Improving the Spatial Accuracy of Low-Cost UAV-Borne LiDAR Systems through Post-Processing

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ABSTRACT

Recent developments in Unmanned Aerial Vehicle (UAV)-borne remote sensing technology have created a new class of Light Detection and Ranging (LiDAR) scanner, capable of being pay loaded to UAVs and relatively affordable in comparison to other airborne LiDAR sensor systems. Shortcomings in this low-cost LiDAR hardware result from lower-quality sensors, which produce lower-quality LiDAR point cloud datasets, that can be considered unsuitable for deriving topographic information from. Present literature demonstrates LiDAR point clouds derived from low-cost sensors such as the DJI Zenmuse L1 are prone to data anomalies resulting from the systematic errors in the airborne LiDAR system itself. Improving the accuracy of this low-cost sensor derived data is imperative to prove that the technology is reliable and worthy of continued development and adoption by surveying firms. This paper is based on the author's undergraduate Honours research project at the University of Southern Queensland (UniSQ), which was awarded the APAS UniSQ Student Project Prize 2024. Post-processing of LiDAR data was performed on a series of datasets produced using a Zenmuse L1, each with differing sensor and flight parameters, within a LiDAR post-processing software. Changes were gauged between each stage of post-processing, and ultimately all sensor and flight parameters were tested against a ground truth survey carried out using conventional surveying methods to ascertain the suitability of post-processed LiDAR data derived from a low-cost UAV-borne LiDAR sensor. Ultimately, the improvement of the datasets from a statistical standpoint indicated only minor changes overall in comparison to a ground truth survey with no conclusive improvement or deterioration resulting from post-processing. Flight parameters and sensor settings were ultimately shown to be more influential on the spatial accuracy of the dataset than any post-processing, with post-processing proving successful in improving the precision of the data to create more desirable final products.

KEYWORDS: *Remote sensing, UAV, LiDAR, post-processing.*

1 INTRODUCTION

Over recent years, the advent of commercially available, relatively affordable Unmanned Aerial Vehicle (UAV)-borne Light Detection and Ranging (LiDAR) sensors has created an alternative means by which surveyors and other spatial professionals are able to collect topographic data for medium and large sites. Conventional survey techniques would require measurements to be taken via Real-Time Kinematic (RTK) Global Navigation Satellite System (GNSS) observations or a total station and prism at hundreds or even thousands of locations across a site to build a digital model. UAV-borne LiDAR offers surveyors the opportunity to minimise risks to staff and vehicles associated with navigating paddocks and open areas (e.g. injuries due to trips and falls, encounters with dangerous wildlife and vehicle damage caused by hidden obstacles). It can also reduce rework required because of human error in the field as the resolution of the resulting point cloud data enables surveyors to 'data mine' the LiDAR point cloud.

At present, most UAV-borne LiDAR sensors require a significant investment of over $100,000 for the sensor alone. However, the release of the DJI Zenmuse L1 (and later L2) LiDAR sensors has brought the price of an entry-level LiDAR sensor down to about $20,000, making it more realistic for small and medium sized surveying businesses to invest in the technology. Even considering the relative affordability of the Zenmuse sensors, the combined costs of the sensor, the UAV system itself, software licenses, as well as training and pilot licensing still presents surveying businesses with a confronting cost of entry into the UAV LiDAR space. Issues regarding the accuracy of the L1 sensor are often anecdotally questioned by naturally sceptical surveyors, who often view emerging technologies as less accurate than existing techniques and are unwilling to invest in emerging technology such as UAV-borne LiDAR as a result.

Despite surveyors' natural tendency to shy away from new technology in favour of 'tried and true' traditional methods, it has been established that UAV-borne LiDAR can be suitable for topographic mapping (Lin et al., 2011), with the Zenmuse L1 payload capable of producing data of sufficient accuracy for use on mostly hardstand materials within topographic surveys over small sites not larger than 5 ha (Kersten et al., 2022). However, the realistic use case for UAV-borne LiDAR sensors to surveyors being to cover large areas of predominantly unimproved land (such as rural paddocks) for the purpose of extracting a digital model of the Natural Surface Level (NSL) requires further analysis regarding the ability of the L1 system to produce LiDAR point cloud data of sufficient and reliable accuracy to derive NSLs across medium-to-large sites. Present literature does not provide a genuine comparison to existing conventional methods, which would realistically be applied to large sites, rather focussing on the comparison of hardstand and built form objects to photogrammetry techniques or Terrestrial Laser Scanning (TLS) data (Stroner et al., 2021; Diara and Roggero, 2022).

Importantly, a level of similarity exists between airborne-LiDAR sensors and UAV-borne LiDAR sensors. In both cases, a LiDAR sensor is pay loaded to an aircraft along with ancillary RTK-GNSS for positioning and an Inertial Measurement Unit (IMU) for initialising sensor orientation. Both methods acquire LiDAR data while in motion along planned flight paths, with the primary differences between airborne and UAV-borne LiDAR being that airborne LiDAR missions are typically carried out on manned aircraft, covering vastly larger areas than a UAV can achieve. The similarities of the two LiDAR data collection methods provide an overlap in literature, which is relevant to UAV-borne LiDAR, with post-processing to remove known error types a particular focus.

One error that occurs in airborne-LiDAR datasets is known as 'step-error' (e.g. Burman, 2000; Crombaghs et al., 2000; Kager, 2004; Willers et al., 2008). Step-error is the presence of erroneous data in both airborne and UAV-borne LiDAR derived point clouds, caused by differing orientation solutions of the onboard IMU following each IMU calibration instance to combat the IMU's drift. Improving the accuracy of airborne-LiDAR orientation solutions can only be done by either investing in better-quality LiDAR sensor systems, which can be prohibitively expensive, or through post-processing to remove the occurrence of this type of error by registering each LiDAR strip to the adjacent strip or strips.

Strip adjustment is the broad term utilised for post-processing of airborne LiDAR strips using algorithms and software. At present, many of these methods have only been explored at a high level to the point of formulating adjustment methodologies (Morin, 2002). Research regarding the suitability of strip adjustments carried out to UAV-borne LiDAR data is limited (Chen et al., 2021), with no reference to ground truth obtained using conventional surveying methods. The only existing method of strip adjustment able to be readily applied with automation on a large scale is StripAlign (Bayesmap, 2025), a software which purports an ability to register airborne LiDAR swathes to remove the step-error artefact from airborne or UAV-borne LiDAR datasets.

Another common source of error in LiDAR derived point clouds affecting the spatial accuracy of the dataset is noise. Noise occurs as a result of imperfect laser returns from the LiDAR sensor, resulting from subject surface reflectance or low-quality LiDAR sensors with large beam divergence (Gatziolis and Andersen, 2008). Within the LiDAR derived point cloud itself, noise can be visualised as a sample of many points with varying elevations over what is in reality a flat surface. While the ranging accuracy of the L1 system is stated as 2-3 cm (DJI, 2025; Livox, 2025), these values are obtained in optimal laboratory conditions. In reality, L1 point cloud data sections can be as thick as 10 cm dependent on field conditions, indicating a ranging accuracy of ±5 cm under more realistic conditions. Mitigating this source of error from the sensor would require a more significant investment in a more powerful LiDAR system, which may be cost prohibitive for a small-to-medium scale surveying firm. As such, the ability to post-process a LiDAR dataset to reduce or remove noise is important for improving the overall spatial accuracy of the dataset and supporting the extraction of accurate levels from any point in the resulting point cloud. Most point-cloud processing software packages contain a noise reduction tool of some sort. The analysis of available point-cloud noise processing methods has already been covered extensively (e.g. Zuowei et al., 2013; Charron et al., 2018; Cheng et al., 2021; Gao et al., 2021). The focus of this study is to investigate if the combination of readily available strip adjustment and noise reduction software for low-cost LiDAR sensors is capable of improving the point cloud datasets to a more acceptable level for topographic purposes.

This paper tests several variables that naturally occur during a UAV-borne LiDAR mission. To simply test a single set of parameters would likely only raise more issues for the sceptical surveyor, who must be convinced beyond doubt that new technology is capable of reliably producing data of at least the same quality than existing methods. To this end, post-processing of LiDAR data was performed on a series of datasets produced using a Zenmuse L1, each with differing sensor and flight parameters, within a LiDAR post-processing software. Changes were evaluated between each stage of post-processing, and ultimately all sensor and flight parameters were tested against a ground truth survey carried out using conventional surveying methods to ascertain the suitability of post-processed LiDAR data derived from a low-cost UAV-borne LiDAR sensor.

