Applied Geography 139 (2022) 102652

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Evaluating the relationship between data resolution and the accuracy of identified helicopter landing zones (HLZs)☆

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ARTICLE INFO

Keywords:
Helicopter landing zones
Landing zone detection
Military geospatial GIS
Accuracy assessment

ABSTRACT

Helicopters provide critical advantages in military operations because of their ability to land at small and unimproved sites. While the military uses models to identify helicopter landing zones (HLZs), little research has been conducted on their accuracy. This study evaluated the performance of an HLZ detection model derived from existing selection criteria that incorporated elevation and land cover data with spatial resolutions ranging from 1 m to 30 m. Multiple HLZs were selected as study sites at three geographically varied locations. The HLZ boundaries identified using the derived model were then compared to surveyed reference boundaries to assess their accuracy. This study found that as the spatial resolution of the data became coarser, accuracy decreased across all sites. However, there were some instances where noticeable increases in error were observed at certain resolutions for some sites. The resolution at which this occurred was always related to the size of features either bounding or located within the landing area. Thus, this study found that the most important consideration when determining ideal resolution for HLZ detection is the geography of the study area. While additional research is needed, this study presents initial findings and a framework upon which future assessments can build.

1. Introduction

Helicopters, and the advantages they provide, are critical in military operations. They offer unique capabilities to commanders in both combat and non-combat situations (USA. HQDA, 2020). These aircraft enable the rapid deployment of units across the battlefield and recent operations in Iraq and Afghanistan have highlighted the importance of this advantage (USA. HQDA, 2015; NATO. Joint Air Power Competence Centre, 2012). Beyond combat operations, helicopters are vital in humanitarian efforts because they can access isolated areas to provide important services such as casualty evacuation (USA. HQDA, 2016). However, to maximize their utility, they must be able to takeoff from and land at locations beyond established airports or heliports (Peinecke, 2014).

Helicopter landing zone (HLZ) identification is one of the many geospatial tasks conducted by planners prior to operations (USA. HQDA, 2019). An HLZ is a bounded area that is suitable for landing one or more helicopters and are identified using helicopter landing suitability (HLS) overlays (USA. HQDA, 2006). While they are similar in nature, there is an important distinction between an HLZ and HLS. HLS simply refers to the suitability of an area – typically at the per-pixel level – for landing a helicopter, given certain criteria, while an HLZ is a specific, bounded area (Kovarik, 2014; USA.; HQDA, 2006; USA.; HQDA, 2019).

Current methods for HLZ detection, both in military and civilian organizations, typically involve the analysis of various data and generation of HLS rasters or vector HLZ boundaries (USA. HQDA, 2019; Kroh, 2020). Generally, rasterized elevation and land cover data at varying resolutions are used to develop these products (Kovarik, 2014). Elevation data are converted into slope rasters and these values are then classified based on their usability (USA. HQDA, 2006). For example, the U.S. Army classifies any slope value less than or equal to 7° as useable by any helicopter (USA. HQDA, 2006). While slope values are categorized into clear classes, land cover is more difficult to classify as either useable or unusable. Even though there are definitive land cover types that are not suitable for HLZs, such as water or dense forest, there are many

☆ (note: in this paper, 'resolution' refers to spatial resolution unless otherwise specified).

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https://doi.org/10.1016/j.apgeog.2022.102652
Received 10 October 2021; Received in revised form 19 January 2022; Accepted 23 January 2022
Available online 2 February 2022

Abbreviations

CORS	Continually operating reference station
DEM	Digital elevation model
DSM	Digital surface model
DTM	Digital terrain model
GCP	Ground control point
GNSS	Global navigation satellite system
HLS	Helicopter landing suitability
HLZ	Helicopter landing zone
JBER	Joint Base Elmendorf-Richardson
NAIP	National Agricultural Imagery Program
NLCD	National Land Cover Database
PCMS	Piñon Canyon Maneuver Site
USGS	U.S. Geological Survey
VTOL	Vertical takeoff and landing

additional considerations for areas that might immediately seem useable (Miller, 2013; Kovarik, 2014; USA. HQDA, 2006). Grasslands and barren areas are generally ideal places to land an aircraft, but various factors, such as obstructions concealed by high vegetation, can make them unusable (USA. HQDA, 2006). Other factors affecting HLS, such as vertical obstructions and soil composition data, can be included in analyses as well (Kovarik, 2014; Miller, 2013).

These HLS rasters and HLZ boundaries are essential when planning air operations because they greatly reduce the number of possible landing sites to consider, allowing planners to quickly template useable HLZs (USA. HQDA, 2017; Kovarik, 2014). Yet, despite their widespread use within the military, there is little research into these models and – more importantly – the accuracy of the resulting products. Existing research into HLZ identification is primarily focused on the civilian applications of wilderness search and rescue (SAR) and the automated landing of unmanned aerial systems (UASs) (Peinecke, 2014; Kroh, 2020; Doherty et al., 2013; Garg et al., 2015, pp. 246–251). Although certain components of these studies are relevant to defense applications, they typically implement overly complex methodologies, incorporate data from unapplicable or unavailable sources (such as inputs from onboard sensors), or focus on real-time detection (Alam and Oluoch, 2021). The primary goal of military HLZ identification is to locate useable areas prior to an operation, often under time and resource constraints, so models must be efficient and able to work with minimal data (USA. HQDA, 2015; USA. HQDA, 2020).

While previous studies that did focus on military applications implemented models consistent with existing doctrine, they primarily focused on generating novel approaches for HLZ detection (Miller, 2013; Blokland, 2018; Kovarik, 2014). Even though these projects contributed important research to the field, they often failed to adequately assess the accuracy of their findings (Miller, 2013; Blokland, 2018; Kovarik, 2014). Of the three studies, only one assessed accuracy by sending military pathfinders, who are specialists in identifying landing zones for both fixed and rotary-wing aircraft, to confirm the results of their analysis (Blokland, 2018). While these pathfinders provided invaluable expert opinions, their observations represent qualitative assessments, and it is difficult to evaluate performance solely based on this feedback. Commanders and planners will rely on these HLS and HLZ products when planning missions, so they must be aware of the uncertainty associated with them and in what instances their accuracy may be degraded.

