial alignment between the pre- and post-burn DTMs limited the validity of this study. Regardless of the effectiveness of the offset, it is recommended future studies refine the methodology used during LiDAR data collection as well as during the early stages of data processing.

Despite the negative results of this accuracy assessment, this study has the potential to contribute to the method development of measuring DoB using LiDAR in complex landscapes, such as the Canadian boreal forest. Addressing the limitations within this study in future research will enhance our understanding of the applicability of LiDAR in measuring DoB. It has been demonstrated that LiDAR is capable of accurately measuring DoB within peatland environments (Simpson et al., 2016), and research shows that LiDAR can create accurate DTMs in complex forest landscapes (Căţeanu & Ciubotaru, 2021). Given this evidence, the continuation of this research is crucial for overcoming the obstacles encountered in this study and achieving accurate DoB measurements using LiDAR.

Discovering an effective methodology that produces accurate DoB measurements using LiDAR could revolutionize DoB sampling, offering a cost-effective approach to traditionally challenging ground sampling techniques. This innovation could significantly increase our ability to estimate carbon emissions associated with wildland fires, as demonstrated by Ballhorn et al. (2009). Incorporating these carbon emission estimates into current climate change models would create a better understanding of the impact of wildland fires as well as the ramifications of increased fire intensity, severity, and frequency. Accurate LiDAR-derived DoB measurements could also significantly impact the study of fire behavior by providing a cost-effective sampling method, capable of rapidly sampling large areas. This would enable the collection of data on an unprecedented scale, with the potential to provide invaluable insights to fire research and fire management.

CONCLUSION

The purpose of this study was to evaluate the accuracy of LiDAR in measuring the depth of burn (DoB) within the Canadian boreal forest. The analysis revealed no significant correlation between LiDAR and ground truth DoB measurements. This suggesting that LiDAR may not be effective for this application in its current form. Further investigation is necessary to understand the specific conditions under which LiDAR can provide accurate measurements of DoB.

The primary limitations of this study include the limited number of plots, loss of ground pins, and issues with spatial alignment of pre- and post-burn DTMs. These limitations likely influenced the lack of correlation observed between LiDAR and ground truth measurements. Future studies should address these limitations by increasing the number and diversity of sampling locations, and refining ground sampling and LiDAR data processing techniques to enhance measurement accuracy in complex forest landscapes.

By addressing these limitations and exploring alternative approaches, future research holds the potential to uncover valuable insights into accurate methods for measuring DoB using LiDAR.

LITERATURE CITED

Ballhorn, U., Siegert, F., Mason, M., and Limin, S. 2009. Derivation of burn scar depths and estimation of carbon emissions with LIDAR in Indonesian peatlands. Proceedings of the National Academy of Sciences, 106(50), 21213-21218.

Béjar-Martos, J. A., Rueda-Ruiz, A. J., Ogayar-Anguita, C. J., Segura-Sánchez, R. J., and López-Ruiz, A. 2022. Strategies for the Storage of Large LiDAR Datasets—A Performance Comparison. Remote Sensing, 14(11), 2623.

Carson, W. W., Andersen, H. E., Reutebuch, S. E., and McGaughey, R. J. 2004. LiDAR applications in forestry—An overview. In ASPRS Annual Conference Proceedings (p. 4).

Căţeanu, M., and Ciubotaru, A. 2021. The effect of lidar sampling density on DTM accuracy for areas with heavy forest cover. *Forests*, *12*(3), 265.

Chasmer, L. E., Hopkinson, C. D., Petrone, R. M., and Sitar, M. 2017. Using multitemporal and multispectral airborne lidar to assess depth of peat loss and correspondence with a new active normalized burn ratio for wildfires. Geophysical research letters, 44(23), 11-851.

Drosos, V., and Farmakis, D. 2006. Airborne laser scanning and DTM generation. Management and Development of Mountainous and Island Areas, 206.

EPA. 2024. Climate Change Indicators: Wildfires. United States Environmental Protection Agency. Retrieved from https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.

Esri. (2023). ArcGIS Pro (Version 3.1.2) [Computer software]. Environmental Systems Research Institute.