2 METHODS

2.1 Study Area

Considerations for selecting a suitable study area included airspace, accessibility, size, surface types, vegetation and proximity to accessible power points. The Sutcliffe Reserve on Plantation Road in Corio, Victoria, covers an area of approximately 80 ha, with low, well-maintained grass, patches of bare earth, and minimal high vegetation. The site has a bitumen driveway and a pair of buildings situated on it, which presented a limited ability to test the accuracy of the sensor on some hardstand surfaces (Figure 1).

Figure 1: Sutcliffe Reserve satellite image from Google Maps.

The reserve is within class G airspace, meaning no specific approvals were required to conduct a UAV operation. With the reserve being public land owned by the City of Greater Geelong, no specific permissions were required, but a generic permission was sought in order to take off and land a Remotely Piloted Aircraft (RPA) from council property. Advantageously, on weekdays the reserve is not busy and seldom used by members of the public. This was an important consideration as Civil Aviation Safety Authority (CASA) laws state that an RPA cannot be flown within 30 m of a person, so ensuring a clear site was essential to executing the mission as efficiently as possible.

2.2 Data Collection

2.2.1 UAV Flight Mission

A total of eight different flight missions were planned with the DJI Pilot 2 application, the standard means of planning and monitoring flight missions on DJI RTK capable RPAs. As RTK corrections are being logged by the drone in flight, it is impossible to observe static positions during the course of a flight mission. Therefore it was considered important for the purpose of this research to remove any positioning anomalies to the aerial survey that might arise as a result of spatial degradation, as the nearest Continuously Operating Reference Station (CORS) was located approximately 9.5 km away in Geelong. This was achieved by setting up a local base station from which the RPA obtained corrections from, for which a control mark had been established using a rapid static GNSS survey via Network RTK.

Due to the nature of LiDAR missions, a range of flight parameters and sensor settings are available, all of which have the potential to impact on the quality of the eventuating LiDAR data. These variables have the potential to impact the quality of the laser returns from the LiDAR sensor itself and change the resolution of the LiDAR data, which could impact the quality of the post-processing outcome.

Flying height is a primary consideration of most UAV-borne surveys, particularly photogrammetry, as the further a sensor (e.g. camera) is from its subject, the poorer the resolution of the resulting dataset. In photogrammetry, this is known as Ground Sampling Distance (GSD). Similarly with LiDAR, the laser beam emitted from the sensor loses resolution due to beam divergence (Gatziolis and Andersen, 2008), i.e. where the laser beam emitted from the LiDAR sensor spreads over the distance between the sensor and the target surface (Figure 2). The Livox Avia LiDAR module, which is the actual LiDAR sensor used in the Zenmuse L1, specifies a beam divergence of up to 0.28° (Livox, 2025) or 4.89 mrad, which allows the approximation of beam divergence at 50 m Above Ground Level (AGL) to be at around 0.25 m – this value doubles to 0.49 m when the flying height is increased to 100 m AGL. A larger beam divergence lowers the signal-to-noise ratio of each light emission, thus leading to a lower overall expectation of accuracy due to 'noisy' returns.

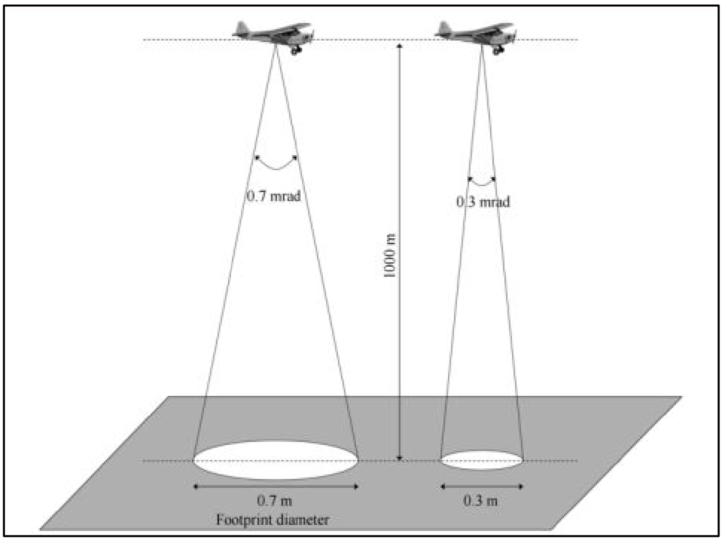

Figure 2: LiDAR beam divergence diagram (Gatziolis and Andersen, 2008).

Therefore improved data resolution is likely conducive to improved accuracy, meaning the lower the UAV-borne LiDAR survey can be flown the better. Considering this, it must also be rationalised that flying lower decreases the Field of View (FOV) of the LiDAR sensor, necessitating more flight lines to cover the same amount of area than a higher-flying UAV would. Constrained by weather windows, project deadlines and flying time due to limited battery power, a balance must be struck between accuracy and realistic flight parameters. Thus, multiple flying heights will be tested to investigate if accuracy is indeed noticeably affected by flying height, and if so whether post-processing can improve the data quality.

Flight direction and orientation requires consideration when planning UAV-borne LiDAR missions. Optimising flight efficiency is a consideration made by the remote pilot to maximise flying time and cover as much area as possible. Orientation is considered for a range of reasons, e.g. orienting the flight mission parallel to a site boundary ensures the most effective and uniform data collection.

Overlap is the term referring to the amount by which each LiDAR strip progresses along the subject site relative to the previous flight line, often referred to in percentages. Higher overlap rates (60-90%) offer benefits including increasing data resolution, offering redundant observations of the ground and improving chances of vegetation penetration due to multiple observation angles, although this also affects the area of land a flight may cover. Lower overlap rates (10-50%) enable the coverage of more area in the same amount of time but may not provide enough information to perform post-processing by best-fit registration due to insufficient levels of common data between LiDAR flight swathes.

Bracing is the term referring to LiDAR flight lines flown perpendicular to the main LiDAR mission (Figure 3). Bracing offers three potential benefits when conducting a UAV-borne LiDAR mission:

1) Flying a second replicate mission to the primary, at a different approach angle, may provide more opportunity for vegetation penetration at different aspects, providing more chance of achieving a true ground measurement.
2) Offering redundant flight missions to augment the overall mission in the event of an inadvertent RTK positioning loss during one of the flights. Often this means that an entire flight may be useless if RTK data loss happened early on.
3) Perpendicular flight lines are recommended by the developer of the StripAlign software used during post-processing to provide bracing to the strip adjustment (Bayesmap, 2025).

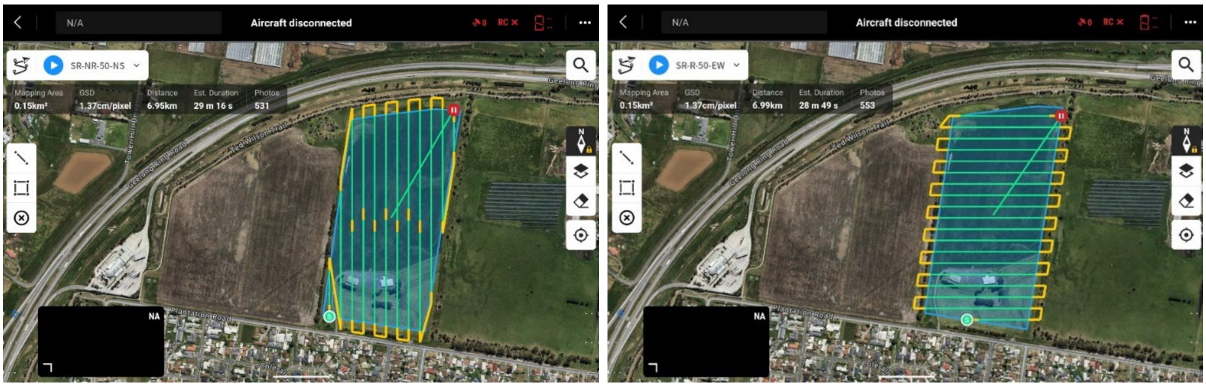

Figure 3: DJI Pilot 2 app, planning a north-to-south and an east-to-west mission.

A unique capability of the DJI Zenmuse L1 & L2 LiDAR sensors is the ability to employ two different scanning patterns: repetitive and non-repetitive (Figure 4). Limited analysis of the differences achieved by these two scanning settings found no noticeable difference between the two (Kersten et al., 2022). However, this study was limited to simplistic cloud-to-cloud analysis with unsatisfactory reference to an actual ground truth survey carried out using more reliable and thorough measurement techniques (such as direct observation methods).