One possible reason that many military HLZ studies have ignored accuracy assessments is that there are no published accuracy standards for these products. While it is impossible to say why this is the case, it is interesting given the importance placed on accurate geospatial data by the military (USA. Office of the Joint Chiefs of Staff, 2017; USA. HQDA, 2017). The National Geospatial-Intelligence Agency (NGA) of the United States maintains standards for various geospatial data and products, to include the base products used in landing zone identification such as elevation data (Geospatial Intelligence Standards Working Group, n.d.; NSG, n.d.). However, there are no documents that cover HLZs or HLZ identification (NSG, n.d.). Given this lack of standards for HLZ products, it is difficult for any research to meaningfully assess the performance of their models. Therefore, it is essential that work be done to model uncertainty in existing HLZ identification methods and develop baseline accuracy standards.

A potential first step in modelling accuracy is to determine how it relates to the resolution of input data. Fortunately, while there is little research on the effects of data resolution on HLZ accuracy, the general relationship between resolution and accuracy is thoroughly understood. Typically, as the spatial resolution becomes coarser, the accuracy of elevation and land cover data also decreases (Chen et al., 2004; Gao, 1997; Liu et al., 2009). With elevation data, one of the most important consequences of using lower resolutions is that terrain features, particularly smaller ones, become smoothed out (Thompson et al., 2001). Similarly, in land cover data, coarser spatial resolutions often lead to greater problems with mixed pixels and thus lower accuracy (Foody, 1994). In addition to these problems with the base data, the accuracy of derivative products is also impacted (Chen et al., 2004). Thus, it is likely that as the resolution of input data is changed for HLZ identification models, accuracy would also change.

2. Materials and methods

2.1. Overview

The goal of this study was to examine the relationship between accuracy and input data resolution when identifying HLZs. More specifically, the research objectives were to (1) determine if there is an optimal resolution to use when identifying HLZs, (2) explore the different factors that influence the accuracy of identified HLZs, and (3) identify the impacts of different geographies on HLZ accuracy. To accomplish this, multiple test HLZs were selected across three separate locations to serve as study sites. Elevation and land cover data were then gathered for each location and an HLZ identification algorithm was developed from existing methodologies and criteria. Next, ground truth data were collected at each site using terrestrial laser scanning and highly accurate reference boundaries were digitized from these surveys. Then, using the developed algorithm and the elevation and land cover data at various resolutions, HLZ boundaries were identified for each site. Finally, these model boundaries were compared to the surveyed reference boundaries to assess performance.

2.2. Study locations and site selection

Three study locations were identified for use in this research. Since this project aimed to assess accuracy across multiple environments, each location had different geographic characteristics. The following locations were selected for this project: (1) West Point, New York, (2) Fort Carson and Piñon Canyon Maneuver Site (PCMS), Colorado, and (3) Joint Base Elmendorf-Richardson (JBER), Alaska.

At each location, individual study sites were identified to serve as test HLZs. These were either existing HLZs or areas that met the criteria to serve as a landing zone. Existing HLZs were identified using military reference maps for each location which marked, and therefore actively used, HLZs. Other suitable areas that were suitable but were not delineated on any maps were also included to supplement existing HLZs. The criteria for these sites were that they must be large enough to land at least one helicopter (>25 m diameter), have a slope generally less than 7°, and be relatively free of vegetation that would obstruct a landing helicopter (USA. U.S. Army Pathfinder School, 2018). One additional constraint for all sites was that they had to have easily identifiable boundaries, whether due to elevation or land cover. This was important because in order to assess the accuracy of identified HLZ boundaries, there had to be an existing boundary to measure the results against. In total, 12 study sites were identified, including 5 at West Point, 4 at Fort Carson/PCMS, and 3 at JBER. Table 1 provides a list of all study sites and a brief description of them.

2.3. Data sources

Both elevation and land cover data were used in this project. The elevation data were in the form of raster bare-earth digital terrain models (DTMs) generated using aerial lidar. The lidar data for both West Point and Fort Carson/PCMS were collected as part of the U.S. Army's BuckEye program, which aims to produce 1 m digital elevation data and 0.5 m true color imagery for areas of interest (USA. HQDA, 2017; U.S. Army BuckEye Program, 2018; U.S. Army BuckEye Program, 2019). A DTM had already been generated for West Point prior to this project, but this study had to derive DTMs from the lidar data for the Colorado sites. For JBER, raw lidar data from the U.S. Geological Survey (USGS) were used to derive a DTM instead of BuckEye data because none were available (USGS, 2015). This process followed a similar methodology to that outlined by Karan et al. and involved using Trimble Business Center and ArcGIS Pro to convert the point clouds into grid formats, segment the data, and then interpolate a DTM from the resulting ground points (2014). The original lidar data had a point spacing of less than 1 m and the derived raster DTM was resampled using bilinear interpolation to a 1 m spatial resolution.

The land cover data used were derived from multispectral imagery collected by either the National Agricultural Imagery Program (NAIP) (West Point and Fort Carson/PCMS) or WorldView-3 (WV3) satellite (JBER) (Maxar, 2021; USDA, 2019). While the NAIP and pansharpened WV3 imagery datasets had spatial resolutions of less than 1 m (approximately 0.5 m and 0.31 m, respectively), they were resampled, using a bilinear interpolation method, to 1 m before being classified. All images were classified in ArcGIS Pro using a maximum-likelihood supervised classification method and the National Land Cover Database (NLCD) schema, which is the standard for all U.S. Geological Survey (USGS) land cover data (Multi-Resolution Land Cover Consortium, n.d. a; Multi-Resolution Land Cover Consortium, n.d.b). Specifically, this study used the following classes: water, developed, barren, forest, shrubland, and herbaceous. After running the classification, a researcher manually corrected any misclassified pixels at each site using aerial imagery and knowledge from having visited each site.

This study tested the following data resolutions: 1, 2, 3, 5, 7, 10, 15, 20, 25, and 30 m. These test resolutions were chosen because they represented an approximate range of some of the highest-resolution imagery (i.e. BuckEye, WorldView 2 and 3, Sentinel 2, and Landsat) and elevation data (i.e. BuckEye, TanDEM-X, ASTER, and SRTM) available at both local and global scales.

