Experiments with Combining LiDAR and Camera Data Acquired by UAS and Smartphone to Support Mapping

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ABSTRACT:

Aerial mapping using Unmanned Aerial Systems (UAS), such as the DJI Mavic 3 Enterprise, has revolutionized photogrammetry, enabling efficient data capture for small-scale projects. The typical nadir perspective of UAS mapping, however, imposes limitations on capturing critical details of features due to its predominantly vertical viewpoint. Overcoming this challenge often requires manual, low-altitude flights by experienced UAS pilots to achieve high-angle oblique perspectives, unless gimbled camera mount is used. This study explores the integration of high oblique angle perspectives using the iPhone 15 Pro, which boasts advanced camera capabilities and an integrated LiDAR sensor, to complement UAS imagery. The iPhone 15 Pro's camera sensors provide a Ground Sampled Distance (GSD) comparable to UAS cameras, while its LiDAR sensor, with about five meters of range, enhances mapping capabilities by delivering accurate depth measurements in close range. By utilizing various georeferencing options for the imagery and LiDAR data from the iPhone 15 Pro with UAS nadir imagery, we can achieve a more comprehensive object space reconstruction, significantly improving the accuracy of geospatial mapping. Both the Mavic 3 Enterprise and the iPhone 15 Pro, though operating independently on their respective platforms, support Real-Time Kinematic (RTK) corrections, facilitating precise positioning for the entire system trajectory. Strategic placement and utilization of Ground Control Points (GCPs) aid in the georeferencing of the complete dataset, enhancing its overall accuracy. To validate the accuracy of the acquired data, checkpoints are established on-site. The positions derived from the integrated UAS and iPhone 15 Pro data are compared against these checkpoints to quantify the accuracy and reliability of the data. Additionally, Post-Processed Kinematic (PPK) techniques are employed to validate the trajectories of all data collection systems, ensuring the reliability of the acquired data, especially in instances where RTK corrections may be lacking. In summary, this research showcases comprehensive, multi-dimensional geospatial datasets by conducting validation studies that assess the accuracy and reliability of georeferenced datasets against known ground truth checkpoints. Such validation studies are crucial for identifying gaps in current methodologies and suggesting areas for improvement, thereby aiming to enhance the quality and accuracy of geospatial mapping applications. Through the integration of UAS and smartphone mapping, complemented by rigorous validation efforts, we aspire to achieve improved geospatial mapping accuracy.

1. INTRODUCTION

UAS have revolutionized the field of surveying and mapping, marking a significant leap from traditional ground-based methods (Fitzpatrick, 2016). One technology that UAS mapping uses is photogrammetry, where drones capture a series of overlapping images during their flight. These images are then stitched together using specialized software, creating comprehensive 3D point cloud models and orthomosaic maps (Ruzgienė et al., 2015). The ability to cover sites quickly and the ease of accessing remote or challenging terrains have dramatically increased efficiency, reducing both the time and cost of surveying operations (Jiang et al., 2021). Furthermore, the integration of RTK positioning in UAS’s trajectories enhances the precision of the spatial data, achieving centimeter-level accuracy. This precision is crucial for applications ranging from urban planning and infrastructure development to environmental monitoring and disaster management. UAS mapping has thus not only transformed the surveying industry by providing scalable, efficient, and accurate data collection methods but also opened new avenues in geospatial analysis and application (Yao et al., 2019).

The evolution of smartphone mapping is rapidly advancing, not only through inherent sensor capabilities but also by integrating additional external sensors to augment accuracy and functionality (Toth et al., 2016). This integration is exemplified by the addition of RTK enabled GNSS receivers to smartphones. RTK correction technology technique that enhances the GNSS data of the smartphone, providing centimeter-level precision in positioning (Tamimi, 2022). By outfitting smartphones with RTK corrections, the trajectory of the system during data collection becomes highly accurate, significantly improving the overall quality of the spatial data gathered. Coupled with the Simultaneous Localization and Mapping (SLAM) technology, which enables real-time mapping and localization in complex environments, smartphones become even more powerful tools for geospatial data collection (Liu et al., 2021). SLAM leverages the smartphone’s onboard sensors like accelerometers, gyroscopes, and cameras to dynamically map the environment while tracking the device's location within it (Liu et al., 2021). The combination of these technologies in smartphones represents a leap forward in mapping capabilities, offering a cost-effective, portable, and versatile alternative to traditional surveying methods.

UAS have advanced the field of aerial mapping, yet they are not without their limitations, some of which can be supplemented by smartphone mapping. One of the primary challenges for UAS is the obstruction of data in environments with vertical structures, such as facades, which are of particular interest for comprehensive object space reconstruction. The nadir perspective of drones often struggles to capture high-angle oblique images necessary for facade mapping and vertical structure analysis due to flight dynamics and safety constraints. The focus of this experiment is on improving data collection in facade-type environments to enhance the full object space reconstruction." (Fraser et al., 2018). Smartphones, with cameras and LiDAR sensors using SLAM technology, are suited for these scenarios. Their portability allows users to navigate narrow spaces and capture images from various angles, including high oblique perspectives that drones might not obtain (Alsubaie et al., 2017). Using smartphones for data collection in these contexts fills gaps left by UAS. Furthermore, the proximity of smartphone data collection maintains a high GSD, ensuring detailed imagery. The georeferencing of UAS and smartphone data offers a solution that combines aerial mapping's coverage with ground-level detail. This approach improves geospatial data accuracy and quality in complex environments by integrating aerial and ground-level details, filling gaps from either system to create a complete dataset without missing points.