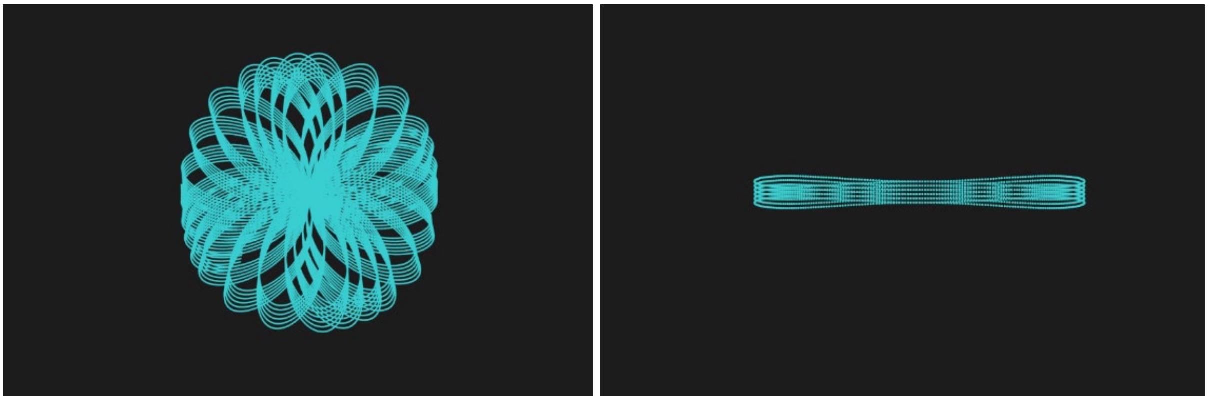

Figure 4: Non-repetitive and repetitive L1 scanning patterns (Aerotas, 2023).

Each mission typically consisted of several flights, required to change batteries or because of a cancelled mission due to either interference from local avian wildlife or the presence of a member of the public under the flight path. The missions conducted in the present study are summarised in Table 1, along with the tested parameters.

Table 1: Missions and their tested parameters.

Mission	Height AGL	Scanning Setting	Direction	LiDAR Overlap (%)
1	50	Repetitive	North-South	80
2	50	Repetitive	East-West	80
3	50	Non-Repetitive	North-South	80
4	50	Non-Repetitive	East-West	80
5	50	Non-Repetitive	North-South	80
6	50	Non-Repetitive	East-West	80
7	80	Non-Repetitive	East-West	20
8	80	Non-Repetitive	North-South	20

Prior to the commencement of the UAV-borne LiDAR survey, 12 Ground Control Points (GCPs) were placed across the site in a 4x3 pattern at approximately even spacing (Figure 5). The GCPs consisted of a 900 x 900 mm piece of plywood, painted in a black-and-white chequer pattern and held down with tent pegs at the corners. The centre point of each GCP was observed for 30 seconds via Network RTK using a Trimble R12i rover. During the 7th mission, RTK was lost for a significant duration of the flight due to the local base station battery running out of power, so it was removed from the post-processing regimen. This is considered acceptable as the 7th mission was a cross-bracing flight for the 8th mission, causing the 8th mission not to be subject to post-processing using bracing. The influence of cross-bracing will be evident from the other flight missions.

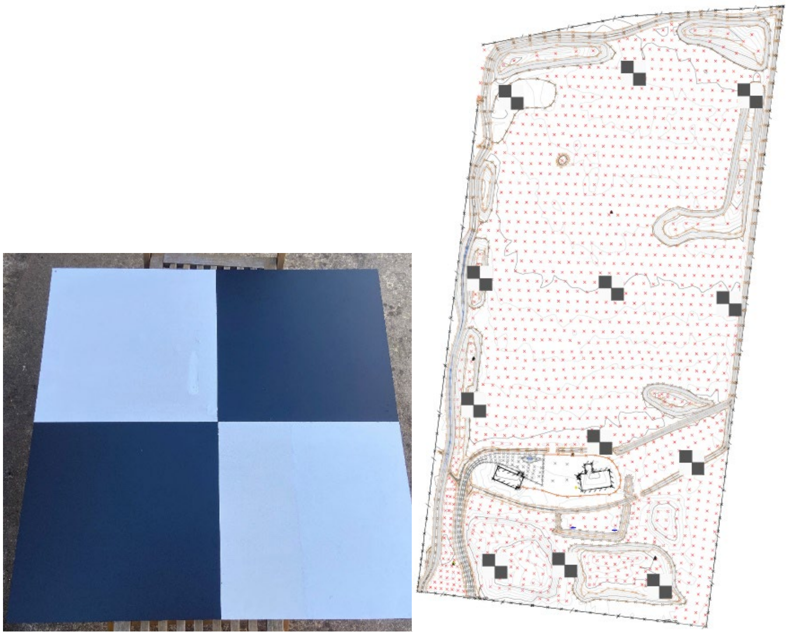

Figure 5: Close-up of a GCP and GCP layout across the study area.

2.2.2 Conventional Survey

Following the UAV-borne LiDAR survey, a conventional survey was carried out across the site with the intention to measure the entire site using methods inherently trusted by surveyors, i.e. total station and RTK-GNSS. Most surveyed points were observed using a Trimble S7 total station on an arbitrary datum with a maximum point spacing of 15 m. The main purpose of this survey was to produce as large a comparison dataset as realistically achievable, which entailed measuring relief features in as much detail as possible. As the primary focus of this study is to evaluate the suitability of UAV-borne LiDAR technology for topographic mapping, the measurement of features (such as buildings, trees and assets) was not performed. Achieving a common datum between the UAV-borne LiDAR survey and the conventional survey necessitated observing the arbitrary total station survey control points with RTK-GNSS so that the total station survey could be transformed later in the office.

2.3 Data Processing

2.3.1 DJI Terra Pre-Processing

In order to convert the UAV-borne LiDAR data from the Zenmuse L1 into a format that can be accepted by other LiDAR processing software packages, the raw flight files must be imported to DJI Terra and pre-processed. However, the lack of options in DJI Terra makes it difficult for the LiDAR-derived point cloud to be manipulated by the user. As such, DJI Terra was simply used as a stepping stone to obtain data that could be transferred to a more robust LiDAR post-processing software. Loading the files into DJI Terra is simple, and processing settings were set so that the only effect that the software had was to initialise a Terra project with a LiDAR-derived georeferenced point cloud, with no data manipulation from the DJI Terra software.

2.3.2 LP360 Post-Processing

Once a new project is started in LP360, each flight mission must be imported to the project using the sensor import function. Once imported, a workflow must be followed to obtain the initial LiDAR point cloud solution that resulted from the DJI Terra job.

The first step is to compute flight lines, where LP360 will initialise all the flight positions which the RPA logged while it was within the DJI Pilot 2 app. It is necessary to manually delete any flight lines that were not calibrated flight lines where the LiDAR sensor was not actively collecting data. The next step is to create TrueView trajectories, where LP360 will derive a trajectory file from the initial flight lines. After each trajectory file has been created, geocoding LAS files will initialise the LAS format point cloud within LP360, now allowing the post-processing to proceed.

Within LP360, the StripAlign plugin is a licensed version of Bayesmap's StripAlign within the LP360 software, called StripAlign for Evo (SaFE). SaFE enables each LiDAR flight line imported from DJI Terra (and imported LiDAR datasets from other sensor sources) to have step-errors removed from each flight line, resulting in a single uniform LiDAR point cloud.

Including additional flight lines perpendicular to the main mission (bracing lines) can prevent bowing to occur in a post-StripAlign dataset. As such, each flight arrangement is post-processed both as a single direction and with cross-bracing in order to detect any potential improvement gained from the additional LiDAR data.

Point cloud smoothing is a tool within LP360 to 'smooth' noise and other similar height discrepancies in point cloud datasets. Considering the ranging accuracy of the L1 is reported to be 3 cm at 100 m (DJI, 2025), this means that each return could range ±30 mm different to the true distance between the sensor and the ground. Removing this level of noise from a LiDAR-derived point cloud is imperative for improving the spatial accuracy of the dataset. The point cloud smoothing tool attempts to remove noise from a LiDAR point cloud by taking a best-fit plane through a sample of points and averaging those points to fit that plane. It is claimed that the function can preserve overall shape and relief of the subject point cloud. By running this function on its own, it is thought that step-errors may be filtered out as the function could simply perceive them as noise in the point cloud and average the points. However, potential sources of error of this process could be that the LiDAR swathes are not orientation corrected, meaning that sections of the swathes which are not overlapping may not be adjusted and simply remain incorrectly oriented.

