Applications of Multispectral Light Detection and Ranging Technology

Subjects: Remote Sensing

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Light Detection and Ranging (LiDAR) is a well-established active technology for the direct acquisition of 3D data. In recent years, the geometric information collected by LiDAR sensors has been widely combined with optical images to provide supplementary spectral information to achieve more precise results in diverse remote sensing applications. The emergence of active Multispectral LiDAR (MSL) systems, which operate on different wavelengths, has recently been revolutionizing the simultaneous acquisition of height and intensity information.

Keywords: Light Detection and Ranging (LiDAR) ; intensity ; sensors ; multispectral

1. Introduction

LiDAR is a renowned and widely used technology [1]. Fast and accurate acquisition of 3D information is the primary advantage of this 3D surveying technology. Laser sensors can be mounted on or carried by several platforms: crewed and uncrewed airborne, satellite, terrestrial, and mobile (including hand-held, backpack, and vehicle-based LiDAR). Additionally, LiDAR data play an important role in the generation of 3D models ranging from cities and other sites, Digital Surface Models (DSMs), and Digital Terrain Models (DTMs). LiDAR technology has evolved dramatically since its appearance in the late 90s. One of the latest and rapidly developing achievements in laser scanning technology is multispectral LiDAR and hyperspectral LiDAR (HSL) systems, having the ability to concomitantly obtain both geometrical and spectral information of the surveyed scene [2]. The utilization of intensity information, in conjunction with LiDAR's geometric data, has enabled the extraction of additional features that could serve various purposes in remote sensing and photogrammetry. While passive multi/hyperspectral images have actively shown satisfactory results for land use and land cover classification as well as target detection, their lack of 3D information limits their capabilities, especially for interpreting complex scenes. Even though LiDAR data can be combined with multi/hyperspectral passive images to improve scene characterization [3][4][5], registration problems in space (i.e., alignment and resolution) as well as time (i.e., changing observation conditions and dynamic scene), make this fusion challenging [6]. This drawback has prompted the development of MSL and HSL scanners as single-data source solutions to simultaneously acquire 3D geometric and radiometric information and alleviate the mentioned problems. For these reasons, MSL systems are currently gaining interest. Compared to conventional monochromatic (single-wavelength) LiDAR data, MSL data ensure a higher level of reliability and accuracy in object detection and scene classification [7][8][9][10][11][12][13][14][15]. Furthermore, MSL technology is able to acquire numerous textures of targets [16]. Additionally, delineation of individual trees is quite often difficult when only geometric spatial information of LiDAR data is taken into account [17]. Notably, contrary to optical imagery sensors, LiDAR is an active remote sensing sensor that has independent data acquisition of external illumination conditions, perfectly addressing the common shadow issue in the processing of optical images. Moreover, as reported by the results in [18][19], MSL data can dramatically enhance object detection in comparison to multispectral images. That is why MSL is becoming a popular source of research data for nD mapping, considering the intensities information as further dimensions.

2. Multispectral LiDAR Applications

As industrialization advances, the conventional methods of identifying and categorizing objects using optical images are no longer sufficient for achieving demanding precise outcomes [16][20]. With the ability to concurrently capture 3D point clouds in different wavelengths, MSL technology has attracted increasing attention for a variety of applications during the last decade. The applications of this revolutionary active remote sensing technology are comprised of the following: forest and urban trees/plants inventories, objects and LULC classification, change detection, bathymetry mapping and coastal zone management, topographic mapping, archaeology and geology, and last but not least, facilitating navigation systems.