2.4. HLZ identification model and methods

Since this study was focused on assessing the accuracy of HLZ detection algorithms and not developing a novel approach, the model used in this study incorporated existing methods and criteria. Fig. 1 shows a flow chart outlining this model for HLZ detection. This methodology was implemented using ArcGIS Pro and a Python script specifically developed for this project so that it could be easily replicated across all locations. After importing all data, the elevation and land cover rasters were resampled to each of the 10 test resolutions and then clipped to a specific area of interest (AOI) around each study site. The elevation and land cover data were resampled using bilinear interpolation and nearest neighbor methods, respectively. Using this resampled and clipped DTM, a slope raster was then calculated as well.

For each resolution, the slope and land cover rasters were reclassified based on existing HLS criteria. The pixels of the slope raster were categorized as either GO, CAUTION, or NO-GO. Slope values less than 7°

Table 1
List of study sites.

Location	Site Number	Approximate Size (sq. m)	Description
West Point (A forested environment with many small mountains forming a series of ridges and valleys)	1	16,691	Medium-sized open field with low grass and small hill running through the center of the landing area. Bounded by a large hill, forest, developed area, and river.
	2	5984	Small landing zone with low grass. Bounded on two sides by high brush and urban areas on the other two.
	3	3369	Small landing zone with moderately high grass. Bounded on all sides by dense forest.
	4	4775	Small landing zone with low grass. Bounded on all sides by dense forest.
	5	7586	Small field with low grass and small hill running halfway through the landing area. Bounded on two sides by forest, a road on one side, and a lake on the last.
Fort Carson/PCMS (A generally flat and arid environment with sparse, low vegetation, and a few isolated valleys and mesas)	6	2656	Small hilltop landing zone with a few isolated bushes. Bounded on all sides by steep slopes.
	7	14,033	Medium-sized open field located at the bottom of a large valley with sparse vegetation, including a few large bushes. Bounded on two sides by a dry riverbed and by steep hills on the other two sides.
	8	27,206	Large-sized open field located at the bottom of a large valley with sparse vegetation, including a few large bushes. Bounded on three sides by a dry riverbed and by a steep hill on the last side.
	9	28,062	Large-sized open field with sparse, low vegetation. Bounded on all sides by asphalt roads.
JBER (A forested environment with rolling hills)	10	77,690	Large-sized open field with low grass and a few isolated obstructions. Bounded on three sides by forest and a road on the last side.
	11	42,884	Large-sized open field with low grass. Bounded on three sides by forest and a road on the last side.
	12	16,077	Medium-sized open field with moderately high grass and a small hill running part way through the landing area. Bounded on all sides by dense forest.

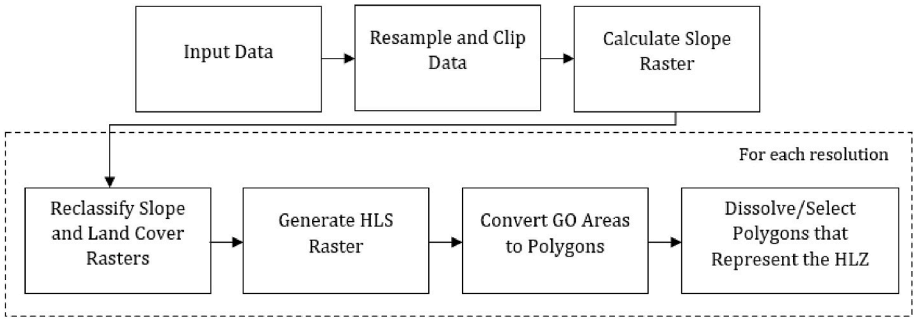

Fig. 1. HLZ identification model flow chart.

were classified as GO and those between 7° and 15° were classified as CAUTION. Any slope values greater than 15° were classified as NO GO. These values correspond to slope thresholds published by the Army and are thus what existing HLZ detection algorithms use (USA. HQDA, 2006). The land cover data were reclassified into a binary GO or NO-GO raster based on the classification of each pixel. Only pixels classified as herbaceous or barren were reclassified as GO because these land cover classes represented areas that are typically suitable for landing sites (USA. HQDA, 2006). All other land cover pixels were classified as NO-GO areas.

Using these reclassified rasters, an HLS raster was then calculated for each site. Since the reclassified land cover raster was in a binary GO or NO-GO format, this was first used to eliminate any definitive NO-GO areas. The remaining areas were then classified as either GO, CAUTION, or NO-GO based on the reclassified slope raster. Since this study was only interested in evaluating HLZ boundaries based on areas marked as GO, these corresponding pixels were selected from the HLS raster and then converted into polygons.

However, since there were also occasionally other technically useable areas within the AOI defined for each site, this study then selected only polygons corresponding to the identified HLZ. Fig. 2 shows an example of the final step in this process. It involved selecting features with sections overlapping the surveyed reference boundary, dissolving them into a single polygon, and then exporting this as a separate feature class. This final polygon represented the HLZ boundary identified by the model for that specific resolution at that particular site. In total, 10 HLZ boundaries were identified at each site corresponding to each of the tested resolutions.

2.5. Ground truth data collection and processing

Ground truth data were collected at each site to assess accuracy. This was accomplished by using a Trimble SX10 total station to collect multiple laser scans and the resulting point clouds were then georeferenced using Propeller AeroPoints as ground control points (GCPs). The AeroPoints continuously collected global navigation satellite system (GNSS) data and then performed corrections using existing continually operating reference stations (CORS) networks, delivering GCP coordinates with sub-20mm horizontal accuracy and sub-50mm vertical accuracy (Propeller, 2019). This level of accuracy, when combined with the sub-14mm accuracy of the SX10 (at less than 100 m in a laboratory environment), meant that the point clouds and subsequent reference HLZ boundaries had relatively high accuracy (Trimble, n.d.).

After collecting these point clouds, they were transformed into gridded digital elevation models (DEMs) in Trimble Business Center and HLZ boundaries were manually digitized in ArcGIS Pro using these as a reference. The laser scanning data were first georeferenced using the coordinates from the surveyed GCPs and were then converted into both a gridded digital surface model (DSM) and a bare-earth DTM. A hillshade was applied to the DSM to show surface obstructions and ground slope was calculated from the DTM to show areas unusable due to steep slopes. Finally, using the hillshade and slope rasters, a researcher manually digitized a polygon bounding the suitable area to serve as the reference HLZ boundary. They implemented the same slope and land cover selection criteria that the model used and is outlined in section 2.4. While the hillshade and slope data had minor gaps due to the limitations of terrestrial laser scanning, the researchers compensated for this in the digitization process by also using photographs and their knowledge from having visited each site.