2. METHODOLOGY

2.1 Study Area

The study area for our project is situated in the city center of a suburb near Detroit, Michigan. This complex is comprised of six buildings, each serving a mix of commercial and residential purposes. These structures, typical of urban settings, rise to three stories and are approximately 14 meters in height and 60 by 20 meters in size. The site itself spans approximately 250 by 60 meters, or 1.5 hectares, presenting a diverse range of architectural features and environmental factors for mapping. In this urban center, obtaining high oblique images using a drone is a challenging task. The density and height of the buildings make aerial navigation and oblique image capture difficult. For our research, the drone was flown at an altitude of 50 meters Above Ground Level (AGL) to map the area; note that these conditions necessitate careful flight planning and maneuvering. Figure 1 shows an aerial perspective of the study area.

Figure 1. Aerial image of the study area. Areas in red are the six buildings of the complex.

In contrast, the use of a smartphone, specifically the iPhone 15 Pro, for data collection in this setting proved to be more advantageous. The smartphone's portability and maneuverability allowed us to efficiently navigate the urban landscape and capture high oblique images of all six buildings. This method is particularly effective in dense city centers where precise control over image capture is required. The handheld nature of the smartphone provides the flexibility needed to obtain the right angles and orientations for detailed facade mapping and vertical structure analysis. Thus, this city center complex serves as an ideal example of a location where smartphone mapping can significantly enhance the data collection process. It complements the limitations encountered with drone based UAS mapping, especially in challenging urban environments where building density and height can restrict aerial image capture.

2.2 Hardware and Data Collection methodology

For the aerial component of our project, the DJI Mavic 3 Enterprise was used for its sophisticated features tailored for precise mapping. This drone has a 20-megapixel camera, featuring a mechanical shutter that significantly reduces motion artifact, a common issue in aerial imaging with rolling shutter cameras. This capability is essential for capturing sharp, high-resolution images, vital for detailed aerial mapping and photogrammetry. The mechanical shutter also ensures consistent image quality during rapid flights making it highly dependable for extensive surveying tasks. The Mavic 3 Enterprise features an RTK module that provides real-time corrections to its GNSS receiver, enhancing its positioning accuracy. The RTK module processes corrections to the data derived from the GNSS signal in real-time, significantly enhancing the positional accuracy of the drone by refining the calculated location compared to uncorrected solutions. The enhanced precision in geolocation data aids in the initial positioning for stitching aerial images. The RTK-corrected trajectory also facilitates precise georeferencing, a process essential for integrating aerial data with ground-level observations and other geospatial datasets. Figure 2 shows the UAS setup.

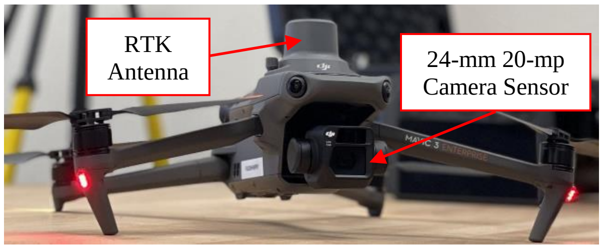

Figure 2. DJI Mavic 3 Enterprise with RTK Module

When we first acquired the Mavic 3E, a camera calibration flight was conducted to ensure accuracy in our future measurements. In a typical calibration flight, the drone captures images at different altitudes and angles over a known area with adequate ground control points. These images are then processed using DJI Terra to analyze the calibration quality. After processing the images from this initial calibration flight, we updated the aerotriangulation results to enhance the precision of our subsequent flights. The resulting calibration parameters are saved and applied to future flights for consistent accuracy. This step was crucial for maintaining the integrity of our data collection and analysis efforts.

For ground-level data acquisition, we utilized the iPhone 15 Pro, chosen for its 24-mm focal length and 48-megapixel camera that captures high resolution images, essential for close-range mapping and object detail retrieval. The high megapixel count allows for finer texture mapping, crucial in urban planning and environmental studies where surface details are imperative. To enhance the iPhone’s geospatial data accuracy, we attached the viDoc RTK Rover. Figure 3 shows the iPhone 15 Pro with the viDoc RTK Rover.