2.1. Ecology and Forestry

Most of the published research on MSL is in the domain of ecology and forestry (42.7%). Forest inventory plays a pivotal role in forest management. Traditionally, ecological studies have relied on laborious, time-consuming, and costly field visits to gather necessary information. However, remote sensing-based inventorying offers highly promising technology for these tasks without any destructive sampling and large-scale fieldwork. Thanks to the better canopy penetration capability of LiDAR sensors over optical ones, the use of laser scanners for accurate estimation of forest variables (such as tree height, basal area, stem volume, diameter at breast height, and above-ground biomass) has been an active research focus [21][22]. Nevertheless, traditional monochromatic laser scanners cannot capture enough information for tree and plant species classification, and a mix of tree species can even complicate that [23][24]. To date, passive multispectral optical sensors and their integration with airborne laser scanners have been widely used for forest tree species classification [25][26][27]. As different tree species reflect light at different wavelengths, modern MS laser scanners improve tree species identification accuracy compared to monochromatic LiDAR systems, particularly when tree species diversity is fairly high (about seven or more species) [13]. In MSL sensors, features describing the 3D structure of tree crowns as well as spectral information can be used for more detailed analysis of backscatters. Hence, the characterization of tree species, even identifying invasive ones, is one of the primary and most popular applications of multi-wavelength laser scanning [28]. Plant reflectance is high at NIR/SWIR wavelengths and low at the green wavelength due to their chlorophyll content, making a combination of the green laser channel and NIR/SWIR wavelength potentially useful for vegetation analysis. In a similar manner to the conventional Normalized Difference Vegetation Index (NDVI) derived from the visible red and NIR spectral bands, multiple wavelengths of MSL facilitate the calculation of NDVI/pseudo NDVI (pNDVI) or other vegetation indices. Tian et al. [29] employed an HSL with 64 wavelength channels (535 nm–850 nm with a 5 nm step), to classify six plant species using fusion of deep learning-based features and vegetation indices.

MSL technology also has the potential to enhance the accuracy of individual tree detection, especially in dense forests with clumped trees, which is quite often challenging using only geometric information [28]. This capability was first explored by Dai et al. [17], and they applied the mean shift segmentation method in a joint domain of spatial and spectral features. Also, the spectral information of MSL was utilized for refining under-segmented crown segments. Theirs results showed a noticeable improvement in dealing with clumped crowns compared to monochromatic wavelength laser scanning. In another study, according to the findings of Huo and Lindberg [30], incorporating intensity values in conjunction with a point density metric resulted in a noteworthy increase of up to 14% in F-scores.

Furthermore, MSL can also be helpful in the more accurate estimation of other parameters of trees. The research conducted by Gaulton et al. [31], utilizing SALCA dual-wavelength MSL, demonstrated improvement in the estimation of canopy cover, gap fraction, and leaf area index. Using three-wavelength Optech Titan LiDAR, Goodbody et al. [32] modeled three forest inventory attributes (i.e., Lorey's height, gross volume, and basal area) as well as three overstorey species diversity characteristics, including Shannon index, Simpson index, and species richness. Their findings revealed that although the incorporation of intensity metrics yielded a modest enhancement in accuracy, the significance of these metrics becomes particularly pronounced when dealing with lower-resolution data in the context of 1 m and 2 m voxel models. The results of Maltamo et al. [33] substantiated the better efficiency of MSL in the prediction of forest canopy fuel parameters, including canopy fuel weight, canopy base height, biomass of living and dead trees, and height and biomass of the understory tree layer and site fertility. In 2023, Rana et al. [34] showed that MSL is superior to the combination of traditional monochromatic LiDAR and color–infrared image in monitoring seedling stands. In addition, the use of MSL makes the physiological and health condition analysis of vegetation possible [35][36][37] and furthermore enables a better understanding of periodic changes in carbon content [38]. Junttila [36] discovered that varying levels of leaf water content in Norway spruce seedlings exhibit distinct spectral responses while measured using terrestrial MSL. Their experiments demonstrated that the normalized ratio of two wavelengths, specifically at 905 nm and 1550 nm, holds significant utility in the estimation of leaf water content. Lately, Shao et al. [39] substantiated that HSL can also be helpful for more accurate wood–leaf separation, which mostly relies on monochromatic LiDAR.

2.2. Objects and LULC Classification

Accurate land use land cover classification plays an essential role in urban planning, monitoring climate changes, and ecosystem protection [40]. In the early studies of LULC classification, multispectral image data were used as the primary source of sensing Earth surface objects in order to facilitate more detailed object detection. Therefore, MSL is a new promising sensor for automated mapping of land cover [41]. The use of MSL technology allows for achieving 3D land cover classification at a finer scale using only MS point cloud data. MSL data have a comparable level of detail to aerial images, which are currently the primary data source in map updating. Several studies have confirmed that laser scanner intensity has merit in classifying urban land cover without the aid of passive multispectral images [42][43][44][45][46][47]. Chen et al. [38]

observed that the spectral patterns of impervious surfaces (e.g., road, rooftops) and single-return vegetation (i.e., grass) have similar patterns in optical imagery. Using MSL, up to 70% overall accuracy can be achieved in land cover mapping solely based on intensity measurements [9]. On the other hand, incorporating both geometric and radiometric records, the accuracy could increase. Hence, MSL systems, integrating both spectral and geometric information, support the classification of point clouds and could have a vital role in nationwide mapping in the future [20]. Besides ecology, LULC mapping has attracted remarkable research attention based on MSL technology (39.3%).