Combining both post-processing functions results in a StripAlign adjustment being performed on the dataset to correct orientation errors, followed by using the point cloud smoothing function to remove the generic noise caused by known laser ranging errors. The intention of combining both functions is to determine if the benefits of each adjustment method could be combined to produce a more accurate dataset than obtainable from any of the other post-processing methods.

2.3.3 Conventional Survey

As the ground truth survey was undertaken on an arbitrary datum in the field, connection to the same Map Grid of Australia 2020 (MGA2020) zone 55 datum as the UAV flight was made via transformation to control points observed during the rapid static ground survey. As the GCPs for the LiDAR survey were obtained using the same Network RTK-GNSS technique, there was immediate parity between any GNSS observations taken and the UAV-borne LiDAR survey.

The total station observations, which were undertaken on an arbitrary datum using a scale factor of unity, were transformed using GNSS observations taken on the control marks in that survey. All total station points were then scaled to grid using a nearby Permanent Survey Mark (PSM) with GDA2020 Horizontal Positional Uncertainty of 0.036 m, the same PSM was also used to verify the Network RTK observations. Points from the conventional survey were then exported to a csv file for later use.

2.4 Results Validation

The necessity of ensuring all point clouds were on the same datum was essential for being able to compute differences between the datasets. Prior to undertaking any comparison computations, the point clouds were compared at each GCP to ensure no major deviations had occurred during post-processing. Each default dataset was checked against the GCPs placed and surveyed for overall agreement. Mission 7 was subjected to RTK positioning failure due to the base station battery running out of power mid-way through the flight, corrupting much of the flight mission and rendering it unusable, so accuracy verification was omitted for Mission 7 as a result.

3 RESULTS

3.1 Mission 1

Analyses were made in a similar manner between each mission, with each mission revealing unique insight into the nature of both the raw LiDAR data acquisition and the effects of post-processing on that data.

3.1.1 Cloud-to-Cloud Analysis

Parameters set for the first mission included a flying height of 50 m AGL, LiDAR overlap of 80% and repetitive scanning. Cloud-to-cloud comparisons between the initial point cloud ('raw cloud') and each subsequent adjusted point cloud indicate changes did occur as a result of each applied adjustment. The comparison between the raw cloud and the point cloud that had undergone the StripAlign adjustment shows evidence of a 'striping' pattern in the same orientation as the flight lines (Figure 6). This striping suggests that the StripAlign function has performed as expected, in that the LiDAR strips have been somewhat rolled around an axis in the attempt to register each LiDAR strip to neighbouring data, with 80.8% of points remaining within 20 mm of the raw cloud. Similar analyses were also carried out for all other missions.

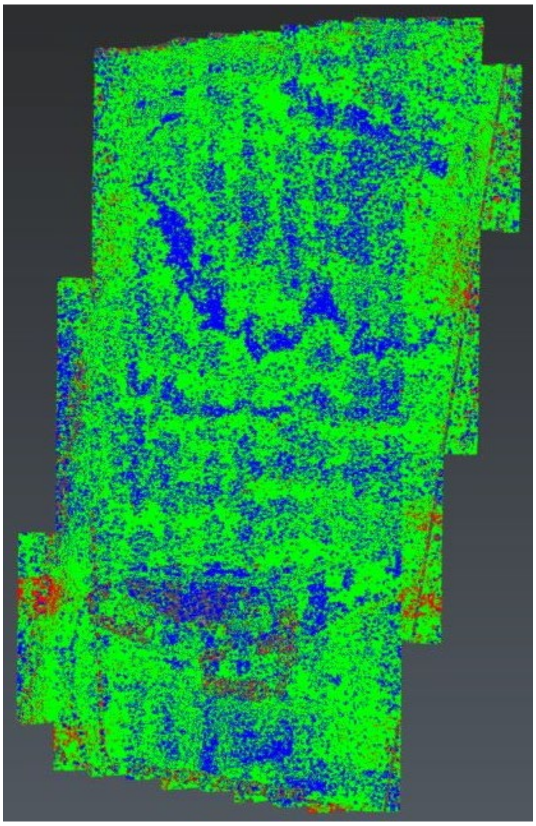

Figure 6: No adjustment vs. StripAlign.

Figure 7 depicts the comparison between the raw cloud and the point cloud that underwent the 'smoothing' function, which appears to fall mostly within 20 mm of the raw cloud position (92.6%). Visually, a significant pattern of change is evident around areas where high point cloud noise could be expected, particularly around areas of high vegetation such as clusters of gum trees on the site. There is also a noticeable amount of noise reduction along the bitumen track, which could be attributed to more erroneous returns resulting from the darker colour of the bitumen, causing a significant reduction in the strength of the LiDAR returns on that surface as the bitumen absorbs much of the emitted light.

Figure 8 shows a combination of both methods, where initially a StripAlign adjustment was performed, followed by the smoothing adjustment, with the intention that the StripAlign would remove the rolling error from the LiDAR strips and the smoothing would improve the point cloud structure.

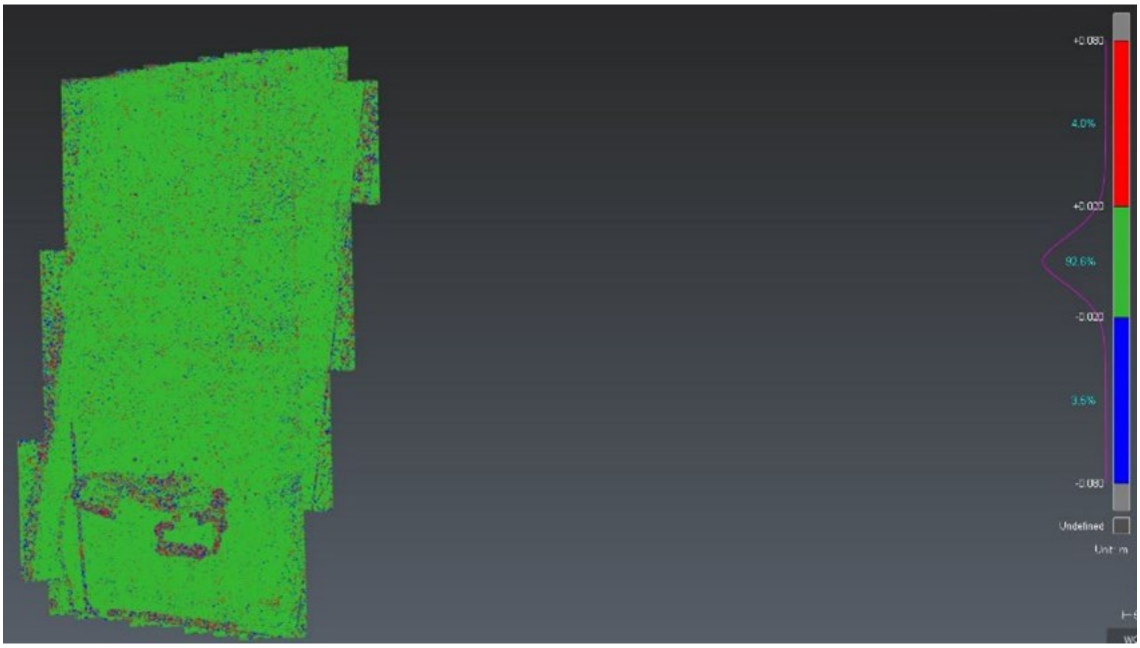

Figure 7: No adjustment vs. point cloud smoothing.