This device equips the smartphone with RTK capabilities, providing real-time corrections to the iPhone’s GNSS data. The integration of the viDoc RTK Rover aims to enhance the positional accuracy of the smartphone system, targeting the standards expected in professional surveying and mapping. The RTK corrections are especially valuable for providing instant trajectory adjustments and eliminating the need for post-processing, offering precise georeferencing of collected data, particularly in open-sky conditions where GNSS signals are unobstructed. In environments where GNSS signals are weak or unavailable, such as under dense canopies or in urban canyons, the system leverages the iPhone's SLAM technology. SLAM enables the device to continuously map its surroundings while estimating its own trajectory using onboard sensors like LiDAR and IMU (Inertial Measurement Unit). In most situations, this approach to data collection quality provides an alternate method for trajectory estimation and geospatial data alignment, even in GNSS-denied environments. Regarding the camera sensor calibration on the iPhone, no additional calibrations were performed beyond the self-calibration done by Pix4Dcatch.

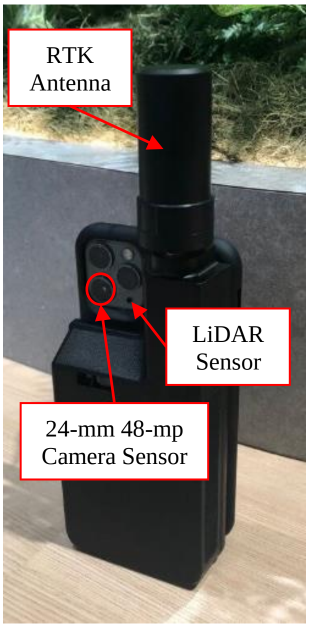

Figure 3. iPhone 15 Pro with viDoc RTK Rover

2.3 Software and Data Integration Proccessing

In the aerial data collection phase, the DJI Pilot application was used to manage the drone's operations. This app designed for DJI drones, providing a comprehensive set of tools for flight planning, automated flight paths, and real-time data capture. DJI Pilot's user-friendly interface and robust functionality enhance the efficiency and accuracy of aerial survey missions, ensuring that high-quality imagery is captured consistently across the surveyed area. The Mavic 3 Enterprise was flown at 200 feet (61 meters) above ground level (AGL) with 80% side lap and overlap.

For ground-level data collection, Pix4Dcatch was the chosen application, leveraging its capabilities in 3D scanning through the utilization of smartphone devices. This software is designed to harness the full potential of the iPhone's advanced camera and LiDAR sensor, facilitating the capture of high-quality spatial data. Pix4Dcatch excels in creating detailed 3D models and point clouds by capturing images and LiDAR data, which is pivotal for mapping intricate ground features and environments where aerial data might be less effective. Figure 4 shows the interface Pix4D while collecting data on the iPhone in comparison to the nadir images collected from the Mavic 3E to illustrate the high oblique angle perspective achieved from smartphone mapping.

Both the ground-level and aerial datasets were processed using Pix4Dmatic, a photogrammetry software renowned for its ability to efficiently handle and process large datasets. Pix4Dmatic is used to merge the high-resolution imagery from the drone with the detailed images and LiDAR data collected by the iPhone. By creating comprehensive, multi-dimensional geospatial datasets we can assess the accuracy and reliability of these datasets against established benchmarks, aiding in the identification of methodological gaps and suggesting potential areas for enhancement. The checkpoints on site represent a traditional survey that ground truths our combined datasets.

