Surveying Practices in the Drone Age:

Elevation Accuracy and Slope Assessment of UAV-Derived Products

Duncan Erik MacIntosh

Department of Geography

California State University, Long Beach

Introduction

California's Mediterranean climate provides a global biodiversity hotspot, creating habitat for hundreds of native plants, animals, and humans. Unfortunately, land conversion is projected to outpace habitat protection (Cox and Underwood 2011). Rapidly encroaching urban development threatens these complex landscapes. Unoccupied Aerial Vehicles (UAVs) can be used as a tool to generate high accuracy geospatial data products that inform land management and development planning. This research at River Ridge Ranch (RRR) in Springville, California, assesses the accuracy of UAVs for fine-scale landscape mapping in an at-risk biodiverse area, and explores the effectiveness of georeferencing methods in UAV derived data. The research addressed the following questions:

1. How accurate are elevations produced from UAV-derived digital terrain models (DTMs)?
2. Are human perceived slope classes a good predictor for DTM-derived slope type?
3. Is it possible to recreate slope classes using Global Positioning System (GPS) elevation, DTM elevation, and DTM slope using principal component analysis (PCA) scores and K-Means clustering?

This research provides an assessment of the current state of surveying practices in UAV landscape mapping and explores how the use of new technologies, such as Post-Processing Kinematic (PPK), can enable the phasing out of more costly surveying methods to better direct the practices of land managers.

Methodology

Various methodologies and techniques were employed to best answer the research questions. A total of 115 GPS points were collected across multiple dates and field excursions to River Ridge Ranch in Springville, California USA (Figures 1 and 2) from May 2018 to February 2019. The ranch covers 722 acres with topography ranging from low sloping pasture to severe sloping hillsides. At each GPS ground truth location the surveyor recorded perceived slope steepness using the following classes: low (type 1, 0-15%), medium (type 2, 15-30%), high (type 3, 30-45%) and severe (type 4, 45+%). Imagery was collected using an eBee Plus manufactured by senseFly™ flown at 400 feet above ground level using autonomous flight planning software and fitted with the S.O.D.A. true-color camera. Identical flight paths were flown (June & July 2018 and February 2019). The February flights were processed using PPK tools that enhance location accuracy without the need for ground control points (GCPs). These were compared with flights collected both with (February 2019) and without (June and July 2018) ground control points. The imagery was mosaicked using Pix4DMapper™, a professional structure-from-motion (SfM) software that combines individual images into one orthomosaic (Turner, Lucieer, and Watson 2012). Additional computer analyses including sink fill, elevation and slope value extraction, and map creation were conducted using ESRI's ArcGIS 10.6.

Figure 1. Image showing the pasture and mountain backdrop of RRR taken by author.

Methodology cont.