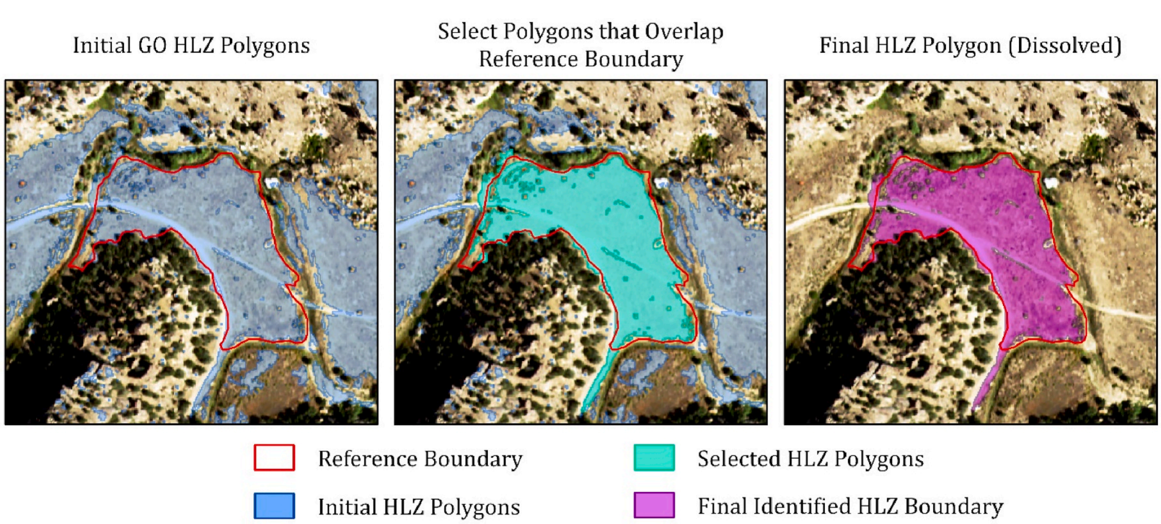

Fig. 2. Selection of final model HLZ boundary.

2.6. Accuracy assessment

Using the reference boundary for each site, the accuracy of HLZ boundaries derived from the model at each resolution were assessed. The overall goal of the accuracy assessment was to determine how well HLZ boundaries at each resolution approximated the reference boundary; the closer the model approximated the reference, the better the performance at that resolution. Fig. 3 gives a visual example of how accuracy was quantitatively assessed using a Python script. Each model boundary was converted into a series of points based on the vertices of the polygon and the distances from these points to the reference boundary (d_n) were calculated. Each d_n value represented a single error value. The average of these d_n values represented the mean error for that resolution at the specific site. This process was repeated at each site and the result was a table showing the performance across all sites and at all resolutions.

This study also qualitatively assessed performance. To do this, researchers visually examined the results at each resolution and looked to see if important features, whether along the boundary or within the landing area, were lost. This included inspecting the fidelity of the model boundary to see how well it represented the reference boundary. Within the landing area, researchers looked to see if the model missed any obstructions, such as bushes or trees, or generated any otherwise unusual results.

3. Results

3.1. General relationship between data resolution and accuracy

At all sites, this study found there to be a positive correlation between spatial resolution and accuracy. That is, as spatial resolution became finer (higher), the accuracy of identified HLZs increased. Table 2 provides, for each resolution across all sites, important statistics for mean error, to include mean, median, minimum, maximum, and range. The average mean error value for each resolution increased steadily from 6.30 m at 1 m resolution to 34.78 m at 30 m. However, the ranges listed in Table 2 also show how variable these results were, particularly at lower resolutions. Fig. 4, which is a graph depicting the mean error values from all sites and at all resolutions, also shows this variability, particularly as resolution became coarser. Using a linear regression ($n = 120$), the strength of the overall positive correlation between data resolution and the mean error ($R^2 = 0.15$) was found to be somewhat weak.

Looking at the study locations individually, Table 3 depicts the same information as Table 2, but broken down by location. The findings at West Point represented the strongest correlation between data resolution and accuracy. All sites at West Point had relatively linear trends between resolution and mean error. Average mean error values for this location increased from 2.61 m at 1 m resolution to 14.91 m at 30 m. Table 3 also shows that the ranges of the mean error values at each resolution were also relatively small. The strength of the correlation ($n = 50$) between resolution and mean error ($R^2 = 0.73$) at West Point was substantially higher than the overall correlation for all sites.

The findings at Fort Carson/PCMS were essentially the opposite of those at West Point: these sites were the least accurate and had the most variability in their errors. The average mean error values increased from 12.76 m at 1 m–64.95 m at 30 m (however, the highest average mean error was 75.25 m at 25 m). Additionally, the positive relationship ($n = 40$) between mean error and resolution for the Fort Canyon/PCMS sites was much weaker ($R^2 = 0.30$) than the correlation at West Point. This was also reflected in the ranges of mean error values (Table 3), with all of them being many times larger than those at West Point. However, it is also important to note that at certain resolutions, specifically 5 m and 20 m, there were noticeable increases in error.

While the relationship between error and resolution at JBER was nearly as strong as that of West Point, it also had instances of accuracy drop-offs that were similar to those observed in the data from Fort Carson/PCMS. Average mean error values increased from 3.85 m at 1 m–27.66 m at 30 m. Additionally, the ranges of these mean error values were similar to – and in some cases smaller than – those at West Point. While there was a strong, positive correlation ($n = 30$, $R^2 = 0.72$) between mean error and data resolution, there were again noticeable increases in error at specific resolutions (10 m and 20 m).

It was also important to qualitatively assess performance at each resolution. While difficult to empirically quantify, the coarsest resolutions that produced acceptable results across all locations appeared to be between 5 m and 10 m. At resolutions coarser than this, the fundamental shape of the HLZs began to be degraded. Additionally, some obstacles and bounding features, such as roads and rivers, were lost after 5 m–10 m. Again, while such assessments are simply observational, they are nevertheless important to consider.