2.3. Change Detection

With the rapid development of society, there are increasing demands for more precise monitoring of surface changes. Recently, the potential of automated change detection from multitemporal airborne MSL was explored for the first time by Matikainen et al. [48]. It was concluded that even small changes can be revealed by direct comparisons between height and intensity data from different dates. As a result of conducted research, MSL data could significantly contribute to increasing the level of automation in nationwide mapping, the frequency of its updates, and consequently improve the contents of topographic databases, which are currently mainly based on visual interpretation of the images [20][48][49].

2.4. Bathymetry

Generally, MSL instruments are not specifically tailored for hydrographic mapping, but as they encompass a green laser, they have exhibited bathymetric capabilities [50]. The first usage of MSL dates in this domain dates back to 2016 when Fernandez-Diaz et al. [51] mapped bathymetry by extracting DSM and intensity images of three channels as well as employing Mahalanobis distance and the maximum likelihood classifiers. Moreover, in the next year, using MSL point cloud data gathered by the Optech Titan sensor and also by extracting several geometric and radiometric features, Morsy et al. [52] classified water areas from land by employing a rule-based classification. In another study using a similar sensor, Yan et al. [53] mapped the water surface based on a 3D maximum likelihood classifier. These studies demonstrated that for mapping the water bodies' areas, MSL is especially more beneficial than conventional monochromatic LiDAR systems. Furthermore, MSL could facilitate the monitoring of hydromorphological status by estimating some critical indicators such as water depth, leaf area index, and chlorophyll content [54].

2.5. Topographic Mapping

Recently, Ali et al. [55] proposed the idea of generating DTM from MSL data. They extracted DTM from each channel of the Optech Titan MSL sensor separately and made a comparison between them. They also examined the potential of four different ground-filtering algorithms, including Adaptive TIN (ATIN), Elevation Threshold with Expansion Window (ETEW), progressive morphological algorithms, and maximum local slope using LiDAR open-source ALDPAT v.1.0 software. Their results showed that in the water area, the slope-based and ETEW methods performed well for the third channel. However, for the other two channels, the morphology-based method yielded better results.

2.6. Archaeology and Geology

One of the interesting and firstly introduced application areas of MSL is archaeological prospection [56]. In 2006, Wehr et al. [57] detected the damaged areas of building surfaces caused by enhanced moisture content and/or vegetation using the designed four-wavelength MSL. Shao et al., 2019 [58] employed a designed AOTF-HSL to preserve historical timber buildings. They classified building ages and wood species using the spectral information of an eye-safe 81-channel HSL. Additionally, MSL data can assist geological studies and mining operations. Hartzell et al. [59] utilized intensity images acquired from an integrated system that included the RIEGL VZ-400 TLS (NIR) and Nikon D700 camera (RGB) to distinguish between four different types of rock. Using AOTF-HSL, Shao et al., 2019 [60], managed to identify four-type coal/rock specimens. Newly, Sun et al. [61] showed that spectral profiles collected by hyperspectral LiDAR can effectively reveal the ore species, especially those in the SWIR range. According to their experiments, HSL has demonstrated encouraging capability for geological material detection and classification and furthermore for tunnel modeling and also mineral disaster prevention applications.

2.7. Navigation

The feasibility of HSL systems for autonomous vehicle perception was recently explored by Taher et al. [62]. A frame-based single photon-sensitive HSL with 30 spectral channels ranging from 1200 to 1570 nm was developed for this purpose. Their results demonstrated that spectral information from an HSL can accelerate scene recognition accuracy in a complicated road environment from 50% to 94% with two channels and 30 channels, respectively. Furthermore, Jiang et al. [63] developed an intensity calibration-free method to aid point cloud matching in SLAM. Their method is based on designing an HSL that collects intensity data in eight wavelengths at the same incident angle and range, and subsequently, computing spectral ratio value vectors between consecutive laser scans, and finally applying them in point cloud matching. So, their method improved the accuracy of LiDAR SLAM positioning by combining LiDAR's intensity information with its range measurements.