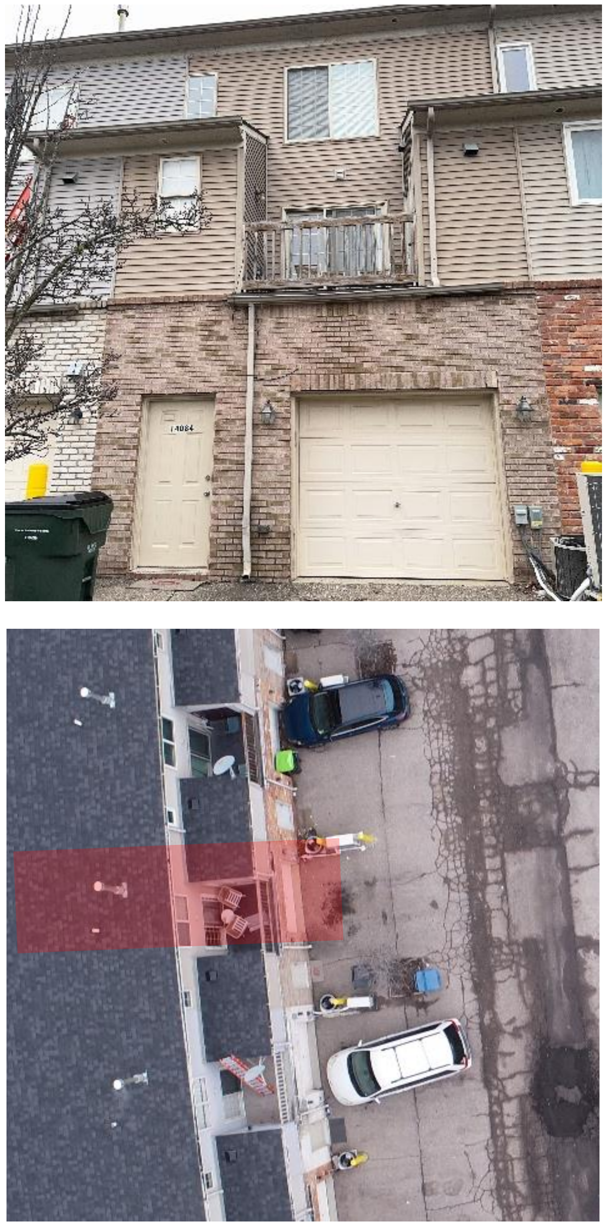

Figure 4. Top – High oblique angle
Bottom – Nadir perspective

To ensure the seamless integration of data from these two sources, a consistent coordinate system was employed - NAD83 Michigan South for horizontal coordinates and NAVD88 GEOID18 for vertical measurements. The use of 24 different GCPs was critical in this process, as they provided common reference points for both datasets, thereby

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aiding in the accurate merging and alignment of the aerial and ground-level data. The GCPs are the corners of all six of the buildings in the city center complex. An additional 24 checkpoints are observed to be used for accuracy assessment.
The merging of the data was approached in two distinct ways. The first way involved processing all the data together in Pix4Dmatic, allowing for a simultaneous and integrated processing workflow. This approach ensures that the datasets are inherently aligned and synergized from the outset. In the second way, the datasets were processed separately, the drone data in one instance and the iPhone's data in another. After independent processing, both point clouds were imported into Pix4Dsurvey. This allows for a more controlled and detailed analysis of each dataset before their final integration, providing an opportunity to fine-tune and adjust individual datasets for optimal accuracy. After proccessing both data sets, Figure 5 shows the virtual improvement of the point cloud by adding in data from smartphone mapping.

Figure 5. Top – Drone point cloud, bottom –Drone and iPhone point clouds together. This is the individually processed datasets imported into Pix4Dsurvey.

2.4 Accuracy Validation

Both the Mavic 3E drone and the iPhone 15 Pro utilized network RTK for trajectory corrections, obtaining these corrections from a network of Continuously Operating Reference Station (CORS). The Emlid Reach RS3 GNSS Receiver played a crucial role in this setup. It was employed for the precise collection of positions for GCPs and checkpoints, also using network RTK achieving 2-3 centimeters of accuracy. These GCPs and checkpoints are vital for georeferencing and serve as a fundamental element in the accuracy validation of the data collected from both the drone and the smartphone. Further enhancing our accuracy validation process, the Emlid Reach RS3 was initially set up as a rover to establish its coordinates through a network RTK observation. After this initial setup, the Reach RS3 was then switched to operate as a base station, as shown in Figure 6. In this capacity, it logs its single position in relation to the satellites, providing a reliable GNSS data stream for post-processing.

In post-processing, conducted using Emlid Studio, the trajectories from the Mavic 3E and the iPhone were corrected using the observation file from the Reach RS3 base station. This step was crucial in verifying the accuracy of the network RTK corrections. Individually processed data means the drone’s images and smartphone’s images/LiDAR data were processed separate from each other and evaluated on their own point clouds. Integrated processed data means the drone’s images and smartphone’s images/LiDAR data were processed together and evaluated as one resulting point cloud. Each dataset was also georeferenced using either RTK or PPK, and some included the influence of GCPs. This involved executing several scenarios to ascertain the most effective way for data integration and accuracy validation, see Table 1.

Figure 6. Emlid Reach RS3 set up as a base station.

Table 1. Various scenarios analyzed.

Scenario	Individually Processed	Integrated Processing	RTK	PPK	GCP
1	X		X		
2		X	X		
3	X			X	
4		X		X	
5	X		X		X
6		X	X		X
7	X			X	X
8		X		X	X

The processing of the various scenarios:

1) We processed the RTK data from both the drone’s images and the smartphone’s images and LiDAR separately, without the use of GCPs, to evaluate the inherent accuracy of the RTK-corrected data from each device.
2) We combined the RTK data from the drone’s images and smartphone images and LiDAR, processing them together in Pix4Dmatic without incorporating GCPs. This allowed us to assess the integration and alignment of the heterogeneous dataset from the two different sources, providing insight into their consistency and compatibility when merged.
3) We processed PPK data for each device individually, also without GCPs, to understand the accuracy of the PPK method in trajectory correction on a standalone basis.

4) We integrated the PPK data from both the Mavic 3E and the iPhone in Pix4Dmatic, without utilizing GCPs, to examine how well the PPK datasets from these diverse sources align with each other.
5) We saw processing the RTK data from each device individually again, but this time we included GCPs in the process. We then analyzed the Root Mean Square Error (RMSE) of the checkpoints to determine the extent to which the inclusion of GCPs improved the accuracy of the datasets. This approach aimed to provide a comprehensive understanding of how combining the imagery and LiDAR data from the iPhone with the image data from the drone through Pix4Dmatic could enhance the overall dataset accuracy when GCPs are applied.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2}{n}}$$

where $\hat{x}_i - x_i$, $\hat{y}_i - y_i$, and $\hat{z}_i - z_i$ are the differences between the calculated positions and the true positions in x, y, and z, respectively, n is the total number of observations taken.