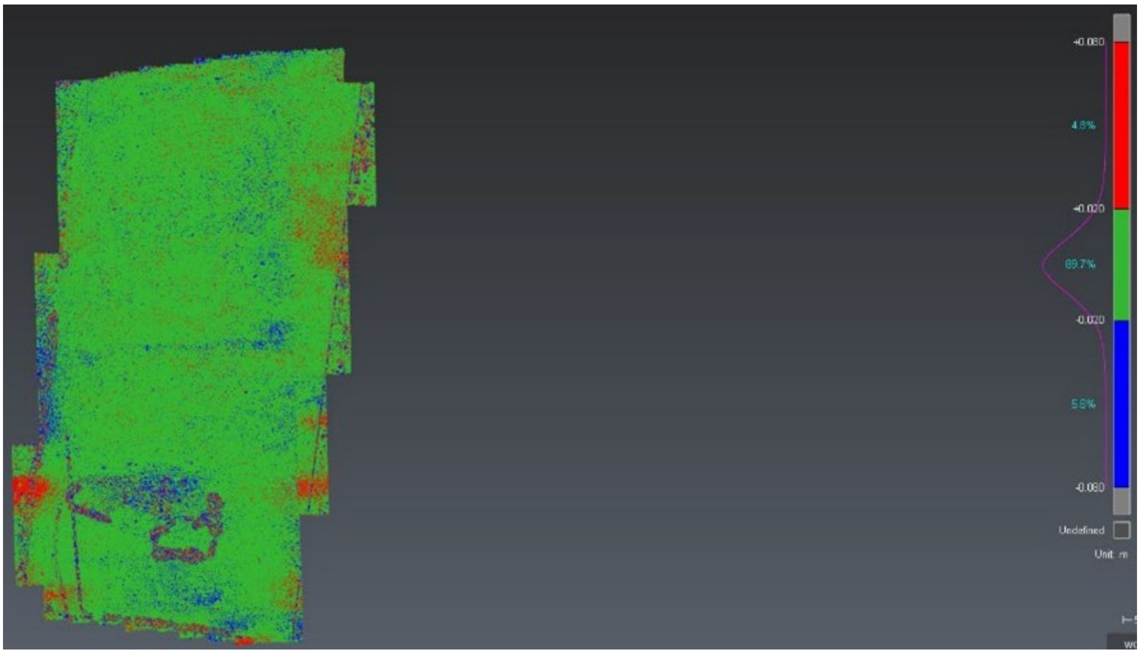

Figure 8: No adjustment vs. StripAlign + point cloud smoothing.

3.1.2 Ground Truth Survey vs. Point Cloud Analysis

Analyses between the ground truth survey point and each point cloud in Figures 9 & 10 show that 94-95% of surveyed points fall within ±50 mm of each variation of point cloud processing. No pattern of change is apparent due to any of the post-processing methods in regard to the ground truth surveys. Similar analyses were also carried out for all other missions.

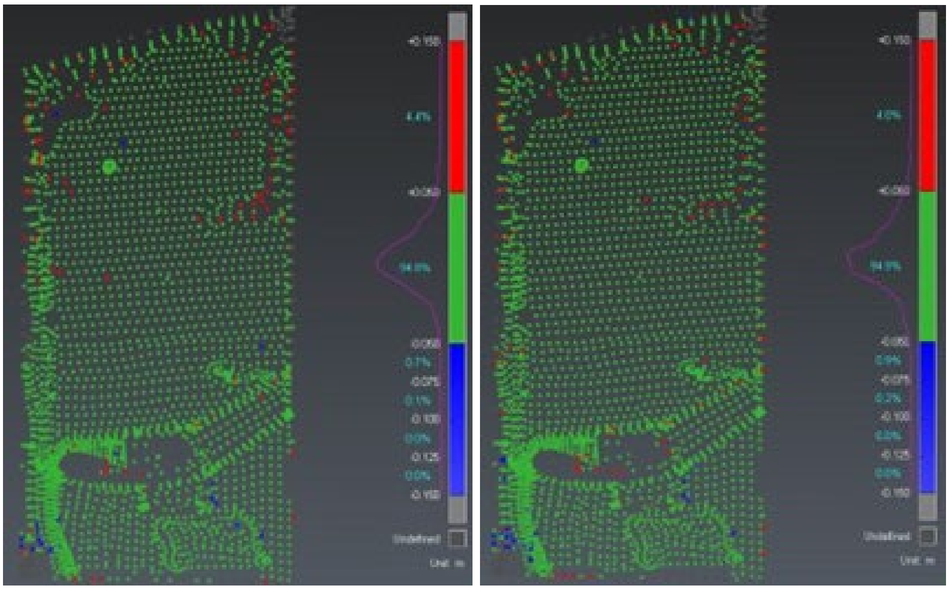

Figure 9: No adjustment cloud vs. points (left) and StripAlign adjustment cloud vs. points (right).

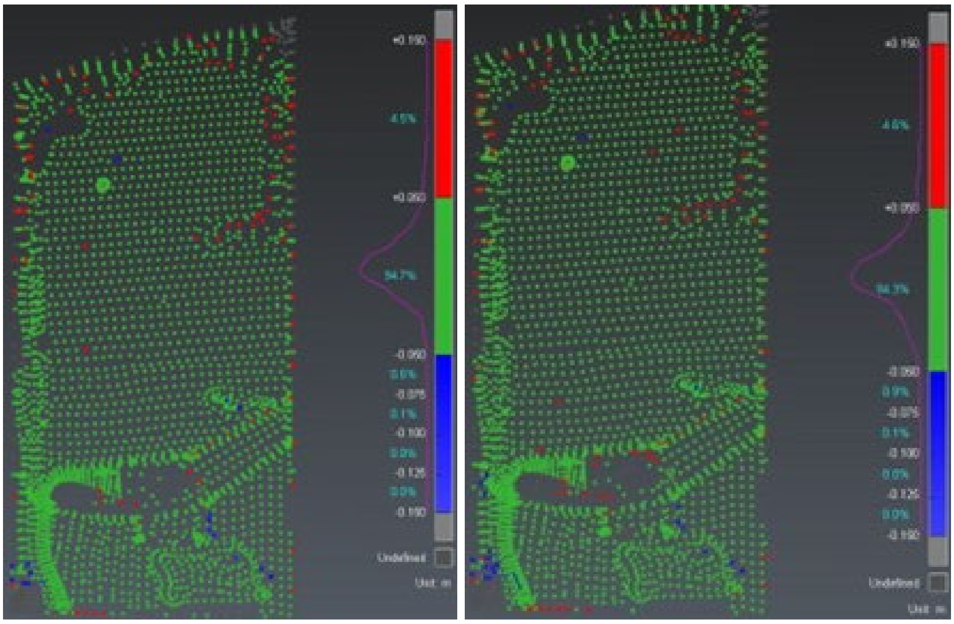

Figure 10: Smoothing adjustment cloud vs. points (left) and StripAlign + smoothing adjustment cloud vs. points (right).

3.2 Point Cloud Precision

3.2.1 Effects of Post-Processing on Point Cloud Structure

Figure 11 shows a cross section of a GCP within one of the point clouds which had undergone no adjustment, only a StripAlign adjustment, only a smoothing adjustment, and both a StripAlign and a smoothing adjustment across the cross section of a GCP. This demonstrates the effects of the smoothing adjustment on the overall precision of the point cloud as no change is evident at this scale as a result of the StripAlign adjustment, but the precision of the point cloud is very clearly more uniform.