3.2. Impacts of location and site-specific geography on accuracy

While the general, positive relationship between data resolution and accuracy was observed at all sites, the results at many were also greatly influenced by irregular conditions on the ground. At sites with clear landing zones and large, homogenous bounding features, the accuracy was generally higher and decreased at a relatively constant rate from 1 m to 30 m. These bounding features could have been created by land cover, such as the large forests typical of West Point, or elevation, such as the steep slopes surrounding the Site 6 (located on a hilltop). On the contrary, sites with obstacles located within the landing zone and/or thinner, less-defined boundaries typically had lower accuracy and significant increases in error at certain resolutions.

At West Point, the sites with the highest levels of error – Sites 1 and 5 – were also the ones with disrupting features running through the landing zones. For example, Site 1 (depicted in Fig. 5) presented a unique challenge for this study as it had a small hill running through the center of the landing zone. This hill (circled in red) was less than 1 m tall, making it virtually undetectable in satellite imagery (see Fig. 5A).

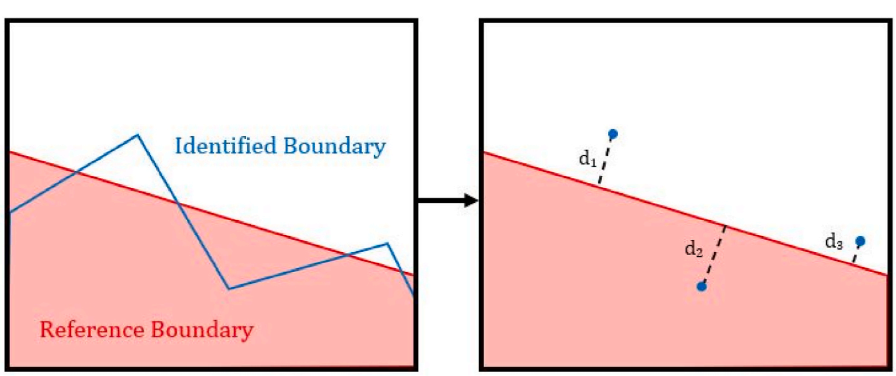

Fig. 3. Diagram of accuracy assessment.

Table 2
Mean error statistics across all locations and sites.

Data Resolution (m)	1	2	3	5	7	10	15	20	25	30
Minimum Mean Error (m)	1.51	1.88	1.98	2.39	2.72	3.43	4.27	5.09	4.62	6.71
Maximum Mean Error (m)	21.03	20.02	19.71	21.89	78.53	90.72	97.32	152.09	145.06	126.00
Mean Error Range (m)	19.53	18.14	17.73	19.50	75.81	87.29	93.05	147.00	140.44	119.29
Average Mean Error (m)	6.30	5.11	5.14	5.84	16.80	19.99	21.07	32.71	34.26	34.78

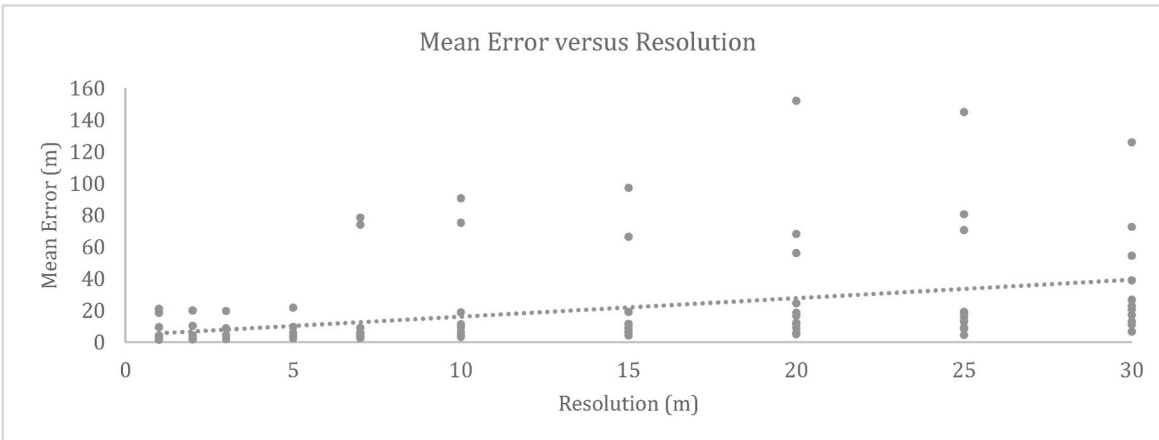

Fig. 4. Mean errors for all sites.

Table 3
Mean error statistics for all sites at each location.

Data Resolution (m)	1	2	3	5	7	10	15	20	25	30
WEST POINT (5 Sites)										
Minimum Mean Error (m)	1.51	1.88	2.39	3.04	3.57	4.16	6.21	5.93	8.51	6.81
Maximum Mean Error (m)	3.49	3.32	3.33	4.36	5.15	9.55	9.04	16.77	16.18	22.95
Mean Error Range (m)	1.98	1.44	0.94	1.32	1.59	5.39	2.83	10.83	7.66	16.14
Average Mean Error (m)	2.61	2.61	2.93	3.56	4.36	5.77	7.18	11.08	11.92	14.91
Median Mean Error (m)	2.83	2.50	3.19	3.50	4.49	5.12	7.10	11.54	12.90	13.11
FORT CARSON/PCMC (4 Sites)										
Minimum Mean Error (m)	2.04	1.96	1.98	2.39	2.72	3.43	4.27	5.09	4.62	6.71
Maximum Mean Error (m)	21.03	20.02	19.71	21.89	78.53	90.72	97.32	152.09	145.06	126.00
Mean Error Range (m)	18.99	18.06	17.73	19.50	75.81	87.29	93.05	147.00	140.44	119.29
Average Mean Error (m)	12.76	9.08	8.53	9.53	41.12	45.19	44.92	70.39	75.25	64.95
Median Mean Error (m)	13.98	7.17	6.21	6.92	41.61	43.30	39.04	62.20	75.66	63.55
JBER (3 Sites)										
Minimum Mean Error (m)	3.42	3.62	4.10	3.80	4.42	5.13	8.79	12.24	13.32	17.12
Maximum Mean Error (m)	4.25	4.51	4.49	5.89	5.95	18.85	19.12	24.63	19.06	39.01
Mean Error Range (m)	0.83	0.90	0.39	2.09	1.52	13.71	10.33	12.39	5.73	21.89
Average Mean Error (m)	3.85	4.00	4.31	4.70	5.11	10.08	12.43	18.51	16.83	27.66
Median Mean Error (m)	3.87	3.86	4.35	4.42	4.96	6.25	9.36	18.66	18.12	26.87