6) We processed the RTK data from both devices together with GCPs. The RMS error of the checkpoints was evaluated to understand the combined effect of RTK data and GCP integration.
7) We proceeded to individually process the PPK data for each device, including GCPs in the process. The RMSE of the checkpoints was measured to assess the accuracy enhancements brought about by PPK processing in conjunction with GCPs. And finally,
8) We conducted integrated processing of the PPK data from both the Mavic 3E and the iPhone, integrating GCPs. The RMS error of the checkpoints was scrutinized to evaluate the efficacy of combining PPK data with GCPs.

These scenarios, each with its unique configuration of RTK/PPK processing and use of GCPs, provided a good basis for a comprehensive analysis of the data collection systems' accuracy. By using PPK processing to validate the RTK corrections we can determine the most effective methodology for georeferencing and alignment, knowing that PPK provides the best trajectory validation.

3. RESULTS

3.1 Individually Processed RTK Data without GCPs

The drone data was generated using photogrammetry, while the iPhone data was derived from a combination of photogrammetry and LiDAR. The results, shown in Table 2 and illustrated in Figure 7, reveal the challenges encountered in achieving absolute accuracy with the drone and iPhone systems without GCPs, with deviations up to 10 cm horizontally and 15 cm vertically observed when compared to 48 checkpoints. These deviations underscore the limitations of relying exclusively on RTK corrections and IMU capabilities without the use of GCPs. The differences between drone and iPhone data also illuminate the complexities of ensuring consistent data quality and accuracy, which are influenced by factors such as GNSS signal quality. A third solution was computed by manually extracting the same checkpoint locations from both point clouds and analyzing the differences, highlighting the discrepancies between them. There were many instances were RTK solution was either float or single, which impacted the trajectory positions of the systems. This would put a heavy dependency on other sensors to estimate the trajectory which affected the overall data collected.

Table 2. X, Y, and Z differences of point clouds generated by iPhone images/LiDAR using RTK to checkpoints observed with a GNSS receiver, Drone images using RTK to checkpoints observed with a GNSS receiver, and iPhone images/LiDAR using RTK to Drone images using RTK.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
iPhone-CHK	6.4	6.4	12.2	15.2
Drone-CHK	10.6	7.3	5.9	14.2
iPhone-Drone	6.1	1.3	14.8	16.1

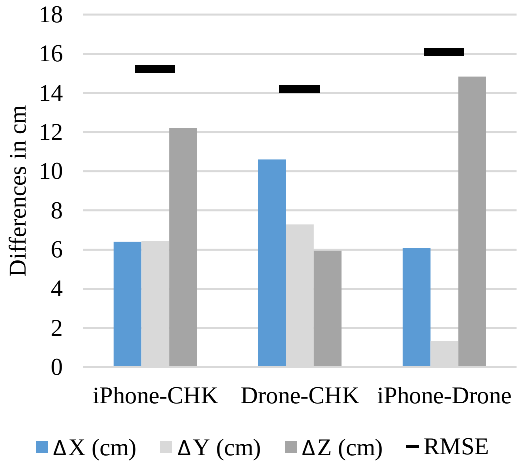

Figure 7. Differences between iPhone images/LiDAR using RTK in comparison to 48 checkpoints, Drone images using RTK in comparison to 48 checkpoints, and iPhone images/LiDAR using RTK in comparison to Drone images using RTK.

3.2 Integrated Processed RTK Data without GCPs

When the drone and smartphone data were integrated into a heterogeneous dataset, there was an improvement in horizontal accuracy. This can be attributed to instances where the RTK solution was not fixed during individual data collection sessions. By integrating data from both sources in areas where one might have had a fixed RTK solution while the other did not, the reconstruction of the point cloud benefited, aiding in the overall spatial accuracy. This process, detailed in Table 3 and illustrated in Figure 8, suggests that processing all the data together in Pix4Dmatic can indeed improve horizontal accuracy by leveraging the complementary data capture capabilities of both devices. This approach helps to mitigate some of the limitations encountered when RTK solutions are intermittently unstable, showcasing the value of combining aerial and ground-based data for improving geospatial reconstruction accuracy.

Table 3. X, Y, and Z differences of the point cloud generated by iPhone images/LiDAR and drone images using RTK corrections in comparison to checkpoints observed with a GNSS receiver.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
RTK-CHK	4.7	5.3	12.1	14.0

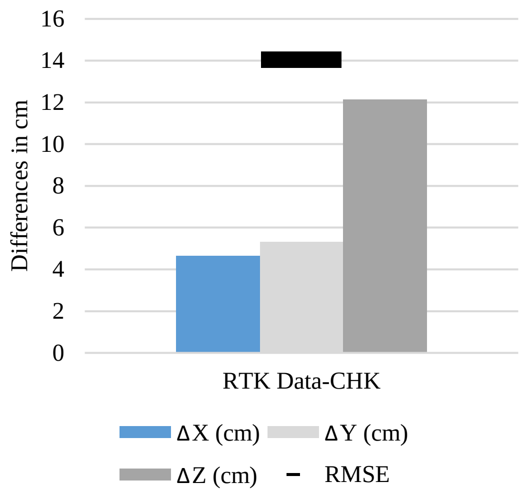

Figure 8. Differences between integrated iPhone images/LiDAR and Drone images using RTK corrections in comparison to 48 checkpoints.