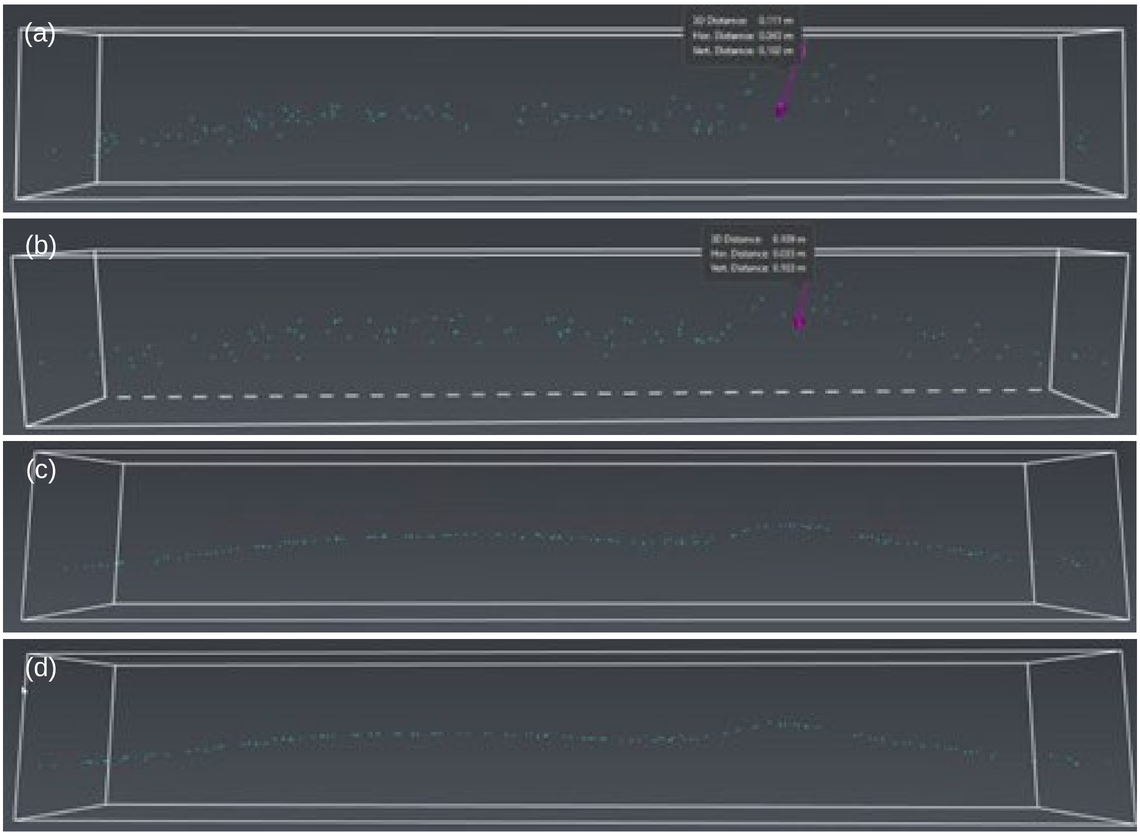

Figure 11: Cross section of a GCP with (a) no adjustment, (b) StripAlign adjustment, (c) cloud smoothing adjustment, and (d) both StripAlign and point cloud smoothing adjustment.

3.2.2 Effects of StripAlign Adjustment to Step-Error

Figure 12 shows a cross section of the intersection of two LiDAR swathes, indicating the misalignment between those swathes and identifying a step-error with the thickness of the point cloud being 0.119 m. Figure 13 shows the same location after a combined StripAlign and smoothing adjustment, with the thickness of the dataset now significantly reduced to 0.019 m.

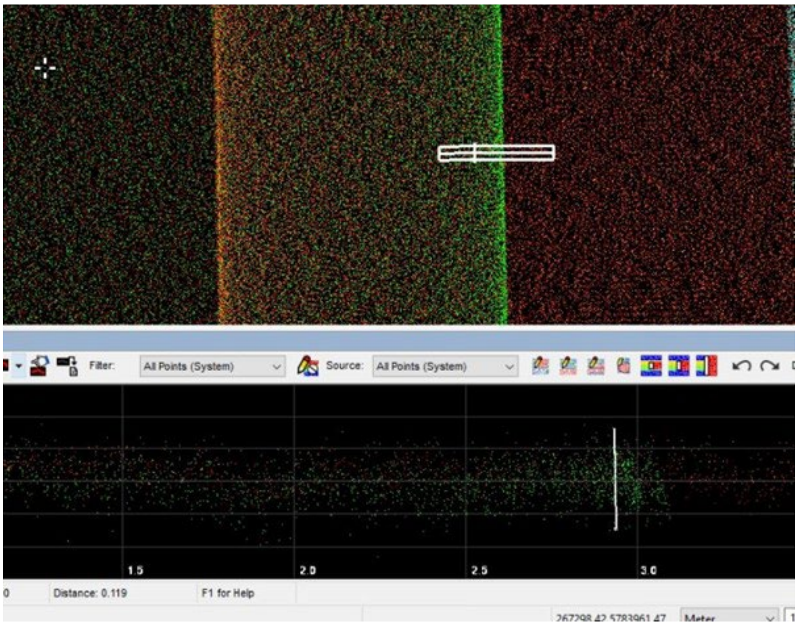

Figure 12: Evidence of step-error occurring in the LiDAR dataset.

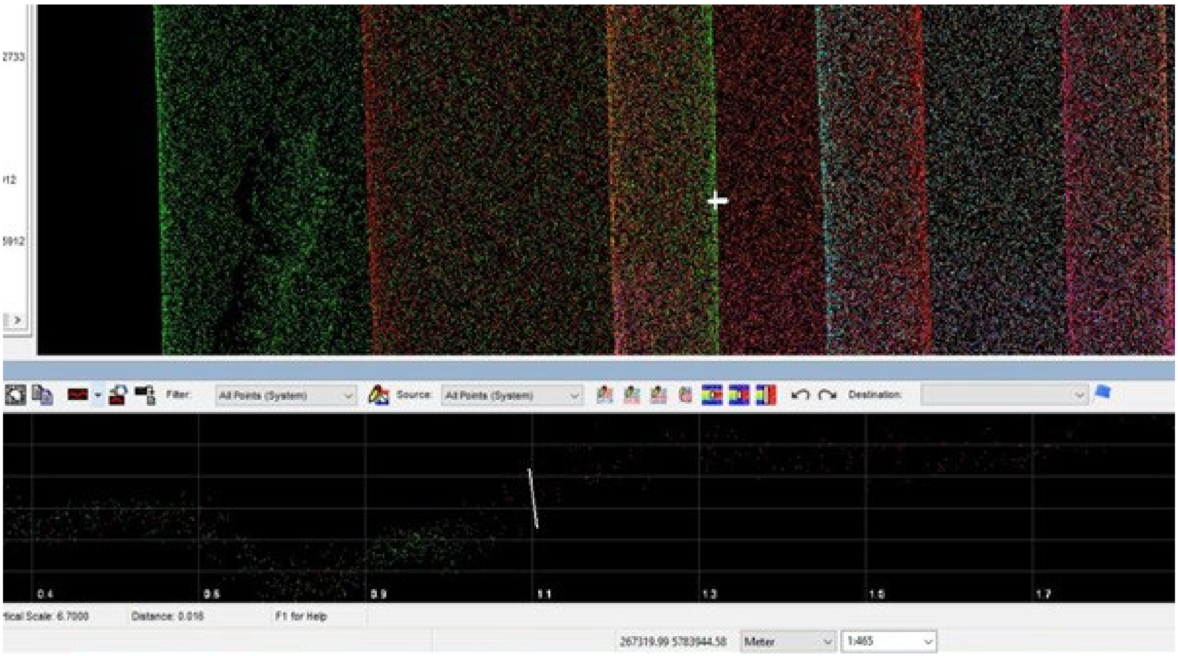

Figure 13: Improvement gained after StripAlign and point cloud smoothing.

3.2.3 Statistical Results

Table 2 shows the overall statistical results from each mission as well as each iteration of processing for each mission. This provides some indication of the effects of the parameters of each mission, as well as how post-processing affected the statistical results.

Table 2: Overall accuracies of the conventional survey vs. point clouds.

Flight No.	Process	Min	Max	Average	Standard Deviation	RMSE	Comparison within +/- 20mm of original (%)
1 - None	Nil	-0.096	0.137	0.007	0.022	0.023	N/A
1 - StripAlign	StripAlign	-0.128	0.150	0.007	0.024	0.025	80.8
1 - Smoothing	Smoothing	-0.099	0.131	0.008	0.022	0.023	92.6
1 - SA + Smoothing	StripAlign + Smoothing	-0.109	0.140	0.009	0.024	0.025	89.7
2 - None	Nil	-0.106	0.146	0.003	0.021	0.021	N/A
2 - StripAlign	StripAlign	-0.124	0.132	0.005	0.028	0.028	79.1
2- Smoothing	Smoothing	-0.094	0.131	0.003	0.023	0.023	89.1
2 - SA + Smoothing	StripAlign + Smoothing	-0.142	0.149	0.008	0.030	0.031	80.9
3 - None	Nil	-0.134	0.123	-0.014	0.025	0.028	N/A
3 - StripAlign	StripAlign	-0.125	0.138	-0.013	0.024	0.027	63.9
3 - Smoothing	Smoothing	-0.141	0.141	-0.019	0.023	0.030	87.6
3 - SA + Smoothing	StripAlign + Smoothing	-0.130	0.135	-0.020	0.022	0.030	80
4 - None	Nil	-0.109	0.137	-0.011	0.022	0.025	N/A
4 - StripAlign	StripAlign	-0.136	0.133	-0.024	0.029	0.038	61.5
4 - Smoothing	Smoothing	-0.138	0.134	-0.024	0.026	0.035	78.8
4 - SA + Smoothing	StripAlign + Smoothing	-0.140	0.132	-0.037	0.031	0.048	62.3
5 - None	Nil	-0.146	0.150	0.025	0.054	0.059	N/A
5 - StripAlign	StripAlign	-0.148	0.237	0.035	0.055	0.065	34
5 - Smoothing	Smoothing	-0.380	0.140	-0.030	0.082	0.087	60.9
5 - SA + Smoothing	StripAlign + Smoothing	-0.167	0.330	0.061	0.074	0.096	31.1
6 - None	Nil	-0.109	0.149	0.021	0.038	0.043	N/A
6 - StripAlign	StripAlign	-0.122	0.130	0.013	0.032	0.035	49.2
6 - Smoothing	Smoothing	-0.136	0.145	0.031	0.041	0.052	59
6 - SA + Smoothing	StripAlign + Smoothing	-0.142	0.149	0.030	0.036	0.046	47.5
8 - None	Nil	-0.091	0.148	0.004	0.023	0.023	N/A
8 - StripAlign	StripAlign	-0.110	0.145	0.004	0.025	0.025	82.6
8 - Smoothing	Smoothing	-0.100	0.143	0.004	0.023	0.023	94
8 - SA + Smoothing	StripAlign + Smoothing	-0.114	0.115	0.005	0.025	0.025	89.7