References

1. Shan, J.; Toth, C.K. Topographic Laser Ranging and Scanning: Principles and Processing; CRC Press: Boca Raton, FL, USA, 2018.
2. Riveiro, B.; Lindenbergh, R. Laser Scanning: An Emerging Technology in Structural Engineering; CRC Press: Boca Raton, FL, USA, 2019; Volume 14.
3. Dalponte, M.; Bruzzone, L.; Gianelle, D. Fusion of hyperspectral and LIDAR remote sensing data for classification of complex forest areas. IEEE Trans. Geosci. Remote Sens. 2008, 46, 1416–1427.
4. Buckley, S.J.; Kurz, T.H.; Howell, J.A.; Schneider, D. Terrestrial lidar and hyperspectral data fusion products for geological outcrop analysis. Comput. Geosci. 2013, 54, 249–258.
5. Kuras, A.; Brell, M.; Rizzi, J.; Burud, I. Hyperspectral and lidar data applied to urban land cover machine learning and neural-network-based classification: A review. Remote Sens. 2021, 13, 3393.
6. Altmann, Y.; Maccarone, A.; McCarthy, A.; Newstadt, G.; Buller, G.S.; McLaughlin, S.; Hero, A. Robust Spectral Unmixing of Sparse Multispectral Lidar Waveforms Using Gamma Markov Random Fields. IEEE Trans Comput. Imaging 2017, 3, 658–670.
7. Ekhtari, N.; Glennie, C.; Fernandez-Diaz, J.C. Classification of airborne multispectral lidar point clouds for land cover mapping. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 2018, 11, 2068–2078.
8. Morsy, S.; Shaker, A.; El-rabbany, A. Classification of Multispectral Airborne LiDAR Data Using Geometric and Radiometric Information. Geomatics 2022, 2, 370–389.
9. Morsy, S.; Shaker, A. Potential Use of Multispectral Airborne LiDAR Data in Land Cover Classification. In Proceedings of the 37th Asian Conference on Remote Sensing (ACRS), Colombo, Sri Lanka, 17–21 October 2016.
10. Luo, B.; Yang, J.; Song, S.; Shi, S.; Gong, W.; Wang, A.; Yanhua, D. Target Classification of Similar Spatial Characteristics in Complex Urban Areas by Using Multispectral LiDAR. Remote Sens. 2022, 14, 238.
11. Dalponte, M.; Ene, L.T.; Gobakken, T.; Næsset, E.; Gianelle, D. Predicting selected forest stand characteristics with multispectral ALS data. Remote Sens. 2018, 10, 586.
12. Kukkonen, M.; Maltamo, M.; Korhonen, L.; Packalen, P. Multispectral Airborne LiDAR Data in the Prediction of Boreal Tree Species Composition. IEEE Trans. Geosci. Remote Sens. 2019, 57, 3462–3471.
13. Budei, B.C.; St-Onge, B.; Hopkinson, C.; Audet, F.A. Identifying the genus or species of individual trees using a three-wavelength airborne lidar system. Remote Sens. Environ. 2018, 204, 632–647.
14. Teo, T.A.; Wu, H.M. Analysis of land cover classification using multi-wavelength LiDAR system. Appl. Sci. 2017, 7, 663.
15. Ekhtari, N.; Glennie, C.; Fernandez-Diaz, J.C. Classification of multispectral lidar point clouds. In Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, TX, USA, 23–28 July 2017; pp. 2756–2759.
16. Matikainen, L.; Karila, K.; Hyyppä, J.; Litkey, P.; Puttonen, E.; Ahokas, E. Object-based analysis of multispectral airborne laser scanner data for land cover classification and map updating. ISPRS J. Photogramm. Remote Sens. 2017, 128, 298–313.
17. Dai, W.; Yang, B.; Dong, Z.; Shaker, A. A new method for 3D individual tree extraction using multispectral airborne LiDAR point clouds. ISPRS J. Photogramm. Remote Sens. 2018, 144, 400–411.
18. Karila, K.; Matikainen, L.; Puttonen, E.; Hyyppa, J. Feasibility of multispectral airborne laser scanning data for road mapping. IEEE Geosci. Remote Sens. Lett. 2017, 14, 294–298.
19. Li, D.; Shen, X.; Yu, Y.; Guan, H.; Li, J.; Zhang, G.; Li, D. Building extraction from airborne multi-spectral LiDAR point clouds based on graph geometric moments convolutional neural networks. Remote Sens. 2020, 12, 3186.
20. Matikainen, L.; Pandžić, M.; Li, F.; Karila, K.; Hyyppä, J.; Litkey, P.; Kukko, A.; Lehtomäki, M.; Karjalainen, M.; Puttonen, E. Toward utilizing multitemporal multispectral airborne laser scanning, Sentinel-2, and mobile laser scanning in map updating. J. Appl. Remote Sens. 2019, 13, 1.
21. Wästlund, A.; Holmgren, J.; Lindberg, E. Forest variable estimation using a high altitude single photon Lidar system. Remote Sens. 2018, 10, 1422.

