HELICOPTER LANDING ZONE SELECTION VIA OBJECT-BASED IMAGE CLASSIFICATION TO DETERMINE SOFT GROUND AND "BROWN-OUT" POTENTIAL

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I. INTRODUCTION

Terrain analysis is crucial for determining suitable helicopter landing zones (HLZ) based on safety concerns and operational tasks. GIS software and various methodologies, such as pathfinder (in-person) operations, imagery interpretation, and slope analysis, have been developed to accurately identify landing zones that meet defined criteria related to safety, obstacle avoidance, slope, weather conditions impacting the terrain, accessibility, size, tactical considerations, and emergencies.

However, the previously mentioned methodologies do not integrate the non-visible region of the electromagnetic spectrum, specifically the red, green, blue, and near-infrared bands and the unique reflections for each land cover class. This capstone project will explore the object-based (oriented) classification of imagery using spectral measurements to identify terrain features suitable for helicopter flight operations. Object-Based/Oriented Classification is a two-step process that first segments an image based on the spectral values of each pixel to identify the edges of homogeneous regions or "objects." The second step of the process is to classify those objects based on distinctive topological properties. (Campbell and Wynne, 2011)

Trimble's eCognition software will segment and classify land cover using imagery data from the National Agriculture Imagery Program and LIDAR data from the United States Geological Survey to determine if the land is suitable. That criterion includes the slope of the terrain and the NDVI or Normalized Density Vegetation Index (healthy metric) and Normalized Density Water Index (water body content) indices. These vegetation and water indices will provide valuable metrics to determine Landing Zone Suitability remotely to mitigate safety concerns with the soft or arid ground. LIDAR data processing will provide the normalized Digital Surface Model (nDSM). It is important to note that the Normalized Difference Moisture Index (NDMI), which provides insight into moisture levels in vegetation, would also add to this research. However, that calculation requires using the SWIR region of the EM spectrum, which is not available from the 4-band imagery that this capstone utilized.

II. LITERATURE REVIEW

The following literature review summarizes some of the research and information that will be foundational to object-based classification research for landing zone identification, which is the emphasis of this capstone project.

A. TECHNIQUES AND METHODOLOGIES

Several methods for identifying helicopter landing zones use in-person reconnaissance, geographic information systems, and imagery interpretation to analyze the terrain based on specific criteria. The *U.S. Army Field Manual 3-21.38, Chapter 4*, presents the criteria for identifying feasible landing zones based on size, slope, terrain, and the approach to those areas. Those determinating parameters are the size of the aircraft as well as the mission requirements. However, this manual intends to use the "in-person" methodology by Army Pathfinders, trained to use this approach. Pathfinders aim to find areas large enough for the aircraft, not too steep in elevation (slope), and free of terrain attributes that could be vertical or horizontal obstructions like trees, brush, water, or rocks.

Olson (1979) discussed a methodology that utilizes imagery interpretation, and geographic information systems (GIS) use that criterion outlined in the U.S. Army Field Manual as parameters in various geoprocessing tools to analyze terrain data. The difference in Kaljahi (2019) countered those methodologies when researching automatic zone detection systems for the safe landing of UAVs by using neighboring pixel algorithms and image segmentation. Unfortunately, Kaljahi's methodology only explored segmentation and classification to find flat land in urban areas in emergency landing scenarios. There is no mention of image segmentation for rural areas or the terrain considerations that come with it.

Mertova and Bures' (2021) and Bradley (2022) do not have that gap in their focus. The article heavily emphasized the complex analysis of terrain features needed to identify landing zones falling more in line with the Field Manual 3-21.38 and the incorporation of GIS technology to analyze slope and available vector landcover datasets. These articles do not include image segmentation for Object-based Information Extraction with eCognition software.

B. NORMALIZED DIFFERENCE INDICES

The capstone study will include the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). EOS Data Analytics (2024) defines NDVI as measuring the vegetation's greenness and density captured in a satellite image. Javed (2023) used land surface temperature to monitor agricultural drought in Afghanistan. Research in articles by Bo-Cai Gao (1996) and McFeeters (2013) focused on identifying liquid water for crop yield and mosquito abatement detection, respectively.