3.2.4 Minimum, Maximum & Average Charts

Figures 14-20 show the maximum, minimum and average values obtained from the point-to-point cloud comparison carried out between each LiDAR point cloud and the ground truth survey, providing an at-a-glance understanding of the effects of each post-processing iteration.

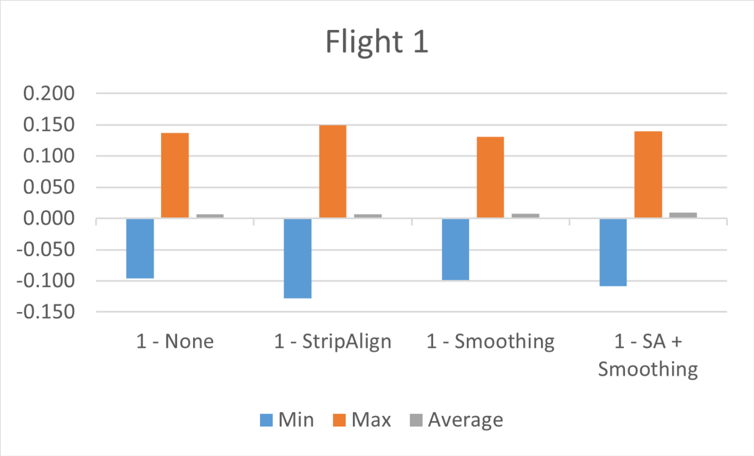

Figure 14: Mission/Flight 1 adjustment method vs. ground truth averages and outliers.

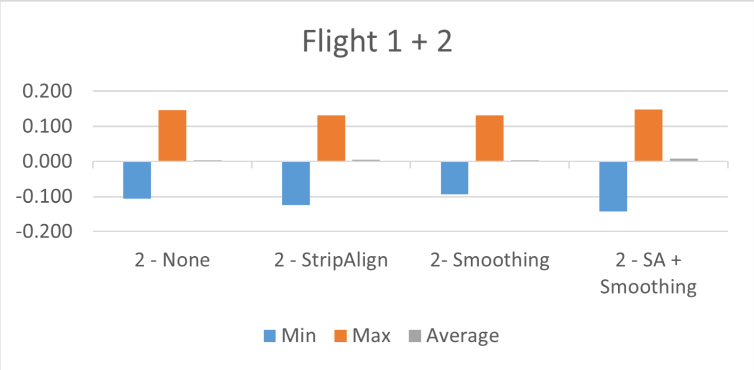

Figure 15: Mission/Flight 1 & 2 adjustment method vs. ground truth averages and outliers.

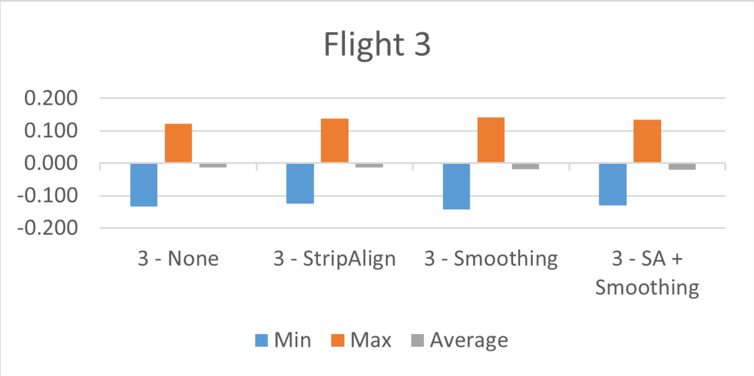

Figure 16: Mission/Flight 3 adjustment method vs. ground truth averages and outliers.

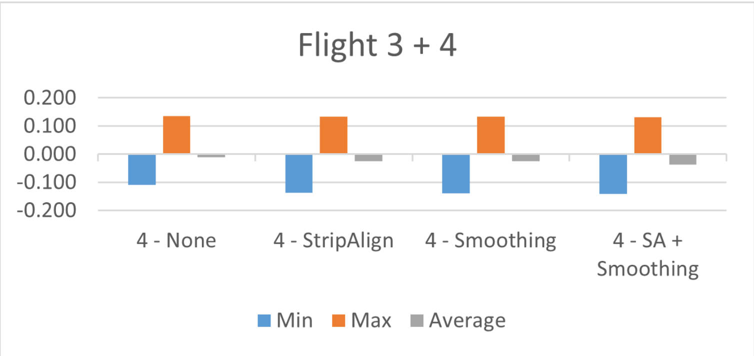

Figure 17: Mission/Flight 3 & 4 adjustment method vs. ground truth averages and outliers.

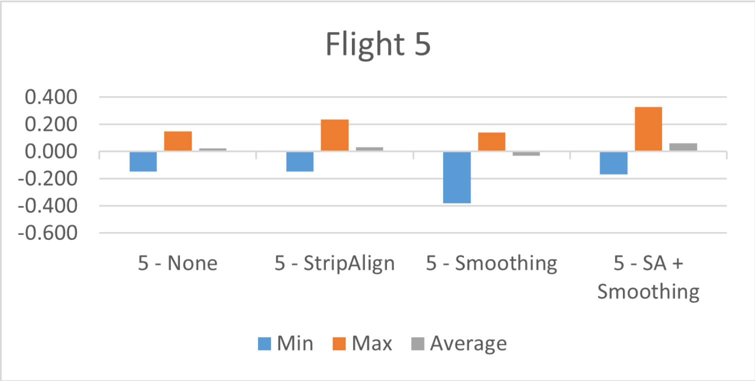

Figure 18: Mission/Flight 5 adjustment method vs. ground truth averages and outliers.

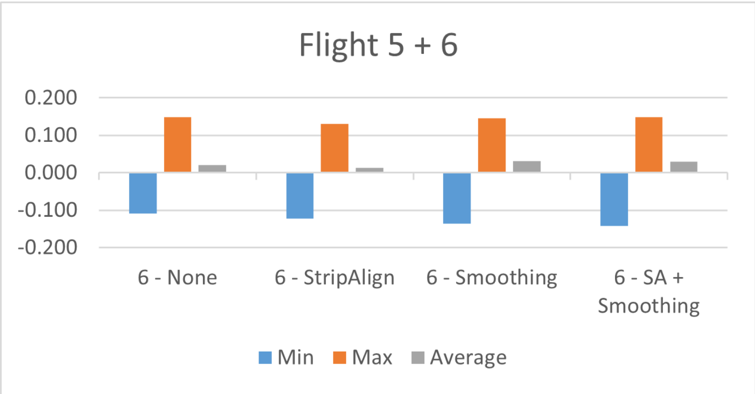

Figure 19: Mission/Flight 5 & 6 adjustment method vs. ground truth averages and outliers.

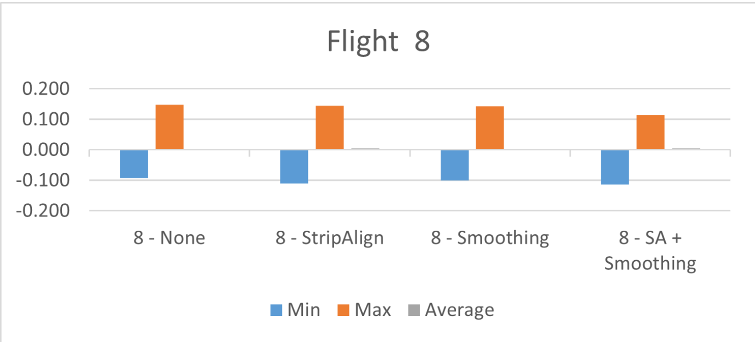

Figure 20: Mission/Flight 8 adjustment method vs. ground truth averages and outliers.

