The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W9-2024
GeoAdvances 2024 – 8th International Conference on GeoInformation Advances, 11–12 January 2024, Istanbul, Türkiye

# SUITABLE LANDING SITE SELECTION FOR UNMANNED AERIAL VEHICLES USING AIRBORNE LASER SCANNING POINT CLOUD

Dheerendra Pratap Singh[a, *], Manohar Yadav[a]
[a]Geographic Information System (GIS) Cell, Motilal Nehru National Institute of Technology Allahabad, Prayagraj-211004, India
dheeru.dp@gmail.com(corresponding author), ssmyadav@mnnit.ac.in

**KEY WORDS:** Airborne laser scanning, point cloud, Terrain surface, landing sites.

**ABSTRACT:**

In the context of autonomous landing for unmanned aerial vehicles (UAVs), selecting a suitable landing site is crucial. This research presents a new method for automatically identifying safe landing sites based on point cloud data acquired through an airborne laser scanning (ALS) system. The proposed approach begins by detecting flat regions using principal component analysis (PCA) and region-growing algorithms. Subsequently, a terrain complexity assessment is conducted through plane fitting using an enhanced progressive sample consensus (PROSAC) algorithm. This assessment assists in identifying the most suitable landing site within a specified landing zone. The method's effectiveness is demonstrated through experiments conducted on two distinct natural terrains from the DALE dataset. The results show that the proposed approach can accurately classify landing zones and identify preferred sites that meet safety criteria. This study's findings underscore the proposed method's effectiveness and feasibility in improving the safety and reliability of autonomous UAV landings.

## 1. INTRODUCTION

### 1.1 Motivations

Unmanned Aerial Vehicles (UAVs) have become indispensable tools across a spectrum of applications, offering versatility in disaster response, environmental monitoring, and infrastructure inspection (Alam and Oluoch, 2021). A critical aspect of maximizing the efficacy and safety of UAV operations is the precise selection of landing sites. This concern takes center stage when conventional landing infrastructure is sparse or impractical(Yan et al., 2020). Innovative solutions integrating advanced technology with UAV operations are imperative in response to this challenge.

Airborne Laser Scanning (ALS), has emerged as a transformative force in UAV landing site selection (Singh and Yadav, 2023). UAVs equipped with LiDAR sensors can capture highly detailed three-dimensional datasets. This capability significantly enhances situational awareness, particularly during the pivotal task of landing site selection. The intricate details provided by LiDAR-generated point cloud data hold immense promise, presenting a nuanced understanding of the terrain and contributing to informed decision-making in selecting optimal and secure landing sites for UAVs (Cho et al. 2007).

The motivation behind this research is rooted in the inherent challenges and opportunities that arise at the intersection of UAV operations and airborne laser scanning technology (Yan et al. 2020). With traditional landing site infrastructure often proving insufficient, there is a pressing need to explore and implement novel solutions. Integrating LiDAR technology into UAVs provides a unique vantage point for capturing the intricacies of the terrain, thereby offering a transformative potential for enhancing the accuracy, safety, and efficacy of UAV landing site selection (Daud et al. 2022).

The dynamics of contemporary environments, characterized by evolving terrains and potential obstacles, necessitate a robust and adaptive approach to landing site selection. This scholarly discourse is motivated by a commitment to address the complexities inherent in UAV landing site selection comprehensively. The overarching goal is to harness the capabilities of airborne laser scanning point cloud data to usher in a new era characterized by precision and autonomy in landing site selection for UAVs (Loureiro et al. 2021)

In the ensuing sections, this paper will navigate through contemporary techniques for analyzing point cloud data generated by airborne laser scanning. It will explore the inherent intricacies associated with UAV landing site selection, shedding light on challenges and promising avenues. Through this exploration, we endeavor to contribute to the ongoing dialogue of advanced technology and UAV operations, fostering advancements that redefine the landscape of landing site selection for unmanned aerial vehicles.

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLVIII-4-W9-2024-343-2024 | © Author(s) 2024. CC BY 4.0 License.