NDWI and NDVI have similar characteristics but differ in their calculations' use of specific regions of IR reflection within the electromagnetic spectrum. The articles from Gao (1996) and Mcfeeters (2013) focused not on helicopter landing zone identification. However, they offered helpful information that will aid in determining safety concerns related to ground conditions that may be too soft or too arid for helicopter landings. Measuring how dry or low NDWI is has the potential to help identify "Brown-Out" conditions, where a helicopter lift creates a dust cloud that can cause pilots to lose their orientation and thus crash.

Using NDVI measurements to analyze vegetation density will help identify regions within vegetation density restrictions found in the U.S. Army Field Manual (2006) and help define parameters inside the eCognition software. Additionally, NDVI is used to identify other types of vegetation harmful to operations, such as trees or bushes. Trees are vertical obstructions that will impact how a helicopter approaches a landing zone so the aircraft does not collide or land on top of vegetation that could get caught in the rotary wings.

C. HELICOPTER LANDING ZONE STUDIES

Previous helicopter landing zone studies typically included raster datasets inside of GIS. P. Kroh (2020) explored the step-by-step instructions on identifying helicopter landing zones with commercial imagery and predetermining vector datasets that outlined the landcover classes. This study used LIDAR to determine the slope of the possible landing sites, but not from an object-based classification perspective. One thing that this study and this capstone will have in common, other than the data types, is the employment of visual verification. Visual verification uses imagery interpretation to confirm the output from the raster algebra, 1s, and 0s math based on pixel values. Verification is helpful because it compares what the eCognition software spectrally identified as trees with what imagery analysis visually identifies as trees.

Mertova and Bures' (2021) also used raster algebra to identify landing sites that met specific dimension criteria using general geoprocessing tools inside the GIS. Essentially, this study identified all groups of pixels that met the slope criteria and then converted those to a vector shapefile. Areas that resulted in specific shapes (circles or ovals) and sizes were determined to be usable for specific airframes. Visual interpretation was also focused on these areas to identify any vertical and horizontal obstructions, e.g., trees, bushes, or water, that would interfere with the safe landing of helicopters.

III. DATA

The first dataset for this capstone project is Light Detection and Ranging (LIDAR). LIDAR measures distances to objects and surfaces using laser pulses. The basic principle of LIDAR is the emission of laser pulses and measuring the time it takes for the light to bounce back after hitting an object. LIDAR creates precise three-dimensional representations of the surveyed area in the form of individual data points that create "point clouds." These clouds are densely packed and provide highly detailed information about the Shape and characteristics of the objects.

General Summary of the Metadata of the LIDAR LAZ dataset:

Entity ID:

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21809102_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21809104_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21809202_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21809204_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21809304_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900101_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900102_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900201_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900202_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900203_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900303_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900204_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21900304_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21901101_.laz

USGS_LPC_North_Carolina_SANDY_LiDAR_LA_37_21901203_.laz

State: North Carolina, Virginia

Agency: United States Geological Survey

Vendor: American Society for Photogrammetry and Remote Sensing (ASPRS)

Datum: North American Datum 1983

Resolution (Point Spacing): Various

Source DEM: 1.524 Meter

Unit: Meters

Sensor Type: Linear Mode LIDAR

Project Name: NC Sandy L 14 2024

Acquisition Date: 27 January – 21 March 2014

The objects that LIDAR data details include terrain, buildings, vegetation, and others. This detailed data can generate products such as digital elevation models (DEMs), digital surface models (DSMs), and contour maps that can provide slope and other terrain characteristics.

The second dataset used for this project capstone is imagery from the National Agriculture Imagery Program (NAIP). NAIP is a United States program that annually collects aerial imagery of agricultural terrain orthorectified and captured at a ground resolution of one meter or less. This imagery accurately provides crop conditions and land use, making this an excellent dataset for image segmentation and classification. Each land cover class will have different spectral measurements. These measurements, once known, can be used to generalize parameter rulesets for eCognition to perform object-based image segmentation and, thus, landcover classification in a streamlined process.