However, it was a large enough obstruction to prevent helicopters from landing on it and thus split the landing zone into two separate areas. At 5 m and coarser resolutions, the elevation data became too smooth and calculated slope values were reduced to less than the threshold (7°) at which the model would have classified it as unusable. These smoothing effects can be seen in Fig. 5B, which shows cross-sections of the elevation and slope rasters at selected resolutions. This change is also apparent in the identified HLZ boundaries, with the hill being completely captured at 3 m and entirely lost at 5 m. This transition point between 3 m and 5 m appeared to be related to the horizontal width of the hill, which was approximately 3.5 m.

The results from Sites 7 and 8 in Colorado showed noticeable decreases in accuracy at certain resolutions. These drop-offs occurred between 5 m and 7 m for Site 7 and between 15 m and 20 m at Site 8. Similar to the findings at site 1, these resolutions appeared to be related to the size of the features at each landing zone. Sites 7 and 8 were bounded on at least one side by a thin, linear feature. For example, the bounding feature at Site 7 was a riverbed and its shortest width (approximately 6 m) appeared to correlate with the resolution at which the noticeable decrease in accuracy occurred. This was also reflected visually in the identified boundaries shown in Fig. 6 (selected resolutions). At resolutions of 7 m and coarser, the identified HLZ crossed the riverbed and other suitable areas separated by this boundary were then incorrectly classified as part of same landing zone. The same was observed at Site 8 which had a riverbed bounding it on three sides with a width of approximately 16 m.

The resulting HLZs from Colorado also demonstrated the challenges of using data that is too detailed in spatial resolution. At Sites 7 and 8, the HLZs identified using 1 m and, to a lesser degree, 2 m resolution data had data gaps in them. These gaps were, for the most part, a result of numerous small shrubs and bushes that covered the landing zones. Fig. 7 provides a picture of Site 7 and shows which bushes would have prevented a helicopter from landing (circled in red) and those that would not have (circled in green). While these conditions were clear on the

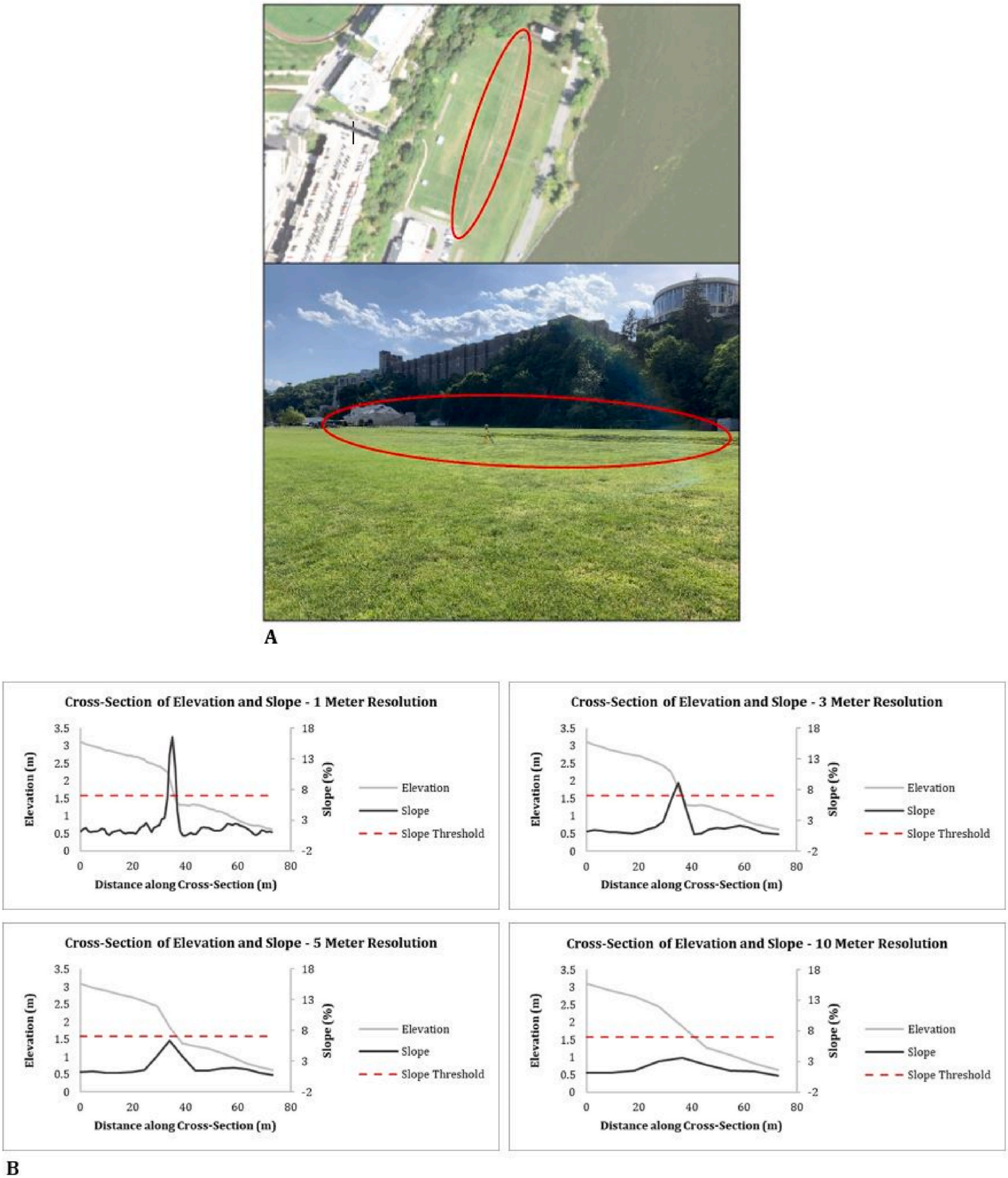

Fig. 5. Slope and elevation cross-sections from Site 1.

ground, many of these smaller features were incorrectly identified as obstructions in the 1 m results shown in Fig. 7. These artifacts were smoothed out in 3 m and coarser data, resulting in more accurate HLZs.