### 1.2 Related work

In recent years, selecting suitable landing sites for Unmanned Aerial Vehicles (UAVs) has become a critical area of research, particularly leveraging advanced technologies like Airborne Laser Scanning (ALS) to enhance precision and safety. The exploration of UAV landing site selection methodologies using ALS point clouds has garnered significant attention, with several studies contributing valuable insights and innovative approaches. Earlier research concentrated on pre-established markers to determine relative position relationships between UAVs and landing sites such as visual indications, two-dimensional codes, light, and natural runways. However, the limitations of these approaches prompted a shift towards utilizing ALS technology.

A method for enabling an autonomous landing of a full-scale unmanned helicopter was proposed by Chamberlain et al. (2011). Their approach used a 3D scanning LiDAR operating in two modes: a downward scan to map the surroundings and a forward scan to identify impediments. Next, they evaluated the region, considering skid contact, wind direction, and the presence of obstacles by overlaying a 3D virtual model of the helicopter on each cell of the generated map. This approach was expanded by Maturana et al. (2015), where experimental findings were provided from both natural and urban settings. To determine intersections between the landing skids and the roll and pitch of the helicopter, a 2D Delaunay triangulation of possible landing site data was constructed during the evaluation process.

Scherer et al., (2012) presented a representative LiDAR-based method that enabled helicopters to select landing zones and plan paths, considering terrain assessment alongside factors like skid interaction, rotor and tail clearance, wind direction, and ground paths. To detect potential obstacles in areas with low vegetation, Maturana et al., (2015) employed a 3D convolutional neural network to train LiDAR point clouds. They successfully applied this method to select landing sites in small-scale areas. However, introducing this approach necessitates a substantial number of prior datasets.

Whalley et al., (2014) introduced a technique where every LiDAR scan was mapped onto a grid, and a sliding window was employed to compute terrain constraints as it traversed the grid. Subsequently, the optimal landing site was determined after the entire grid had been processed. Lorenzo et al. (2017) introduced a landing site detection method that employs parallel processing across multiple core systems. They enhanced speed by constructing an octree for the neighborhood search step—the site evaluation involved computing the normal of each point in parallel, considering geometric constraints.

Huang et al., (2018) utilized region segmentation and plane fitting to detect flat regions. Their method involved selecting the point with the most minor curvature within the largest flat area as the landing location. While effective in more straightforward terrain, this strategy may not guarantee a safe distance from other obstructions in more complex settings. Takahashi et al. (2018) combined the sliding window technique with terrain assessment to highlight a crucial component in identifying safe landing places. LiDAR's long detection range and high accuracy make it a versatile tool for obstacle detection and guiding safe landings in various missions, including those involving helicopters, Mars, lunar exploration, and UAVs(Alam & Oluoch, 2021).

The work of Zhao et al., (2020), which introduced an ultraviolet (UV) light-based landing aid system for unmanned aerial vehicles, exemplifies early attempts to integrate technology for safer landings. Furthermore, Abujoub et al., (2020) adopted onboard LiDAR to evaluate ship motion via the Signal Prediction Algorithm (SPA), showcasing LiDAR's adaptability in diverse environments and scenarios. Chen et al., (2020) built a system incorporating binocular cameras and LiDAR for autonomous landings in uncharted territory. They constructed a system equipped with LiDAR and binocular cameras for autonomous landings in unknown environments.

Despite LiDAR's high accuracy, the dense data it generates can lead to complexity in computation. Coarse-to-fine approach in different dimensional spaces has been proposed to reduce computation complexity and enhance efficiency (Cramer 2010). The literature also emphasizes the importance of terrain evaluation criteria for landing site selection (Johnson et al., (2002); Xiao et al., (2019); and Lorenzo et al., (2017)). Mango et al. (2020) used LiDAR-based techniques to determine safe landing locations by considering the incidence angles, terrain roughness, and smoothness. When choosing a landing place, they also assessed the hazards associated with local surface slope, height, and roughness. These studies highlight the significance of terrain-related factors in ensuring safe landings.

Challenges persist, including the need for comprehensive evaluation criteria. Sebastian Scherer's approach, incorporating multiple factors like terrain safety, wind direction, ground paths, skid interaction, and rotor and tail clearance, exemplifies a holistic evaluation strategy (Scherer et al. 2012). Inspired by this, the proposed method in this paper considers terrain safety and factors in fuel usage, data trust, avoiding obstacles, and certification of the second landing. The optimal landing site selection is framed as an uncertainty analysis problem, aligning with methodologies proposed by Cui et al., (2017). Employing fixed cost weights based on the uncertainty technique to score landing pages, the proposed approach dynamically optimizes landing locations, emphasizing the importance of real-time decision-making in complex and dynamic environments.