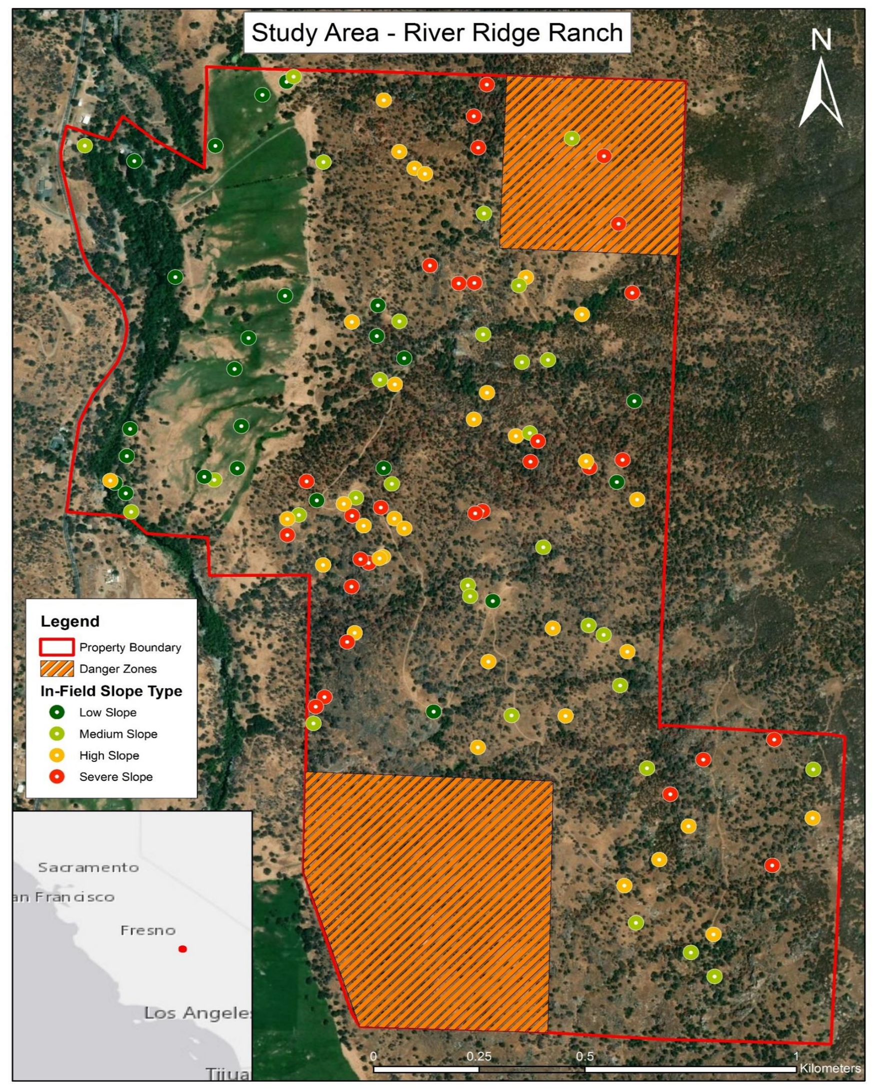

Figure 2. Shows a map of RRR along with the positions of all 115 GPS points.

GPS points were collected to represent higher accuracy elevations. Elevation accuracy was quantified by comparing these points using the Root Mean Square Error (RMSE) and Mean Absolute Difference (MAD) (Equations 1a and 1b) as well as conducting a multivariate statistical analysis (Fonstad et al. 2013; Hugenholtz et al. 2013; James and Robson 2014; Ishiguro, Yamano, and Oguma 2016).

1a. Root Mean Square Error [RMSE] $= \sqrt{\dfrac{\sum_{i=1}^{N}\left(Z_{i\,(\mathrm{UAS\ DEM})} - Z_{i\,(\mathrm{GPS})}\right)^2}{N-1}}$

1b. Mean Absolute Difference [MAD] $= \dfrac{\sum_{i=1}^{N}\left|Z_{i\,(\mathrm{UAS\ DEM})} - Z_{i\,(\mathrm{GPS})}\right|}{N}$

Equations 1a and 1b. Shows the RMSE and MAD equations.

- Multinomial logistic regression was performed using IBM's SPSS statistics package inputting field slope type as the dependent variable, all slope categorical data as factors and all scalar continuous elevation values as covariates.
- PCA and K-Means clustering were chosen as multivariate statistical methods to recreate field slope classes.
- SPSS was used to conduct the PCA.
- Clustering was performed using k-means clustering limited to 4 classes using the PAST 2.7 statistical package. The clusters were brought back to the original analysis to generate variable and factor mean values to determine the correlation of clusters to slope classes (α=.01)

Results and Discussion

Elevation Accuracy

The June Digital Surface Model (DSM) (MAD=1.89m) and July DSM/DTM (MAD = 1.87m and 1.56m respectively) with no georeferencing were more accurate than expected. The PPK DSM was less accurate with values of 3.07m and 2.14m while the PPK DTM generated more accurate elevations of 1.09m and 1.01m (RMSE and MAD respectively). Interestingly, the PPK DSM GCP method produced an RMSE of 3.14m and 2.09m for the MAD, while the DTM produced lower values of 1.01m and 0.91m for the RMSE and MAD. The USGS 10m elevation model produced the highest RMSE and MAD values with an RMSE of 32.14m and 31.76m for MAD (Table 1).

Table 1. Elevation RMSE and MAD values calculated across all models.

	June DSM	June DTM	July DSM	July DTM	PPK DSM	PPK DTM	PPK GCP DSM	PPK GCP DTM	USGS DEM
RMSE	2.46	**3.49**	2.96	2.12	**3.07**	**1.09**	**3.14**	**1.01**	32.14
MAD	**1.89**	2.83	**1.87**	**1.56**	**2.14**	**1.01**	**2.09**	**0.91**	31.76

Results and Discussion cont.

Multinomial Logistic Regression

Significant results from the multinomial regression are provided in Table 2. Only the July DTM slope model proved to be a good predictor for medium – type 2 - UAV-derived slope (α=.01). There were no variables with significant values for the in-field slope type of 3 (high slope). The slope type of 4 (severe slope) was dropped from analysis as a reference category.