At JBER, while the overall geography was relatively similar to West Point, noticeable increases in error were also observed at both Sites 10 and 11. These sites were bounded on at least one side by a road and, similarly to what occurred at Sites 7 and 8 in Colorado, they were crossed at the first resolution greater than the smallest width of the boundary.

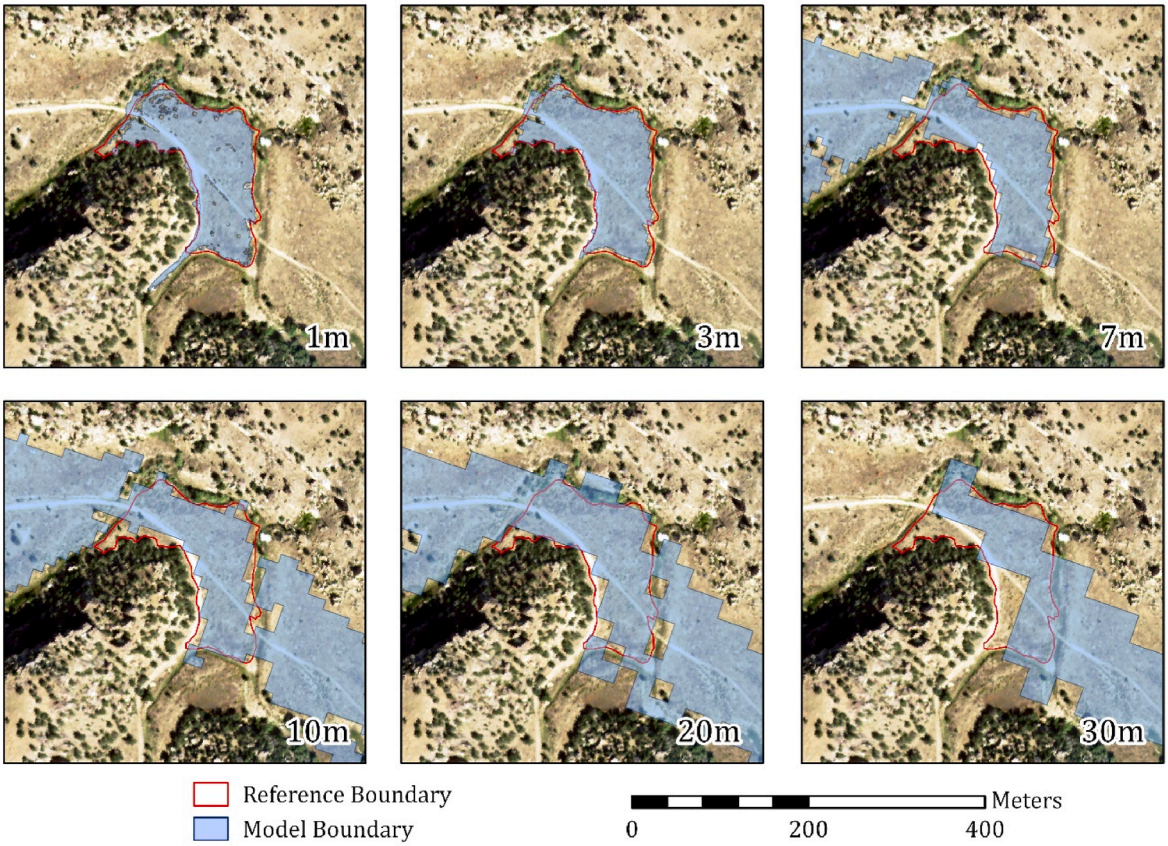

Fig. 6. Selected outputs for Site 7.

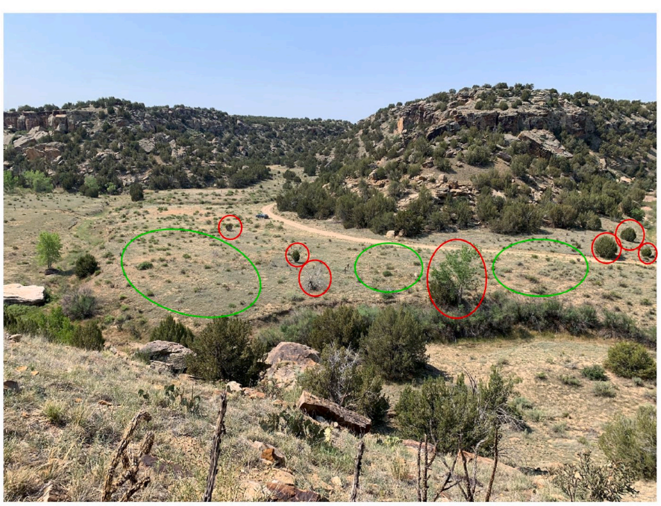

Fig. 7. Picture of Site 7.

4. Discussion

At all study sites, there was a positive correlation between resolution and accuracy, meaning that as resolution became finer, the accuracy increased. While there are no similar HLZ studies to compare these findings to, this general relationship is well documented in previous remote sensing research (Gao, 1997; Liu et al., 2009; Chen et al., 2004). These studies found that as data resolution decreased, there was a subsequent increase in error for both the base data and derived products (Gao, 1997; Liu et al., 2009; Chen et al., 2004). Even though these prior studies focused on applications such as hydrology and geomorphology, their research was fundamentally related to modelling geography using remotely sensed data. Thus, it is logical that the findings of this study are consistent with those of previous, albeit somewhat unrelated, research.

While these general trends in accuracy are important, it is also necessary to consider how the varying environmental conditions of each location impacted the findings. All three locations were chosen because they had different topographic and vegetative characteristics. West Point represented a dense, temperate forest with varied terrain (Olson et al., 2001). On the contrary, Fort Carson/PCMS represented an arid environment with sparse vegetation, generally flat terrain, and isolated canyons and mesas (Olson et al., 2001). JBER, which was mostly similar to West Point, represented a boreal forest with slightly less varied terrain (Olson et al., 2001). While the general trends held true across all locations, this assessment was impacted by the specific elements at each site.