General metadata summary of NAIP imagery:

NAIP Entity ID: M_3607525_SE_18_060_20220625

State: North Carolina

Agency: United States Department of Agriculture (USDA)

Vendor: USDA-FSA-APFO (Aerial Photography Field Office)

Map Projection: UTM (Universal Transverse Mercator)

Projection Zone: 18N

Datum: North American Datum 1983

Resolution: 0.6 meters

Units: Meter

Number of Bands: 4 (typically Red, Green, Blue, and Near-Infrared)

Sensor Type: CNIR (Color Near-Infrared)

Project Name: 202205_NORTH_CAROLINA_0X6000M_UTM_CNIR

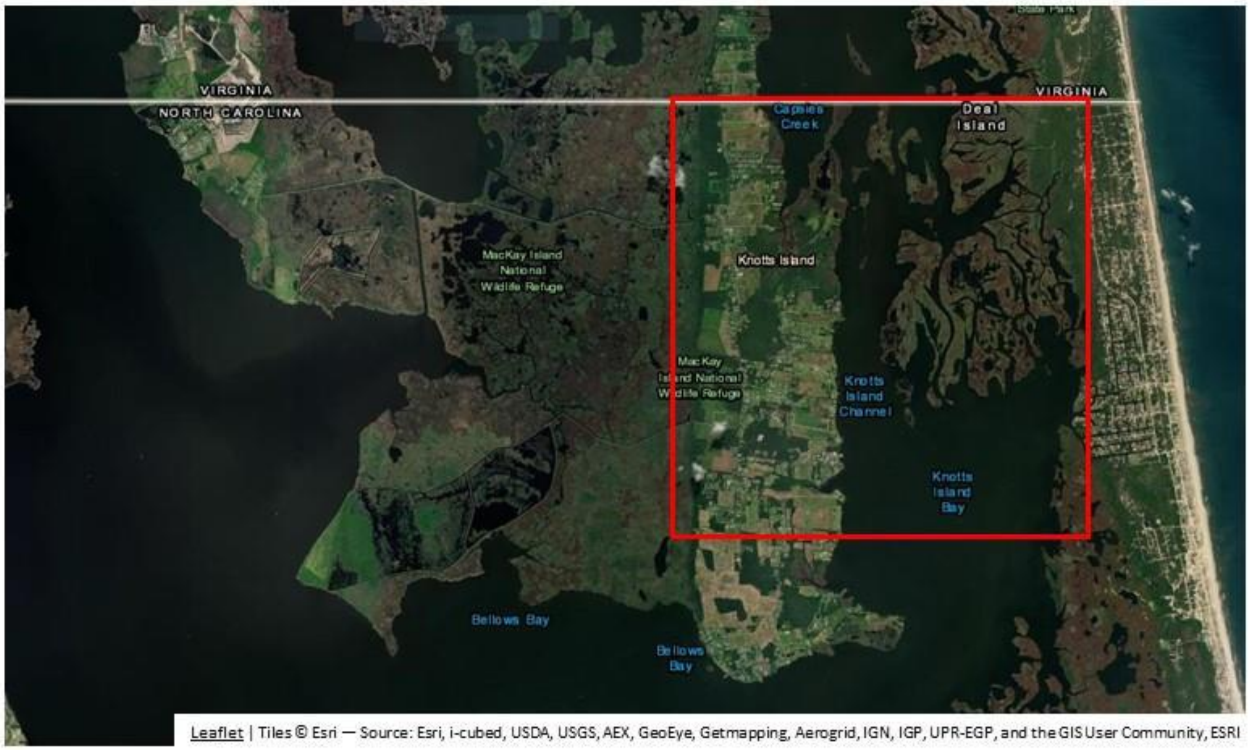
Acquisition Date: June 25, 2022

Analysis of NAIP imagery calculates and collects the NDVI and NDWI measurements and other spectral properties. According to EOS Data Analytics, NDVI is calculated from the visible and near-infrared (NIR) bands of satellite imagery using the formula: (NIR - Red) / (NIR + Red), where NIR and Red represent the reflectance values in the near-infrared and red spectral bands. Meanwhile, the calculation for NDWI metrics uses the formula (Green - NIR) / (Green + NIR). (2024)

Combining these spectral metrics and LIDAR helps to define the terrain's slope; the capstone project will be able to provide measurement data of the groundwater and lack thereof in the form of NDVI and NDWI. These indices are derived from remote sensing data and provide valuable information about the Earth's surface. They serve distinct purposes related to vegetation health, moisture content, and water body detection. Each index has its unique advantages and applications. They are often combined to gain comprehensive insights into environmental conditions and, therefore, can be used to create eCognition rulesets to identify land cover within specified spectral ranges. For example, if an individual wanted to identify the grass landcover class spectrally, they would establish a ruleset parameter to find terrain within ranges of high NDVI and low nDSM metrics. In other words, there is healthy vegetation and a low surface height. Since vegetation height is a critical safety concern to HLZs, the analysis must identify the vegetation, its height, moisture, and water indices.