The literature review highlights the evolution of UAV landing site selection methodologies, transitioning from traditional markers to advanced technologies like ALS, particularly LiDAR, to enhance precision, safety, and efficiency. The proposed UAV landing site selection method using ALS point clouds aims to contribute to this evolving landscape by addressing challenges and incorporating a comprehensive evaluation strategy.

## 2. METHOD

### 2.1 Study area and datasets

Light Detection and Ranging (LiDAR) is a remote sensing method to estimate the range between two objects. The components used in airborne LiDAR are a pulsed laser, a scanner, a Global Positioning System (GPS), and an Inertial Measurement Unit (IMU). A UAV equipped with LiDAR sends pulsed laser beams to the target area on the ground. The site reflects the beam of light on the floor it encounters. A sensor measures the change of the reflected pulse signal compared to the transmitted signal to calculate the range between the UAV and the target. Each point cloud has three-dimensional coordinates corresponding to the particular point on the earth's surface from which the laser pulse was reflected. These point clouds generate a new Digital Elevation Model (DEM) from which a 3D representation of the target can be developed (Figure 1).

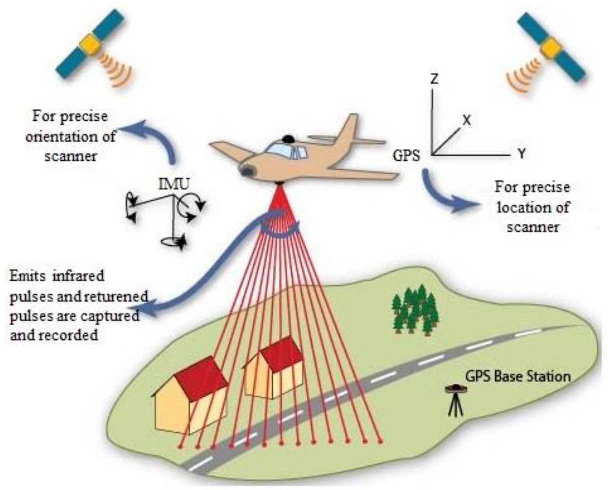


**Figure 1**: Airborne laser scanning system.

In this experimental study, we utilized the DALES dataset (Varney et al., (2020), a well-established open-source dataset for point cloud segmentation and classification. The dataset comprises extensive Airborne Laser Scanning (ALS) data collected over Surrey, British Columbia, Canada, employing a Riegl Q1560 dual-channel ALS system.

Consisting of 40 tiles, each covering a 500×500 square meter area, the dataset maintains an average point density of 50 points per square meter. Encompassing a 10 square kilometres area, it contains 12 million points and offers. The ground truth labels for eight categories, including ground, car, truck, fence, pole, building, power line, and vegetation.

| Dataset | Size in points (Area) | Features |
|---|---|---|
| #1 | 11,915,905 (245153 $m^2$) | Urban with residential buildings and trees |
| #2 | 12,954,374 (248601 $m^2$) | Urban with mixed types of buildings and PL/TL lines |

**Table 1**: Dataset overview

Our study specifically focused on tiles 5105_54405 and 5105_54460 from the DALES dataset (Figure 2). These tiles serve as the primary basis for our experimental analysis. Additionally, to validate the efficacy of our proposed method across diverse terrains and scenarios, we incorporated datasets representing both urban Datasets A and B environments. All experiments were meticulously conducted within the defined study area, emphasizing the unique characteristics presented by the DALES dataset. Figure 2 illustrates the two datasets used in our study area and experimental evaluations.