22. Coops, N.C.; Tompalski, P.; Goodbody, T.R.H.; Queinnec, M.; Luther, J.E.; Bolton, D.K.; White, J.; Wulder, M.; van Lier, O.R.; Hermosilla, T. Modelling lidar-derived estimates of forest attributes over space and time: A review of approaches and future trends. Remote. Sens. Environ. 2021, 260, 112477.

23. Kukkonen, M.; Maltamo, M.; Korhonen, L.; Packalen, P. Comparison of multispectral airborne laser scanning and stereo matching of aerial images as a single sensor solution to forest inventories by tree species. Remote Sens. Environ. 2019, 231, 111208.

24. Wallace, A.; Nichol, C.; Woodhouse, I. Recovery of forest canopy parameters by inversion of multispectral LiDAR data. Remote Sens. 2012, 4, 509–531.

25. Holmgren, J.; Persson, Å.; Söderman, U. Species identification of individual trees by combining high-resolution LiDAR data with multi-spectral images. Int. J. Remote Sens. 2008, 29, 1537–1552.

26. Krzystek, P.; Serebryanyk, A.; Schnörr, C.; Cervenka, J.; Heurich, M. Large-scale mapping of tree species and dead trees in Šumava National Park and Bavarian Forest National Park using Lidar and multispectral imagery. Remote Sens. 2020, 12, 661.

27. Maltamo, M.; Vauhkonen, J. Forestry Applications of Airborne Laser Scanning. Concepts and Case Studies; Springer: Dordrecht, The Netherlands, 2014.

28. Mielczarek, D.; Sikorski, P.; Archiciński, P.; Ciężkowski, W.; Zaniewska, E.; Chormański, J. The use of an airborne laser scanner for rapid identification of invasive tree species Acer negundo in riparian forests. Remote Sens. 2023, 15, 212.

29. Tian, W.; Tang, L.; Chen, Y.; Li, Z.; Qiu, S.; Li, X.; Zhu, J.; Jiang, C.; Hu, P.; Jia, J. Plant species classification using hyperspectral LiDAR with convolutional neural network. In Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS), Kuala Lumpur, Malaysia, 17–22 July 2022; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2022; pp. 1740–1743.

30. Huo, L.; Lindberg, E. Individual tree detection using template matching of multiple rasters derived from multispectral airborne laser scanning data. Int. J. Remote Sens. 2020, 41, 9525–9544.

31. Gaulton, R.; Pearson, G.; Lewis, P.; Disney, M. The Salford Advanced Laser Canopy Analyser (SALCA): A multispectral full waveform LiDAR for improved vegetation characterisation. In Remote Sensing and Photogrammetry Society Conference Remote Sensing and the Carbon Cycle; Burlington House: London, UK, 2010.

32. Goodbody, T.R.H.; Tompalski, P.; Coops, N.C.; Hopkinson, C.; Treitz, P.; van Ewijk, K. Forest inventory and diversity attribute modeling using structural and intensity metrics from multispectral airborne laser scanning data. Remote Sens. 2020, 12, 2109.