Harrap, R., and Lato, M. 2010. An overview of LIDAR: collection to application. NGI publication, 2, 1-9.

Höfle, B., and Rutzinger, M. 2011. Topographic airborne LiDAR in geomorphology: A technological perspective. Zeitschrift fur Geomorphologie-Supplementband, 55(2), 1.

Hyyppä, H., Yu, X., Hyyppä, J., Kaartinen, H., Kaasalainen, S., Honkavaara, E., and Rönnholm, P. 2005. Factors affecting the quality of DTM generation in forested areas. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(3/W19), 85-90.

Kulig, J., Townshend, I., Edge, D., and Reimer, W. 2013. Impacts of wildfires: aftermath at individual and community levels?. Australian Journal of Emergency Management, The, 28(3), 29-34.

McRae, J. D., Alexander, E. M., Stocks, J. B. 1979. Measurement and Description of Fuels and Fire Behavior on Prescribed Burns: A Handbook. Canadian Forest Services.

Natural Resources Canada. 2020. Fire regime. Government of Canada. Retrieved from https://natural-resources.canada.ca/climate-change/impacts-adaptations/climate-change-impacts-forests/forest-change-indicators/fire-regime/17780.

Natural Resources Canada. 2022. Climate change and fire. Government of Canada. Retrieved from https://natural-resources.canada.ca/our-natural-resources/forests/wildland-fires-insects-disturbances/climate-change-fire/13155.

Natural Resources Canada. 2023a. Canada's record-breaking wildfires in 2023: A fiery wake-up call. Government of Canada. Retrieved from https://natural-resources.canada.ca/simply-science/canadas-record-breaking-wildfires-2023-fiery-wake-call/25303.

Natural Resources Canada. 2023b. The Government of Canada Is Supporting Canadians Through 2023 Wildfire Season. Retrieved from https://www.canada.ca/en/natural-resources-canada/news/2023/06/the-government-of-canada-is-supporting-canadians-through-the-2023-wildfire-season.html.

Natural Resources Canada. 2024. Boreal Forest. Government of Canada. Retrieved from https://natural-resources.canada.ca/our-natural-resources/forests/sustainable-forest-management/boreal-forest/13071.

Ontario. 2023. Ontario Strengthening Wildland FireFighting Efforts. Retrieved from https://news.ontario.ca/en/release/1003637/ontario-strengthening-wildland-firefighting-efforts.

Polat, N., and Uysal, M. 2015. Investigating performance of Airborne LiDAR data filtering algorithms for DTM generation. Measurement, 63, 61-68.

Roi, G. 2018. Boreal Zone. The Canadian Encyclopedia. Retrieved from https://www.thecanadianencyclopedia.ca/en/article/boreal-forest.

Simpson, J. E., Wooster, M. J., Smith, T. E., Trivedi, M., Vernimmen, R. R., Dedi, Shaki, M., and Dinata, Y. 2016. Tropical peatland burn depth and combustion heterogeneity assessed using UAV photogrammetry and airborne LiDAR. Remote Sensing, 8(12), 1000.

Šiljeg, A., Barada, M., Marić, I., and Roland, V. 2019. The effect of user-defined parameters on DTM accuracy—development of a hybrid model. Applied geomatics, 11, 81-96.

Stanton, C., and Bourchier, R. 2015. Forest Regions. In The Canadian Encyclopedia. Retrieved from https://www.thecanadianencyclopedia.ca/en/article/forest-regions.

Sterenczak, K., Zasada, M., and Brach, M. 2013. The accuracy assessment of DTM generated from LIDAR data for forest area–a case study for scots pine stands in Poland. Baltic Forestry, 19(2), 252-262.

Wandinger, U. 2005. Introduction to lidar. Lidar: Range-resolved optical remote sensing of the atmosphere (pp. 1-18). New York, NY: Springer New York.

Weber, M. G., and Flannigan, M. D. 1997. Canadian boreal forest ecosystem structure and function in a changing climate: impact on fire regimes. Environmental Reviews, 5(3-4), 145-166.