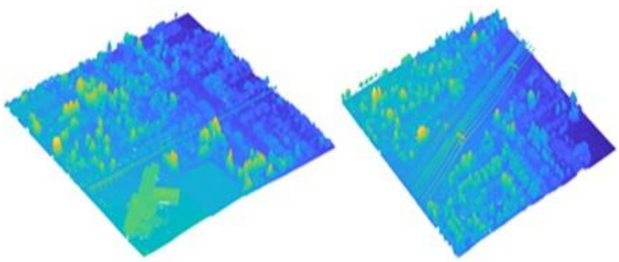

**Figure 2**: Input ALS point cloud dataset#1 and #2.

### 2.2 Proposed methodology

Our methodology presents a systematic approach for automating the selection of suitable landing sites for Unmanned Aerial Vehicles (UAVs) by leveraging overlapping block-based point cloud processing. The methodology flowchart for suitable landing site selection from the ALS point cloud is depicted in Figure 3, which illustrates the detailed steps of our approach.

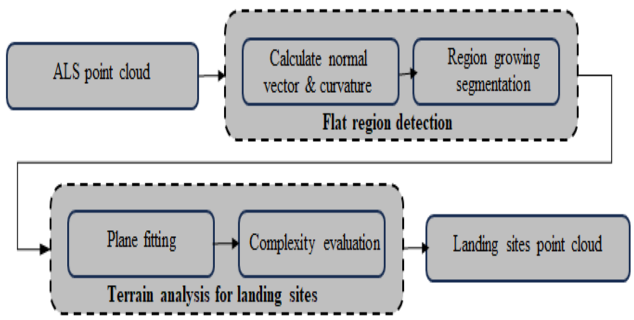


**Figure 3**: Methodology flow-chart for suitable landing site selection from ALS point cloud

We employ a 20x20 block size to partition the input point cloud into overlapping blocks. Each block consists of an inner and outer component, with the outer block's dimensions determined by adding the inner block size to a 5-meter landing site radius.


https://doi.org/10.5194/isprs-archives-XLVIII-4-W9-2024-343-2024  

This approach accounts for the dimensions of the aerial vehicle and provides a margin for safe landing.

During labelling, we focus on points within the inner block to ensure precise consideration for potential landing areas. The labels assigned to each point within the inner block are determined by evaluating its parameters and the nearest neighbours within the landing site radius. We execute block processing in a left-to-right and bottom-to-top sequence to ensure alignment of adjacent blocks without overlap.

We compute key parameters for interconnected blocks, including inner and outer block indices and boundary points. This computation results in a mapping that categorizes points into four classes: "dangerous," "unsuitable," "risky," and "suitable."

To enhance the efficiency of the labelling algorithm, particularly for large point clouds, we introduce overlapping block processing. Our primary goal is identifying an ideal, obstacle-free, and level landing area. We divide the point cloud into ground and non-ground points, designating non-ground points as "dangerous." We pay special attention to "unsuitable boundary points" along the boundary, "unsuitable points along dangerous points" in proximity to dangerous points, and the classification of "unsuitable" points based on neighbour count and proximity to hazardous points.

"Unsuitable" points undergo additional classification using overlapping block-based processing in the subsequent phase. This classification considers nearest neighbours and other attributes such as vertical variance, relief, slope, and residuals. Points with attribute values surpassing specified thresholds are labelled as "risky."

It is important to note that the labelling process is confined to the inner block, and the labels array is updated accordingly to ensure precise categorization of points within the defined landing area. Unlabeled points that meet predefined criteria are designated as "suitable," indicating secure landing points without dangerous or unsuitable surroundings.

In summary, our methodology offers a comprehensive and systematic approach to automate the selection of suitable landing sites for UAVs using ALS point cloud data. The approach is designed to handle large point clouds efficiently while accurately identifying safe landing areas. The detailed steps outlined in our methodology provide a robust framework for enhancing the safety and reliability of autonomous UAV landings.

### 2.3 Experiment setup:

The experimental analysis focused on utilizing the selected ALS point cloud datasets, processed on a system featuring an Intel i5-8300h 2.3GHz processor and an NVIDIA GeForce GTX 1060 graphics card. The primary goal was to evaluate the effectiveness of the proposed method for identifying suitable landing sites for Unmanned Aerial Vehicles (UAVs).

## 3. RESULTS

The initial phase involved the application of Principal Component Analysis (PCA) and an improved region-growing algorithm to detect non-flat regions within the point clouds. Figure 4 visually represents the successful identification of non-flat areas, marked in red and flat parts in grey.