33. Maltamo, M.; Räty, J.; Korhonen, L.; Kotivuori, E.; Kukkonen, M.; Peltola, H.; Kangas, J.; Packalen, P. Prediction of forest canopy fuel parameters in managed boreal forests using multispectral and unispectral airborne laser scanning data and aerial images. Eur. J. Remote Sens. 2020, 53, 245–257.

34. Rana, P.; Mattila, U.; Mehtätalo, L.; Siipilehto, J.; Hou, Z.; Xu, Q.; Tokola, T. Monitoring seedling stands using national forest inventory and multispectral airborne laser scanning data. Can. J. For. Res. 2023, 53, 302–313.

35. Wallace, A.M.; McCarthy, A.; Nichol, C.J.; Ren, X.; Morak, S.; Martinez-Ramirez, D.; Woodhouse, I.H.; Buller, G.S. Design and evaluation of multispectral LiDAR for the recovery of arboreal parameters. IEEE Trans. Geosci. Remote Sens. 2014, 52, 4942–4954.

36. Junttila, S.; Sugano, J.; Vastaranta, M.; Linnakoski, R.; Kaartinen, H.; Kukko, A.; Holopainen, M.; Hyyppä, H.; Hyyppä, J. Can leaf water content be estimated using multispectral terrestrial laser scanning? A case study with Norway spruce seedlings. Front. Plant Sci. 2018, 9, 299.

37. Junttila, S.; Vastaranta, M.; Liang, X.; Kaartinen, H.; Kukko, A.; Kaasalainen, S.; Holopainen, M.; Hyyppä, H.; Hyyppä, J. Measuring Leaf Water Content with Dual-Wavelength Intensity Data from Terrestrial Laser Scanners. Remote Sens. 2017, 9, 8.

38. Chen, X.; Ye, C.; Li, J.; Member, S.; Chapman, M.A. Quantifying the carbon storage in urban trees using multispectral ALS data. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 2018, 11, 3358–3365.

39. Shao, H.; Cao, Z.; Li, W.; Chen, Y.; Jiang, C.; Hyyppä, J.; Chen, J.; Sun, L. Feasibility study of wood-leaf separation based on hyperspectral LiDAR Technology in indoor circumstances. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 2022, 15, 729–738.

40. Marsoner, T.; Simion, H.; Giombini, V.; Egarter Vigl, L.; Candiago, S. A detailed land use/land cover map for the European Alps macro region. Sci. Data 2023, 10, 468.

41. Karila, K.; Matikainen, L.; Litkey, P.; Hyyppä, J.; Puttonen, E. The effect of seasonal variation on automated land cover mapping from multispectral airborne laser scanning data. Int. J. Remote Sens. 2018, 40, 3289–3307.

42. Xiao, K.; Qian, J.; Li, T. Multispectral LiDAR point cloud segmentation for land cover leveraging semantic fusion in deep learning network. Remote Sens. 2022, 15, 243.

43. Wichmann, V.; Bremer, M.; Lindenberger, J.; Rutzinger, M.; Georges, C.; Petrini-Monteferri, F. Evaluating the potential of multispectral airborne LiDAR for topographic mapping and land cover classification. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2015, 2, 113–119.

44. Zhang, Z.; Li, T.; Tang, X.; Lei, X.; Peng, Y. Introducing improved transformer to land cover classification using multispectral LiDAR point clouds. Remote Sens. 2022, 14, 3808.

45. Shi, S.; Bi, S.; Gong, W.; Chen, B.; Chen, B.; Tang, X.; Qu, F.; Song, S. Land cover classification with multispectral LiDAR based on multi-scale spatial and spectral feature selection. Remote Sens. 2021, 13, 4118.

46. Ghaseminik, F.; Aghamohammadi, H.; Azadbakht, M. Land cover mapping of urban environments using multispectral LiDAR data under data imbalance. Remote Sens. Appl. 2021, 21, 100449.

47. Pan, S.; Guan, H.; Yu, Y.; Li, J.; Peng, D. A comparative land-cover classification feature study of learning algorithms: DBM, PCA, and RF using multispectral LiDAR data. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 2019, 12, 1314–1326.

48. Matikainen, L.; Hyyppä, J.; Litkey, P. Multispectral airborne laser scanning for automated map updating. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2016, 41, 323–330.