3.2.5 Overall Statistical Analyses Chart

Figure 21 shows all the key statistical results (in metres) graphed to demonstrate the comparable statistical accuracies of each iteration of post-processing on each mission against each other. Immediately noticeable is that the raw values derived from the flights carried out at 80 m AGL are significantly higher than those obtained from all flights at 50 m AGL, indicating that (as expected) the accuracy of the raw data acquired in the field significantly diminishes the further the LiDAR sensor is from the target surface.

When cross-bracing was introduced, the values obtained from the unprocessed dataset immediately improve significantly, with the Root Mean Square Error (RMSE) improving from 0.059 m (Mission/Flight 5) to 0.043 m (Mission/Flight 5 & 6). For the purposes of this study, it is speculated that redundant data observations introduced by the bracing dataset (i.e. Mission/Flight 6) have allowed the improvement of the overall accuracy of the dataset without the need for post-processing. Furthermore, comparing post-processing results between Mission/Flight 5 and Mission/Flight 5 & 6 indicates that significant improvement is achieved in the second instance. However, considering the results improve without any post-processing, it is difficult to draw a conclusion as to whether that is simply because of redundant LiDAR measurements or if it is indeed a result of a 'bracing' effect created by perpendicular LiDAR swathes.

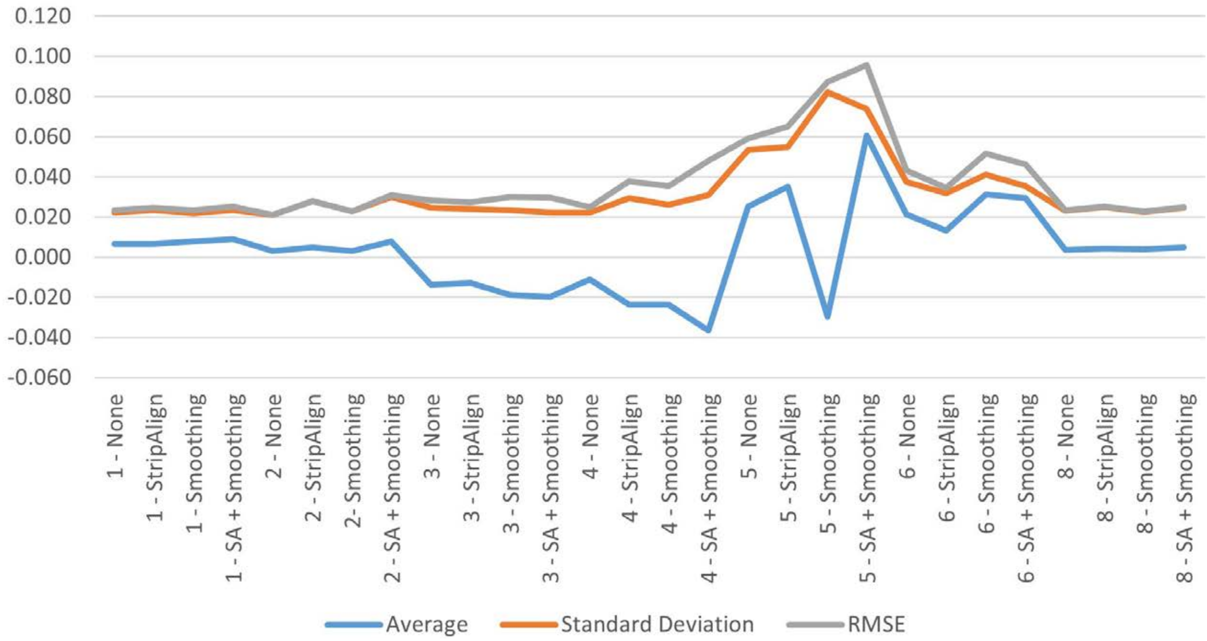

Figure 21: Overall statistical results.

4 DISCUSSION

Testing of the two scanning settings in the DJI Zenmuse L1 yielded a small but noticeable difference in accuracy when compared against one another, with repetitive scanning producing slightly less noisy point clouds than scanning in non-repetitive mode. This could be due to the shape of the L1's footprint being oval with the major axis of the oval being oriented to the travel direction of the UAV during a typical LiDAR flight mission. While not proven, it is speculated that as the non-repetitive scanning pattern reaches the top and bottom of its pattern (or the 12 o'clock and 6 o'clock positions), the laser footprint would be spread over a greater area of the target surface as the laser's 'angle of attack' is less perpendicular to the typically obtained angle. Combined with the ovalene shape of the L1's laser, this would produce more opportunity for erroneous returns, and as such noisier point clouds.

By varying the overlap of adjacent LiDAR swathes, it was hypothesised that the lower rates of overlap would perform poorer when applying the StripAlign adjustment during post-processing. However, this was not the case as in all except a single instance of applying StripAlign, the overall statistical accuracy either decreased or remained constant. At 50 m AGL, the raw acquisition from 20% overlap was so similar to the results obtained from 80% overlap that it appears that greater overlap rates, combined with StripAlign's inability to improve the statistical accuracy, are only beneficial in improving the data resolution through increased observations to the subject surface.

From a statistical standpoint, none of the post-processing methods was conclusive in improving the accuracy of UAV-borne LiDAR data beyond the initially obtained accuracy of the raw data. However, post-processing did improve the general structure of the data produced by low-cost LiDAR sensors. StripAlign adjustments appear to be successful in removing instances of step-error from the data, and smoothing adjustments appear to create a more uniform point cloud surface.

5 CONCLUDING REMARKS

This paper has investigated several variables used during a UAV-borne LiDAR mission. Post-processing of LiDAR data was performed on a series of datasets produced using a Zenmuse L1, each with differing sensor and flight parameters. Changes were evaluated between each stage of post-processing, and ultimately all sensor and flight parameters were tested against a ground truth survey carried out using conventional surveying methods to ascertain the suitability of post-processed LiDAR data derived from a low-cost UAV-borne LiDAR sensor. It was found that the application of post-processing methods is effective in improving the precision of the datasets, but not necessarily their accuracy.

Strip adjustment techniques appear to be effective at mitigating symptoms of poor IMU orientation solutions, by registration of adjacent LiDAR strips to one another, removing the occurrence of data anomalies known as step-errors. Similarly, the presence of noise within point cloud datasets derived from low-cost LiDAR systems can be mitigated using software tools that apply smoothing algorithms. However, while the structure of the point cloud datasets is improved by these adjustment methods, creating a more precise dataset, the statistical accuracy in comparison to a ground truth survey remains largely unchanged and, in some cases, decreases slightly.

The testing of different flight parameters proved to be more conducive to changing the accuracy results, with accuracies decreasing the further the sensor is flown from the target surface. No correlation between rates of overlap appears to be present, with similar accuracies achieved between high (80%) and low (20%) overlap rates. Bracing flights, with the sensor being flown over the site again perpendicular to the original flight mission, did not appear to have any significant effect on post-processing results. However, in all tested cases the unprocessed iteration of the cross-braced mission showed an immediate improvement over its non-braced counterpart, leading to the conclusion that increased observations to the target surface may improve redundancy of observations and allow for a better statistical mean to be achieved within the LiDAR data.

The combination of both best-practice flight parameters and post-processing is effective in producing the highest quality data possible from low-cost, UAV-borne LiDAR sensor systems. With the optimal flight parameters for the Zenmuse L1 appearing to be a 50 m AGL flying height (or lower), high overlap rates and ‘double grid’ flights to achieve redundant cross-braced observations. Optimal flight parameters will produce the most accurate LiDAR observations possible, while the application of post-processing to such a point cloud will improve the precision of the dataset and produce a point cloud product more suitable for extracting topographic data or supplying directly to the end user.

ACKNOWLEDGEMENTS

This paper is based on the author's undergraduate Honours research project at the University of Southern Queensland (UniSQ), which was awarded the APAS UniSQ Student Project Prize 2024. Dr Xiaoye Liu (UniSQ) is gratefully acknowledged for providing guidance and supervising this study. Spiire Australia is thanked for making available all the equipment, materials and software necessary for the completion of this research.

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