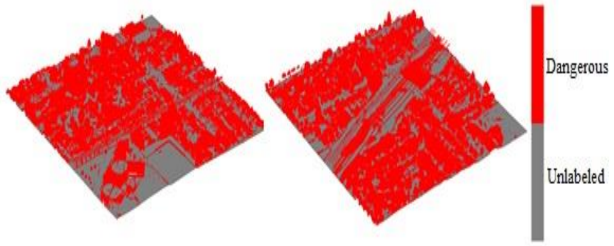


**Figure 4:** Dangerous with unlabeled point cloud.

Within the flat regions, points unsuitable for UAV landing were detected as shown in Figure 5.

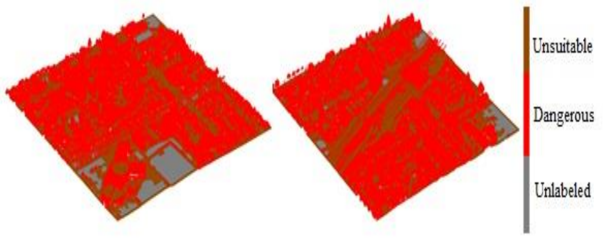


**Figure 5:** Unsuitable points in flat region.

Points near dangerous areas were classified as risky points as shorn in Figure 6 This step was critical in pinpointing areas that could pose challenges or hazards during UAV landing.

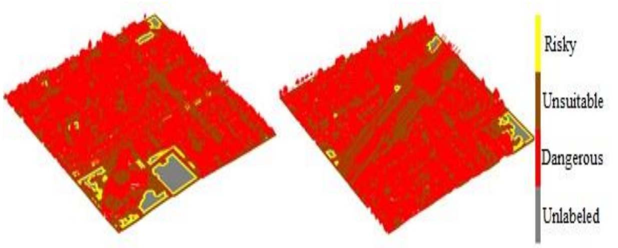


**Figure 6:** Risky points detected from suitable points.

**Suitable Landing Sites Identification**

The final output (Figure 7) showcased the successful identification of suitable landing sites for UAVs, labeled and represented in green. These regions were deemed safe for UAV landings, having undergone a meticulous classification process to eliminate potential obstacles.

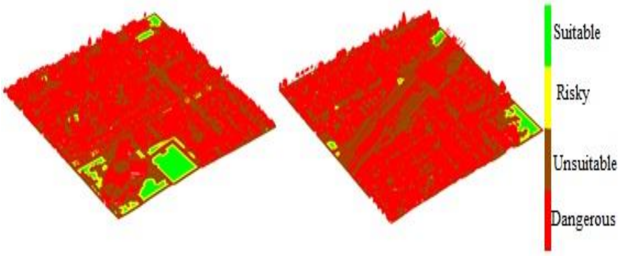


**Figure 7:** Suitable identified landing sites.

We detect non-flat regions using PCA and the improved region growing algorithm and marked them as red color and flat region as grey color as shown in Figure 4. Despite being on flat regions, the spots close to the purple-marked risky points are unsuitable for landing. The yellow points are classified as risky points as shown in Figure 6.

The result of suitable sites detected for UAVs landing is shown in Figure 7. In this the suitable site for UAVs landing is labeled as suitable and represented by green color. In this region UAVS can land without any problem. All the issues they create problem during UAVS landing are removed in different stage. Despite being on flat regions, the spots close to the purple-marked risky points must be more suitable for landing.

## 4. DISCUSSION AND CONCLUSION

### 4.1 Discussion

Our study demonstrates the effectiveness of our method in identifying suitable landing sites for Unmanned Aerial Vehicles (UAVs) using point cloud data from airborne laser scanning (ALS). Leveraging advanced techniques like Principal Component Analysis (PCA) and an improved region-growing algorithm, we accurately detected non-flat regions in the point clouds. These non-flat regions were then analyzed to identify points unsuitable for UAV landing, especially those near hazardous areas, classified as risky points. Our method effectively categorized issues within the defined landing area, ensuring the identification of only suitable landing sites devoid of dangerous or unsuitable surroundings.