Figure 1 shows the study area along the coastline near the North Carolina and Virginia border, rich with waterways, ponds, trees, and wetlands landcover classes. Moreover, this study region boasts various land cover types, including fields that may show seasonal suitability and potential "brown-out" areas. Seasonal suitability is a way to characterize terrain with different attributes; thus, suitability depends on the season in which the data collection occurred. An example would be a field full of crops. At specific points of the year, that Field will be flat and just a dirt field. At other times of the year, that Field could have corn or other crops growing to various heights. As stated, to analyze the various land cover categories identified using NAIP data, Trimble's eCognition software and LIDAR-derived surface models developed with ESRI's ArcGIS Pro software are used.

Final Project Study Area
North Carolina – Virginia Border



Study Area

1.6 km

The study area for this project is comprised of both developed and undeveloped land near Knotts Island, North Carolina. The undeveloped land is part of the MacKay Island National Wildlife Refuge and Deal Island. A large majority of this land is wetlands, channels, tall grass, and forest landcover. The developed land in the study area consists of farmland, piers, and commercial buildings consistent with community functions such as stores and infrastructure. For these reasons, this study areas provides a diverse range of land types to segment and classify to prove the utility of an iterative ruleset to identify suitable plots of land as determined by the United States Army Field Manual.

Figure 1: Study area for HLZ Suitability Analysis near Knotts Island, North Carolina.

IV. METHODOLOGY AND SOFTWARE

The capstone project uses the following methodology, summarized in several steps. First, LIDAR point cloud data, retrieved from the United States Geological Survey 3DEP LIDAR Explorer Application, will be converted from LAZ compression files to LAS format using ESRI's ArcGIS Pro, consolidating them into a new LAS dataset, and clipping the mosaiced file to the study area outlined in Figure 1.

Using LIDAR data enables the creation of a Digital Elevation Model (DEM) using Ground Points and the Digital Surface Model (DSM) using First Return points, which will be interpolated and converted into a raster format. The DEM represents the bare Earth and actual topographic features, while the DSM represents the highest points across the landscape. By subtracting the DEM from the DSM, a nDSM layer was created to represent features' height above ground level, i.e., vertical obstructions, which exports to a .TIFF file format for feature height analysis in Trimble's eCognition. The DEM, exported to a .TIFF format, will be used to analyze the slope of the terrain.

The third step will use the NAIP imagery analyzed in eCognition to create NDVI and NDWI indices. In eCognition, the supervised object-based segmentation of NAIP imagery uses three algorithms: quadtree-based segmentation, multi-resolution segmentation emphasizing vegetation and water contrast, and spectral difference segmentation.

The reason for multiple algorithms is that using a single segmentation algorithm is unlikely to produce all the objects needed for feature extraction, especially when targeting multiple, diverse features such as tree canopies and bodies of water. To effectively obtain accurate feature extraction of multiple landcover classes, it may be necessary to employ multiple segmentation algorithms. On the other hand, one routine used to extract a specific feature of interest will likely be entirely different from another feature type. In short, using three algorithms enables a specific but comprehensive extraction of various features present in the data. Each algorithm conditions the data for the following algorithms to run on.