The classification accuracy chart (Table 3) shows that the in-field slope type of 1 (low slope) had a highest classification accuracy of 91.7% classification across models. For type 2 – medium slopes - the models correctly classified slope points across models with an accuracy of 86.2%. Type 3 – high slopes were least accurate with only 54.5 percent correctly predicted across models. However, severe slope (type 4) models were 86.2% accurate.

Table 2. Shows the significant models and corresponding values.

Slope Type		Sig.
1	July DTM	0.03
1	PPK GCP DTM	0.09
1	USGS Slope = 1	0.09
2	July Slope = 2	0.00

Table 3. Shows the logistic regression classification matrix.

	Predicted				Percent
Observed	1	2	3	4	Correct
1	22	1	1	0	91.7%
2	2	25	2	0	86.2%
3	2	4	18	9	54.5%
4	0	0	4	25	86.2%
Overall Percent	22.6%	26.1%	21.7%	29.6%	78.3%

PCA and K-Means

The K-means clustering method was performed using the SPSS statistics package to conduct a PCA followed by clustering using PAST statistics software. Notable from the output are the high and low positive loadings for each component and variable. Interesting in this matrix are the high positive values of GPS and elevation models in Factor 1 with low values in Factors 2 and 3. Also worth noting are the low negative values of the PPK and PPK GCP slope models in Factor 3. The mean scores per component in the PCA were calculated for enhanced interpretation (Figures 4 and 5). In addition to the descriptive statistics outlined above, the variable means by cluster and slope type were calculated to determine their connection, if any.

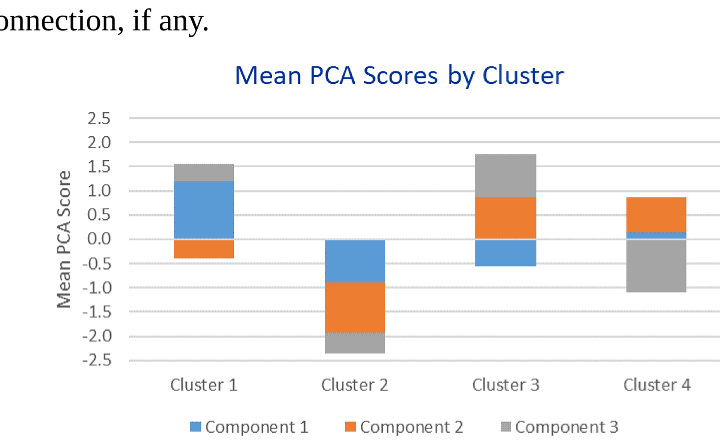

Figure 4. Shows the mean PCA scores by cluster.

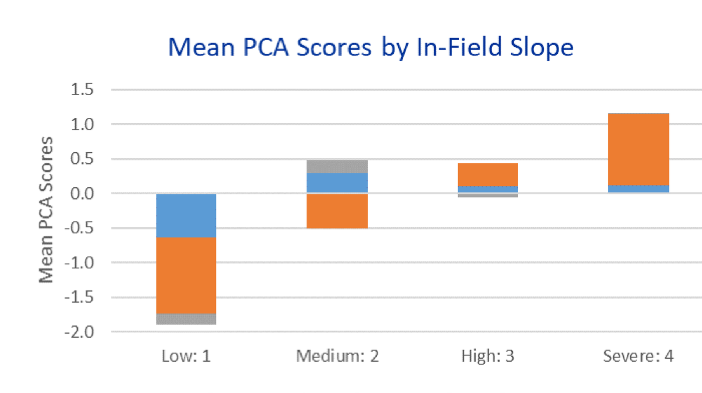

Figure 5. Shows the mean PCA scores by in-field slope type.

Focusing on the slope model values as an easily identifiable class definition, a pattern emerges between the values with Cluster 1 to Medium Slope (2), Cluster 2 to Low Slope (1), Cluster 3 to Severe Slope (4), and Cluster 4 to High Slope (3) (Table 4). This conclusion is also supported by the mean FAC scores by cluster. Cluster 1 was shown to be connected to higher elevation values, including mid and high. Cluster 2 was predicted to represent low elevation model values, as well as low slope values, which was also supported by the variable means conclusion. Cluster 3 was predicted to represent mid elevation values, as well as high slope values, which partially supports the variable means conclusion. Finally, Cluster 4 was predicted to represent high slope values, as well as low slope values, which partially supports the variable means conclusion as well. Additionally, there is some disparity in the variable means between the high and severe slope class correlation. It appears that there is potential misclassification of high points into the severe slope cluster and vice versa, severe points into the high slope cluster.