3.3 Individually Processed PPK Data without GCPs

The analysis of individually processed PPK data without the use of GCPs revealed a slight improvement in vertical accuracy, reducing the average difference to 10-11 cm. As detailed in Table 4 and illustrated in Figure 9, this method still proved inadequate for accurately referencing both datasets. Like previous observations, significant discrepancies were noted not only against the checkpoints but also between the drone and iPhone data. This underscores the persistent challenge of aligning datasets from different sources with a high degree of precision, highlighting the limitations of PPK processing alone in overcoming the inherent variability and inaccuracies without the support of GCPs for external validation.

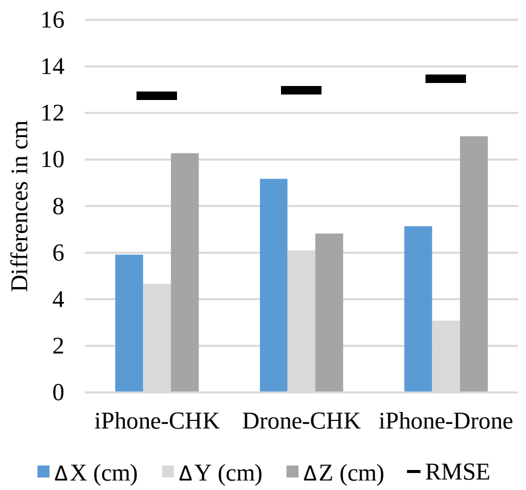

Figure 9. Differences between iPhone images/LiDAR using PPK in comparison to 48 checkpoints, Drone images using PPK in comparison to 48 checkpoints, and iPhone images/LiDAR using PPK in comparison to Drone images using PPK.

Table 4. X, Y, and Z differences of point clouds generated by iPhone images/LiDAR using PPK to checkpoints observed with a GNSS receiver, Drone images using PPK to checkpoints observed with a GNSS receiver, and iPhone images/LiDAR using PPK to Drone images using PPK.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
iPhone-CHK	5.9	4.7	10.3	12.7
Drone-CHK	9.2	6.1	6.8	13.0
iPhone-Drone	7.1	3.1	11.0	13.5

3.4 Integrated Processed PPK Data without GCPs

The integration of PPK processing with data from both the drone and smartphone led to horizontal errors of 4-5 cm, as evidenced in Table 5 and illustrated in Figure 10. This improvement can be attributed to highly accurate trajectory calculations and the comprehensive data capture achieved by utilizing both aerial and ground-based systems. However, vertical accuracy remained the same compared to proccessing the PPK data separately, with a difference of about 11 cm, indicating that additional georeferencing support is still required. This outcome highlights the effectiveness of PPK in enhancing spatial accuracy through the combination of diverse data sources.

Table 5. X, Y, and Z differences of the point cloud generated by iPhone images/LiDAR and drone images using PPK corrections in comparison to checkpoints observed with a GNSS receiver.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
PPK-CHK	3.7	4.7	10.9	12.4

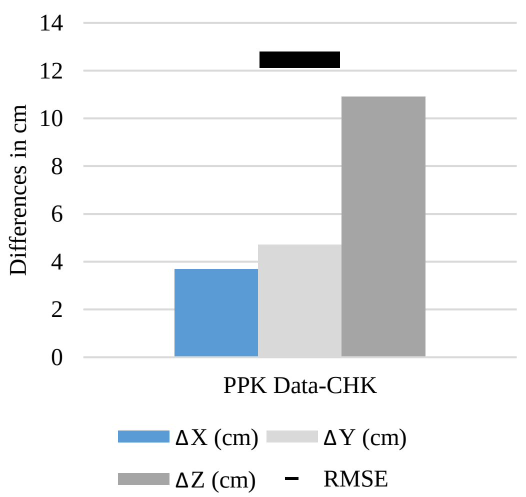

Figure 10. Differences between integrated iPhone images/LiDAR and Drone images using PPK corrections in comparison to 48 checkpoints.

3.5 Individually Processed RTK Data with GCPs

The use of GCPs in the processing of RTK data yielding significant improvements in accuracy for both the drone and smartphone data. Specifically, the iPhone data showed remarkable precision, with differences narrowing to 2-3 cm in the horizontal direction and about 1 cm in the vertical. Similarly, the drone data exhibited notable advancements, achieving approximately 2 cm accuracy in both horizontal and vertical measurements. When comparing the datasets

This contribution has been peer-reviewed.
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processed with GCPs against each other, the horizontal discrepancy was observed to be around 4 cm, while the vertical error was slightly lower at 2 cm. These results, detailed in Table 6 and illustrated in Figure 11, underscore the critical role of GCPs in significantly enhancing the geospatial accuracy of data. The utilization of GCPs not only improved the absolute accuracy of each dataset but also brought the drone and smartphone data into closer alignment with each other.