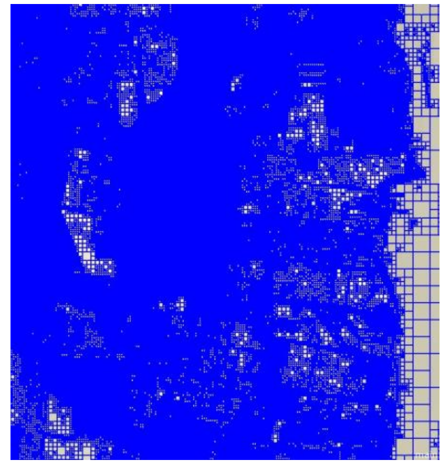


Figure 2: Screenshot of Quadtree Segmentation. 12 April 2024

Quadtree segmentation (Figure 2) is the first technique that divides the NAIP imagery into smaller squares of varying sizes, unlike traditional methods such as chessboard segmentation, which creates equal-sized squares. This approach intelligently creates more homogeneous squares based on input layers and parameter settings. Quadtree is a preliminary step before merging with algorithms like Multi-Resolution Segmentation and Spectral Difference. Coupling quadtree segmentation with these merging algorithms enables the creation of meaningful objects with computational time, which is especially beneficial for generating objects required for subsequent analysis. (UVM, n.d.) After Quadtree Segmentation, the Ruleset moves on to Multi-Resolution Segmentation.

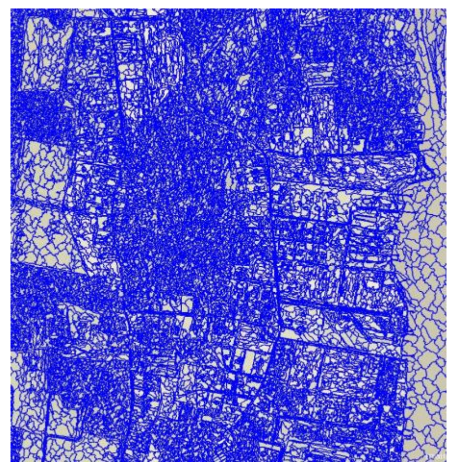


Figure 3: Screenshot of Multi-Resolution Segmentation. 12 April 2024

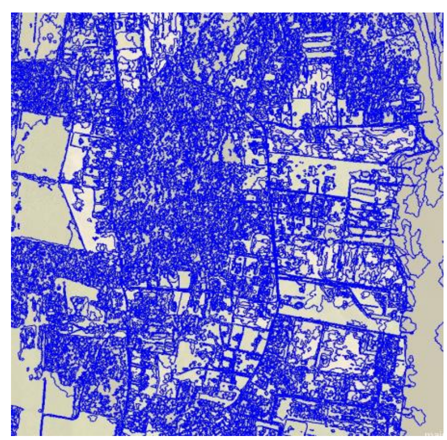


Figure 4: Spectral Difference Segmentation. 14 April 24

Multi-resolution segmentation (Figure 3) is an efficient algorithm suitable for various datasets, including imagery and LiDAR data. It is a default choice when uncertainty exists about the most appropriate segmentation algorithm. Then, the spectral difference segmentation

(Figure 4) algorithm merges objects with similar layer values, which is particularly useful for spectrally distinct features like water or impervious surfaces. This method capitalizes on the principle that objects with different compositions or conditions exhibit varying colors in spectral imagery, allowing enhanced segmentation based on spectral variance observed in scenarios such as agricultural fields with different crop stages or varying vegetation types. (UVM, n.d.)

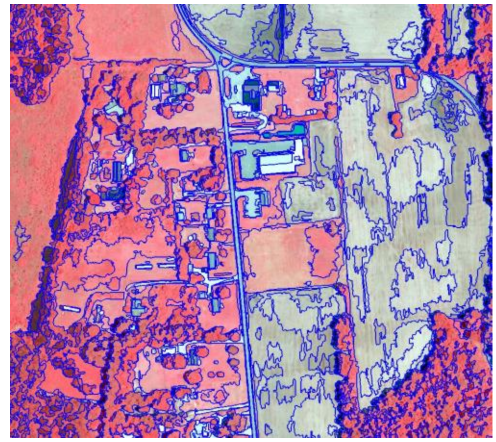


Figure 5: Screenshot of Segmented NAIP emphasizing the NIR Band of the 4-Band imagery. 14 April 24