49. Matikainen, L.; Karila, K.; Hyyppä, J.; Puttonen, E.; Litkey, P.; Ahokas, E. Feasibility of multispectral airborne laser scanning for land cover classification, road mapping and map updating. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, 42, 119–122.

50. Mandlburger, G. A review of active and passive optical methods in hydrography. Int. Hydrogr. Rev. 2022, 28, 8–52.

51. Fernandez-Diaz, J.C.; Carter, W.E.; Glennie, C.; Shrestha, R.L.; Pan, Z.; Ekhtari, N.; Singhania, A.; Hauser, D.; Sartori, M. Capability assessment and performance metrics for the Titan multispectral mapping lidar. Remote Sens. 2016, 8, 936.

52. Morsy, S.; Shaker, A. Evaluation of distinctive features for land/water classification from multispectral airborne LiDAR data at Lake Ontario. In Proceedings of the 10th International Conference on Mobile Mapping Technology (MMT), Cairo, Egypt, 6–8 May 2017.

53. Yan, W.Y.; Shaker, A.; La Rocque, P.E. Water mapping using multispectral airborne LiDAR data. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.—ISPRS Arch. 2018, 42, 2047–2052.

54. Goraj, M.; Karsznia, K.; Sikorska, D.; Hejduk, L.; Chormanski, J. Multi-wavelength airborne laser scanning and multispectral UAV-borne imaging. Ability to distinguish selected hydromorphological indicators. In Proceedings of the 18th International Multidisciplinary Scientific GeoConference SGEM2018, Albena, Bulgaria, 2–8 July 2018; Volume 18, pp. 359–366.

55. Ali, M.E.N.O.; Taha, L.G.E.D.; Mohamed, M.H.A.; Mandouh, A.A. Generation of digital terrain model from multispectral LiDAR using different ground filtering techniques. Egypt. J. Remote Sens. Space Sci. 2021, 24, 181–189.

56. Briese, C.; Pfennigbauer, M.; Ullrich, A.; Doneus, M. Multi-wavelength airborne laser scanning for archaeological prospection. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2013, 40, 119–124.

57. Wehr, A.; Hemmleb, M.; Maierhofer, C. Multi-spectral laser scanning for inspection of building surfaces-state of the art and future concepts. In Proceedings of the 7th International Conference on Virtual Reality, Archaeology, and Intelligent Cultural Heritage, Nicosia, Cyprus, 30 October–4 November 2006; pp. 147–154.

58. Shao, H.; Chen, Y.; Yang, Z.; Jiang, C.; Li, W.; Wu, H.; Wang, S.; Yang, F.; Chen, J.; Puttonen, E. Feasibility study on hyperspectral LiDAR for ancient Huizhou-style architecture preservation. Remote Sens. 2019, 12, 88.

59. Hartzell, P.; Glennie, C.; Biber, K.; Khan, S. Application of multispectral LiDAR to automated virtual outcrop geology. ISPRS J. Photogramm. Remote Sens. 2014, 88, 147–155.

60. Shao, H.; Chen, Y.; Yang, Z.; Jiang, C.; Li, W.; Wu, H.; Wen, Z.; Wang, S.; Puttonen, E.; Hyyppä, J. A 91-channel hyperspectral LiDAR for coal/rock classification. IEEE Geosci. Remote Sens. Lett. 2019, 17, 1052–1056.

61. Sun, H.; Wang, Z.; Chen, Y.; Tian, W.; He, W.; Wu, H.; Zhang, H.; Tang, L.; Jiang, C.; Jia, J. Preliminary verification of hyperspectral LiDAR covering VIS-NIR-SWIR used for objects classification. Eur. J. Remote Sens. 2022, 55, 291–303.

62. Taher, J.; Hakala, T.; Jaakkola, A.; Hyyti, H.; Kukko, A.; Manninen, P.; Maanpää, J.; Hyyppä, J. Feasibility of hyperspectral single photon lidar for robust autonomous vehicle perception. Sensors 2022, 22, 5759.

63. Jiang, C.; Chen, Y.; Tian, W.; Feng, Z.; Li, W.; Zhou, C.; Shao, H.; Puttonen, E.; Hyyppä, J. A practical method utilizing multi-spectral LiDAR to aid points cloud matching in SLAM. Satell. Navig. 2020, 1, 29.