Table 6. X, Y, and Z differences of point clouds generated by iPhone images/LiDAR using RTK with ground control points to checkpoints observed with a GNSS receiver, Drone images using RTK with ground control points to checkpoints observed with a GNSS receiver, and iPhone images/LiDAR using RTK with ground control points to Drone images using RTK with ground control points.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
iPhone-CHK	3.3	2.5	0.8	4.2
Drone-CHK	2.5	1.8	1.7	3.5
iPhone-Drone	3.8	3.2	2.0	5.4

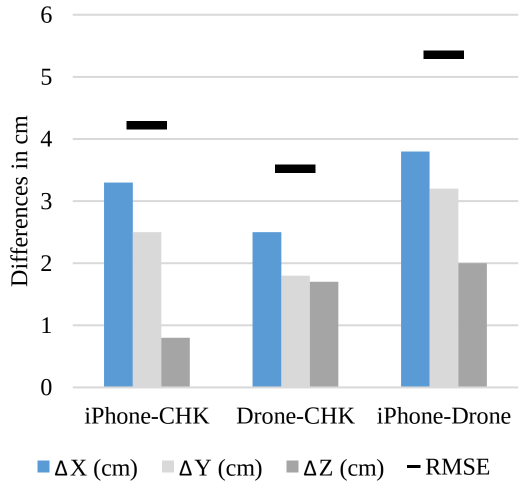

Figure 11. Differences between iPhone images/LiDAR using RTK and 24 GCPs in comparison to 24 checkpoints, Drone images using RTK and 24 GCPs in comparison to 24 checkpoints, and iPhone images/LiDAR using RTK and 24 GCPs in comparison to Drone images using RTK and 24 GCPs.

3.6 Integrated Processed RTK Data with GCPs

The integrated processing of RTK data with the use of GCPs delivered impressive results, unequivocally demonstrating that processing all the data together offers the best approach for data alignment. The combined processing significantly enhanced the spatial accuracy across both datasets, achieving a horizontal accuracy of 2 cm and a vertical accuracy of 1.5 cm when evaluated against the remaining 24 checkpoints. This improvement, as detailed in Table 7 and illustrated in Figure 12, underscores the efficacy of integrating GCPs in the processing workflow. By processing the drone and smartphone data together with GCPs, we were able to attain a high level of precision and accuracy.

Table 7. X, Y, and Z differences of the point cloud generated by iPhone images/LiDAR and drone images using RTK corrections with ground control points in comparison to checkpoints observed with a GNSS receiver.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
RTK/GCP-CHK	2.2	2.0	1.5	3.3

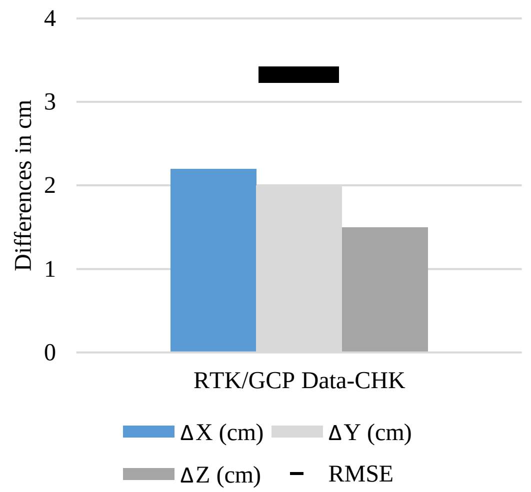

Figure 12. Differences between integrated iPhone images/LiDAR and Drone images using RTK corrections and 24 GCPs in comparison to 24 checkpoints.

3.7 Individually Processed PPK Data with GCPs

Individually processed PPK data with GCPs mirrored the outcomes seen in section 3.5, suggesting that PPK adjustments do not significantly improve accuracy over RTK corrections when GCPs are present. This similarity in results, as detailed in Table 8 and illustrated in Figure 13, indicates that the precision afforded by PPK processing may not offer substantial benefits over RTK in smaller survey areas, such as our 1.5-hectare site, because an RTK solution is likely to remain consistent throughout the flight duration. This observation underscores the necessity for further research on the effectiveness of PPK-corrected trajectories in larger survey areas to comprehensively assess PPK's impact on enhancing geospatial data accuracy from drones and smartphones across various project scales. In larger sites, where RTK solutions may experience more interruptions, PPK could provide a more reliable alternative.