At both West Point and JBER, the geography mostly dictated that finding a useable HLZ meant identifying a small, suitable site within a large amount of unsuitable area. The 'finding a needle in a haystack' analogy may be too dramatic, but the concept is similar. The terrain at West Point included mainly large hills that were covered mostly by either dense forest or developed areas, and JBER was much the same. These obstacles tended to be large and homogenous, with little variation. Other than the small hills at Sites 1, 5, and 12, the HLZs themselves also had little variation and essentially no obstacles located within their boundaries. Given these circumstances, HLZ identification was relatively simple: all the model had to do was roughly approximate the boundary of the useable area and the results were deemed acceptable.

Fort Carson/PCMS represented essentially the opposite geography: most of the terrain was flat and open, meaning that the challenge was identifying small obstacles and any elements that would make an area unsuitable. While there were isolated canyons and mesas that provided some major obstacles, the primary obstructions were dried up riverbeds and scattered, medium-sized bushes (interestingly, this actually made study site selection difficult as it was almost impossible to find areas with clearly defined boundaries). This meant that input resolution had to allow the model to identify relatively small features, as opposed to the relatively larger ones at West Point and JBER. These impacts of site geography lead into another important finding of this study: the relationship between feature size and data resolution.

This relationship appeared to be the underlying reason why there were differences observed in the results based on the geography of a site. The primary finding in this regard is that in order to maintain accuracy, the spatial resolution of the data must be smaller (finer) than the size of the feature to be detected. The model produced better results at relatively coarser resolutions for sites with large features, such as those bounded by forests or large slopes. Since these features were larger than even the coarsest resolution tested (30 m), they were always represented in the data. While the actual shape of the landing zone became distorted as the resolution decreased, there were never any significant losses in accuracy. At sites with narrow, linear bounding features that were smaller than the coarsest resolution tested (Sites 7, 8, 9, 10, and 11), all experienced noticeable accuracy decreases at the first resolution that was larger than this feature width. In addition to bounding features, resolution was also important for detecting obstructions within the defined landing zone. These findings were true regardless of the feature's size or whether it was slope or land cover based.

This relationship between feature size and resolution is also consistent with previous research. These studies found that it was important to match the resolution of data to the specific conditions on the ground (Deng et al., 2007; Moody and Woodcock, 1994; Nelson et al., 2009; Xiaoye, 2008). This is because features begin to be lost once the pixels in a raster become larger than objects on the ground due the problems of smoothing and mixed pixels (Deng et al., 2007; Nelson et al., 2009). Therefore, it is reasonable that in this study the same should occur.

However, if the accuracy of HLZ products is to be fully understood, future studies must examine performance at both more and increasingly varied sites. This should include all possible geographies, to include alpine, tundra, jungle, desert, and urban environments. Moreover, while this study chose to only assess useable HLZs, future research should also investigate model performance at sites known to be unusable. This would allow researchers to determine whether the model produces false positives and to what extent this varies with resolution. While this may be too broad of a scope for a single project, many different projects focusing on individual locations could produce the breadth of knowledge required to begin formulating comprehensive accuracy predictions.

Additional research should also focus on the HLS rasters themselves. Since these overlays are the basis for identifying HLZs and are often included on products used by planners, it is important to understand their accuracy. If future studies focus on a single location or environment, it would be quite feasible to assess both the HLS rasters and resulting HLZ boundaries. Moreover, researching the performance of these rasters would likely improve the overall understanding of how data resolution effects accuracy in HLZ products. One important development from such work would be confidence intervals based on the spatial resolution of input layers. Determining these confidence intervals would allow analysts to apply the uncertainty of the model to the radius needed for any particular vertical takeoff and landing (VTOL) aircraft and provide HLS and HLZ layers with specific confidence values (i.e. 90%, 95%, and 99%).

Future research could also improve the usability of their findings by both modifying the accuracy assessment methodology. This study simply assessed error as distance from the model boundary to the reference boundary and did not account for whether points from the model boundary were inside or outside of the reference boundary. If model points were outside of the reference boundary, they would represent unusable areas, but if they were inside then they would still represent useable areas. These differences would be important to consider and future research should attempt to account for the different implications of overestimating or underestimating the useable landing area.

Finally, future studies should experiment with different data types and HLZ criteria. Since methodologies do exist that incorporate more data, research that assessed the performance and accuracy of these models would be useful in determining what is best for military applications. While additional data may not always be available, studies may find that their use is advantageous when possible. Future research should also incorporate additional criteria to see how these requirements affect performance. A common criterion in HLZ identification is the size necessary to land a certain number of aircraft, so future studies that incorporate this into their analysis may be able to better apply their findings to real-world scenarios.

5. Conclusion

Identifying accurate HLZs will continue to be an important part of planning for military operations. This study found there to be a positive correlation between input data resolution and the accuracy of derived landing zone boundaries. While this general relationship held true across all locations, the geography of each site also substantially impacted results. These findings are important for military landing zone identification because they show that analysts must be deliberate in their selection of data. They must find a resolution that is best suited for their area of interest based on both accuracy and mission requirements. Beyond military applications, these findings are important for general-purpose helicopter planning and operations because organizations other than the military also rely on accurate HLZ products. However, this study represents only the first step in what will be a lengthy process of modelling HLS and HLZ accuracy. While this research cannot recommend any accuracy requirements or ideal data resolutions, it provides a foundation upon which future projects can build. Subsequent studies should expand their scope to more locations, evaluate both HLS and HLZ accuracy, and incorporate more data and criteria into their analyses. In doing so, they will be creating the knowledgebase necessary to develop standardized accuracy requirements for all military HLS and HLZ products.

CRediT authorship contribution statement

John Erskine: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Christopher Oxendine:** Conceptualization, Resources, Funding acquisition, Project administration, Supervision. **William Wright:** Methodology, Investigation, Writing – review & editing. **Matthew O'banion:** Methodology, Writing – review & editing. **Andrew Philips:** Conceptualization, Writing – review & editing.

Acknowledgements

Funding for this study was provided by the National Geospatial-Intelligence Agency (NGA) of the United States (no associated grant number). The authors would also like to acknowledge cadets and faculty from the Department of Geography and Environmental Engineering at the United States Military Academy for their immense help in planning and executing this research study.

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