Table 4. Shows the clusters and corresponding in-field slope classes.

Cluster	Slope Type
Cluster 1	Medium Slope
Cluster 2	Low Slope
Cluster 3	Severe Slope
Cluster 4	High Slope

Conclusion

Given the supposed high positional accuracy of the PPK and PPK GCP models, the associated RMSE/MAD calculations were surprisingly high. The inclusion of GCPs increased the accuracy by 10cm. This is a meaningful finding as the more accurate these models are in representing the real world, the more likely they can be used confidently as an efficient method of data collection to inform land management and planning. The multinomial logistic regression generated statistically significant results, finding that the USGS model was a good predictor of low to low slope classification, while the July DTM slope model was a good predictor of medium to medium slope classification. It was also possible to generally recreate the slope classes using K-means clustering limited to 4 classes to match the slope class breakdown. The comparison shows that clusters roughly matched mean values for field slope classes and component mean loadings. It was unexpected that the July model had a significant variable showing predictor capabilities in the field slope class given that the July model did not have GCPs and, therefore, was less accurately georeferenced than the PPK and PPK GCP models. The same can be said about the USGS model as its high RMSE and MAD values would be expected to lead to less accurate slope models. However, the USGS slope model had a good predictor capability of low-low slope. There were no predictor capabilities in the more accurate PPK and PPK GCP models where one would expect to see such results.

This research is part of a broader MA thesis project focused on analyzing UAV terrain mapping in complex environments. These results are preliminary. Based on the results thus far, it appears that additional research could benefit from the use of real time kinematic pairing, a GPS correction technology providing real-time correction of location data for UAVs at the centimeter level. Also, incorporating additional GPS points to the ranch study area could be expected to enable a more statistically viable test to be performed on the dataset and could potentially improve results given the large size and varied landscape of the study area. Although acquiring additional GCPs would enhance the imagery, pursuing this strategy would have high resource costs due to the challenges of collecting data over such an expansive study area comprised of varying and often inaccessible terrain. All limitations considered, this study resulted in the successfully navigation of multiple challenges in analyzing the current state of georeferencing methods and use of sUAV remote sensing as a tool in landscape preservation and conservation.

Acknowledgements

The work conducted in this project could not have been done without the assistance of Professors Suzanne Wechsler, Paul Laris, Christine Rodrigue, and Scott Winslow of the CSULB Geography Department nor without the permission of land owner and manager Gary Adest of River Ridge Ranch, Springville CA. Additionally, a special thank you goes out to the SenseFly support technicians who provided assistance with troubleshooting and navigating challenges encountered with data collection using the equipment in this study.

References

Cox, R. and E. Underwood. 2011. The Importance of Conserving Biodiversity outside of Protected Areas in Mediterranean Ecosystems. PLoS ONE. 6(1).

Fonstad, M., Dietrich, J., Courville, B., Jensen, J., and P. Carbonneau. 2013. Topographic Structure from Motion: A New Development in Photogrammetric Measurement. *Earth Surface Processes and Landforms*. 38: 421-430.

Hugenholtz, C., Whitehead, K., Brown, O., Barchyn, T., Moorman, B., LeClair, A., Riddell, K., and T. Hamilton. 2013. Geomorphological Mapping with a Small Unmanned Aircraft System (sUAS): Feature Detection and Accuracy Assessment of a Photogrammetrically-Derived Digital Terrain Model. *Geomorphology*. 194: 16-24.

Ishiguro, S., Yamano, H. and H. Oguma. 2016. Evaluation of DSMs Generated from Multi-Temporal Aerial Photographs Using Emerging Structure from Motion-Multi-View Stereo Technology. *Geomorphology*. 268: 64-71.

James, M. and S. Robson. 2014. Mitigating Systematic error in Topographic Models Derived from UAV and Ground-Based Image Networks. *Earth Surface Processes and Landforms*. 39: 1413-1420.

Turner, D., Lucieer, A., and C. Watson. 2012. An Automated Technique for Generating Georectified Mosaics from Ultra-High Resolution Unmanned Aerial Vehicle (UAV) Imagery, Based on Structure from Motion (SfM) Point Clouds. *Remote Sensing*. 4: 1392-1410.

Email: duncan.csulb.geog@gmail.com