The experimental setup, employing the DALES dataset, a system with an Intel i5-8300h 2.3GHz processor, and an NVIDIA GeForce GTX 1060 graphics card, provided a robust foundation for our evaluations. Initially, we applied PCA and the region-growing algorithm, as illustrated in Figure 3, successfully identifying non-flat areas and distinguishing them from flat regions. Subsequently, Figure 5 accurately identified unsuitable points within flat areas for UAV landing. Additionally, Figure 6 showcased the successful classification of risky points near dangerous regions, indicating the method's ability to identify potential hazards during UAV landing.

Figure 7 presents the final output, showing the successful identification of suitable landing sites for UAVs, labelled and represented in green. These regions were deemed safe for UAV landings, having undergone meticulous classification to eliminate potential obstacles. Our method effectively utilized ALS point cloud data, automating the selection of suitable landing sites for UAVs and demonstrating its potential to enhance the accuracy, safety, and efficiency of UAV landing site selection in diverse environments.

### 4.2 Conclusion

Our study presents a novel method for automatically identifying safe landing sites for Unmanned Aerial Vehicles (UAVs) using point cloud data obtained from airborne laser scanning (ALS). The approach leverages advanced techniques such as Principal Component Analysis (PCA) and an improved region-growing algorithm to detect non-flat regions within the point clouds and classify them based on suitability for UAV landing. Our experiments, conducted on the DALES dataset, demonstrated the method's effectiveness in accurately identifying suitable landing sites and classifying risky areas, thereby enhancing the safety and reliability of UAV landings.

The proposed method addresses the challenges associated with UAV landing site selection, mainly when traditional landing infrastructure is limited or impractical. By integrating ALS technology with UAV operations, our method provides:

- A robust framework for automating the selection of safe landing sites.
- Contributing to advancing autonomous UAV operations in various applications such as disaster response(Mohd Daud et al. 2022).
- Environmental monitoring.
- Infrastructure inspection.

Overall, our study contributes to the ongoing dialogue on integrating advanced technology with UAV operations, offering a promising approach to enhance the precision, safety, and efficiency of UAV landing site selection. Future research directions could further refine the method's algorithms and evaluate its performance in real-world scenarios to validate its practical utility in diverse environments.

To address the challenge of selecting optimal landing sites for autonomous Unmanned Aerial Vehicles (UAVs), this study presents a novel approach leveraging LiDAR point cloud data. Leveraging the distinctive attributes of 3D point clouds within a designated landing area, we employ Principal Component Analysis (PCA) in conjunction with an enhanced region-growing algorithm to expedite the identification of expansive flat terrains. Subsequently, we perform plane fitting to assess terrain parameters within these flat regions comprehensively.

Simulation outcomes affirm the efficacy of our method, as it successfully identifies two landing sites characterized by favorable terrain conditions and maintains a safe distance from ground obstacles. Additionally, the computational runtime of our approach aligns with engineering specifications. Nevertheless, further investigations are warranted to enhance real-time performance and facilitate the integration of our algorithm into the onboard processor of UAVs.

## REFERENCES


Abujoub, Shadi, Johanna McPhee, and Rishad A. Irani. 2020. "Methodologies for Landing Autonomous Aerial Vehicles on Maritime Vessels." *Aerospace Science and Technology* 106.

Chamberlain, Lyle, Sebastian Scherer, and Sanjiv Singh. 2011. "Self-Aware Helicopters: Full-Scale Automated Landing and Obstacle Avoidance in Unmapped Environments." *Annual Forum Proceedings - AHS International* 4: 3210–19.

Chen, Lyujie et al. 2020. "Robust Autonomous Landing of UAV in Non-Cooperative Environments Based on Dynamic Time Camera-LiDAR Fusion." http://arxiv.org/abs/2011.13761.

Cho, Am et al. 2007. "Fully Automatic Taxiing, Takeoff and Landing of a UAV Using a Single-Antenna GPS Receiver Only." *ICCAS 2007 - International Conference on Control, Automation and Systems*: 821–25.

Cramer, Michael. 2010. "The DGPF-Test on Digital Airborne Camera Evaluation Overview and Test Design." *Photogrammetrie-Fernerkundung-Geoinformation*: 73–82.

Cui, Pingyuan, Dantong Ge, and Ai Gao. 2017. "Optimal Landing Site Selection Based on Safety Index during Planetary Descent." *Acta Astronautica* 132: 326–36.