Table 8. X, Y, and Z differences of point clouds generated by iPhone images/LiDAR using PPK with ground control points to checkpoints observed with a GNSS receiver, Drone images using PPK with ground control points to checkpoints observed with a GNSS receiver, and iPhone images/LiDAR using PPK with ground control points to Drone images using PPK with ground control points.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
iPhone-CHK	3.8	2.1	1.6	4.6
Drone-CHK	2.2	2.5	0.9	3.4
iPhone-Drone	4.0	1.2	1.1	4.3

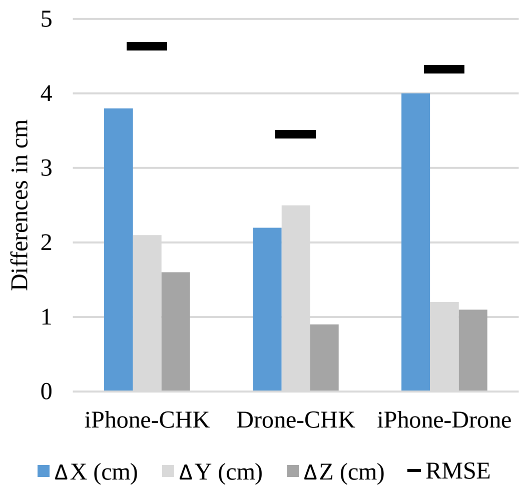

Figure 13. Differences between iPhone images/LiDAR using PPK and 24 GCPs in comparison to 24 checkpoints, Drone images using PPK and 24 GCPs in comparison to 24 checkpoints, and iPhone images/LiDAR using PPK and 24 GCPs in comparison to Drone images using PPK and 24 GCPs.

3.8 Integrated Processed PPK Data with GCPs

When analyzing integrated processed PPK data with the use of GCPs, we observed results like section 3.6. This approach, as documented in Table 9 and illustrated in Figure 14, yielded an RMSE of approximately 3-4 cm for the entire project, showcasing the effectiveness of having GCPs in refining the geospatial accuracy. Such outcomes reaffirm the value of integration of GCPs significantly contributes to achieving absolute accuracy across datasets from both the iPhone and drone even with PPK corrected trajectories of both systems.

Table 9. X, Y, and Z differences of the point cloud generated by iPhone images/LiDAR and drone images using PPK corrections with ground control points in comparison to checkpoints observed with a GNSS receiver.

Systems	ΔX (cm)	ΔY (cm)	ΔZ (cm)	RMSE
PPK/GCP-CHK	2.1	2.4	1.7	3.6

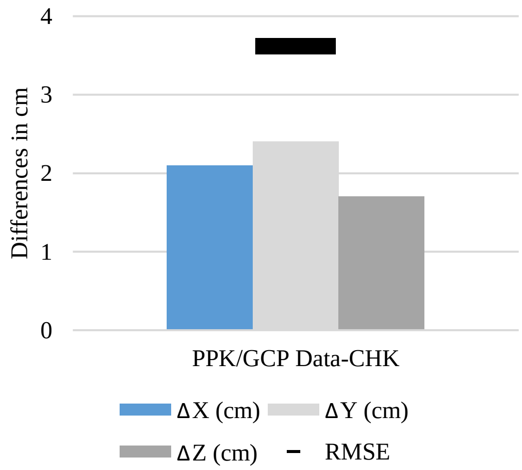

Figure 14. Differences between integrated iPhone images/LiDAR and Drone images using PPK corrections and 24 GCPs in comparison to 24 checkpoints.

4. DISCUSSION AND CONCLUSION

This research focused on combined UAS and smartphone based mapping with various georeferencing options to enhance the accuracy and comprehensiveness of geospatial data. The use of GCPs and the application of RTK and PPK techniques played pivotal roles in our methodology, aiming to refine the precision of our geospatial mapping efforts.

Our findings underscore the critical importance of integrating GCPs in achieving high levels of accuracy in geospatial data. The experiments conducted across various scenarios revealed that while individual RTK and PPK processing methods provide certain levels of precision, the inclusion of GCPs enhances the accuracy of the data collected. This was evident in the improvements observed when GCPs were integrated into the processing of both RTK and PPK data.

The observation that individual processing of PPK data with GCPs did not significantly outperform RTK processing with GCPs emphasizes the importance of high-quality GCPs in geospatial accuracy. However, it's important to note that surveying GCPs is a significant cost factor, and there is often a desire to limit their number in these surveys. Therefore, while well-placed and accurately measured GCPs can provide the required precision for most surveying tasks, reducing the necessity for additional RTK or PPK corrections, this may not always be the most cost-effective approach. The primary value of RTK and PPK may thus be most evident in scenarios where GCPs are sparse or absent, offering a balance between cost and accuracy.

The data from the iPhone 15 Pro and the DJI Mavic 3 Enterprise also highlighted the complementary nature of these technologies in capturing geospatial data. The iPhone, with its LiDAR sensor, provided enhanced depth perception in the vertical axis, which, when mixed with the aerial imagery from the drone, resulted in a richer, more detailed spatial dataset. The findings suggest a promising avenue for future research to further validate the efficacy of these integrated mapping methodologies.

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