Huang, Jian Yu, Yu Fu Qu, and Ji Xiang Jiang. 2018. "Method for Identifying the Landing Area of Unmanned Aerial Vehicle." *Chinese Journal of Liquid Crystals and Displays* 33(3): 238–44.

Johnson, Andrew E., Allan R. Klumpp, James B. Collier, and Aron A. Wolf. 2002. "Lidar-Based Hazard Avoidance for Safe Landing on Mars." *Journal of Guidance, Control, and Dynamics* 25(6): 1091–99.

Lorenzo, Oscar G. et al. 2017. "Landing Sites Detection Using LiDAR Data on Manycore Systems." *Journal of Supercomputing* 73(1): 557–75

Loureiro, Gabriel, André Dias, Alfredo Martins, and José Almeida. 2021. "Emergency Landing Spot Detection Algorithm for Unmanned Aerial Vehicles." *Remote Sensing* 13(10).

Mango, Davide, Roberto Opromolla, and Christoph Schmitt. 2020. "Hazard Detection and Landing Site Selection for Planetary Exploration Using LIDAR." *2020 IEEE International Workshop on Metrology for AeroSpace, MetroAeroSpace 2020 - Proceedings*: 392–97.

Maturana, Daniel, and Sebastian Scherer. 2015. "3D Convolutional Neural Networks for Landing Zone Detection from LiDAR." *Proceedings - IEEE International Conference on Robotics and Automation* 2015-June(June): 3471–78.

Mohd Daud, Sharifah Mastura Syed et al. 2022. "Applications of Drone in Disaster Management: A Scoping Review." *Science & Justice* 62(1): 30–42.

Scherer, Sebastian, Lyle Chamberlain, and Sanjiv Singh. 2012a. "Autonomous Landing at Unprepared Sites by a Full-Scale Helicopter." *Robotics and Autonomous Systems* 60(12): 1545–62.

———. 2012b. "Autonomous Landing at Unprepared Sites by a Full-Scale Helicopter." *Robotics and Autonomous Systems* 60(12): 1545–62.

Shah Alam, Md, and Jared Oluoch. 2021. "A Survey of Safe Landing Zone Detection Techniques for Autonomous Unmanned Aerial Vehicles (UAVs)." *Expert Systems with Applications* 179.

Singh, Dheerendra Pratap, and Manohar Yadav. 2023. "3D-MFDNN: Three-Dimensional Multi-Feature Descriptors Combined Deep Neural Network for Vegetation Segmentation from Airborne Laser Scanning Data." *Measurement: Journal of the International Measurement Confederation* 221.

Takahashi, Marc D. et al. 2018. "Full-Scale Flight-Test Results for a Rotorcraft Safe Landing Area Determination Algorithm for Autonomous and Piloted Landing Approaches." *Journal of the American Helicopter Society* 63(4).

Varney, Nina, Vijayan K. Asari, and Quinn Graehling. 2020. "DALES: A Large-Scale Aerial LiDAR Data Set for Semantic Segmentation." *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops* 2020-June: 717–26.

Whalley, Matthew S. et al. 2014. "Autonomous Black Hawk in Flight: Obstacle Field Navigation and Landing-Site Selection on the RASCAL JUH-60A." *Journal of Field Robotics* 31(4): 591–616.

Xiao, Xueming, Meibao Yao, Hutao Cui, and Yuegang Fu. 2019. "Safe Mars Landing Strategy: Towards Lidar-Based High Altitude Hazard Detection." *Advances in Space Research* 63(8): 2535–50.

Yan, Lu et al. 2020. "A Safe Landing Site Selection Method of UAVs Based on LiDAR Point Clouds." *Chinese Control Conference, CCC* 2020-July: 6497–6502.

Yan, Zhi, Tom Duckett, and Nicola Bellotto. 2020. "Online Learning for 3D LiDAR-Based Human Detection: Experimental Analysis of Point Cloud Clustering and Classification Methods." *Autonomous Robots* 44(2): 147–64.

Zhao, Taifei, Ping Liu, Shuang Zhang, and Qianwen Ma. 2020. "UAV Assisted Landing Guided by UV LEDs." *Applied Optics* 59(20): 5910.