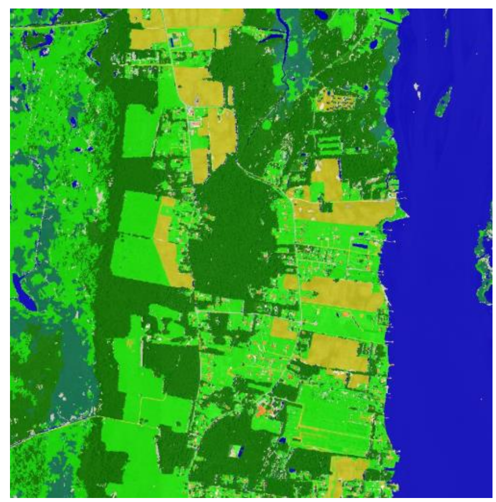


Figure 6: Screenshot of Classified NAIP with each landcover symbolized. 14 April 24

These processes segment the image to an appropriate pixel grouping across all land cover classes based on similar spectral metrics. Figure 5 visualizes the study by emphasizing NIR measurements. Based on those spectral groupings, the capstone assigned one of nine land cover classes (Figure 6). Manual object image exploration (i.e., selecting pixels from across the image and gathering measurements) collected various metrics from objects from each of the landcover classes in each of the 4-Bands (Red, Green, Blue, NIR) and metrics from the calculations related to NVDI and NDWI indices.

Table 1 below presents data on various parameters for different land cover types. The parameters include spectral values such as Red, Blue, Green, and Near-Infrared (NIR) bands, as well as derived metrics like the nDSM, NDWI, NDVI, and other statistical measures like Z-Deviation, Homogeneity, and Contrast.

Table 1: Imagery Interpretation Data for Segmented Objects

Buildings	Red	Blue	Green	NIR	nDSM	NDWI	NDVI	Z-Dev	Homog	Contrast
1	128.88	123.95	133.00	109.37	2.98	0.09	-0.08	1.25	0.09	1042.72
2	94.35	92.42	99.26	58.85	3.77	0.25	-0.21	1.34	0.06	1573.46
3	136.00	103.22	123.77	131.01	3.85	-0.04	-0.01	2.14	0.08	954.96
4	137.51	128.45	140.55	113.84	9.38	0.10	-0.10	2.26	0.14	923.55
5	176.36	156.25	170.31	167.40	3.77	0.00	-0.02	1.21	0.21	1054.95
6	213.26	203.91	209.30	218.75	2.74	-0.02	0.01	1.22	0.23	1806.79
Mean	**147.73**	**134.70**	**146.03**	**133.20**	**4.42**	**0.064**	**-0.068**	**1.57**	**0.135**	**1226.07**
Median	**136.76**	**126.20**	**136.78**	**122.43**	**3.77**	**0.05**	**-0.05**	**1.30**	**0.12**	**1048.84**
Min	**94.35**	**92.42**	**99.26**	**58.85**	**2.74**	**-0.04**	**-0.21**	**1.21**	**0.06**	**923.55**
Max	**213.26**	**203.91**	**209.30**	**218.75**	**9.38**	**0.25**	**0.01**	**2.26**	**0.23**	**1806.79**
Standard Deviation	**41.38**	**40.47**	**38.67**	**54.71**	**2.48**	**0.11**	**0.08**	**0.49**	**0.07**	**370.36**

Water	Red	Blue	Green	NIR	nDSM	NDWI	NDVI	Z-Dev	Homog	Contrast
1	95.73	76.14	106.86	15	0.004	0.75	-0.73	0.04		
2	57.31	56.94	61.28	15	0.64	0.61	-0.58	0.35	0.92	5077.02
3	15.47	53.19	31.75	15.04	0.45	0.36	-0.01	0.33	0.94	1066.01
4	65.97	58.08	65.69	15.01	0.09	0.62	-0.63	0.5	0.99	102.54
5	59.02	58.57	61.28	16.11	0.06	0.58	-0.57	0.17	0.81	2734.65
6	68.95	59.63	70.01	15.01	0.62	0.65	-0.64	1.02	0.95	829.1
Mean	**60.41**	**60.43**	**66.15**	**15.20**	**0.31**	**0.60**	**-0.53**	**0.40**	**0.92**	**1961.86**
Median	**62.50**	**58.33**	**63.49**	**15.01**	**0.27**	**0.62**	**-0.61**	**0.34**	**0.94**	**1066.01**
Min	**15.47**	**53.19**	**31.75**	**15.00**	**0.00**	**0.36**	**-0.73**	**0.04**	**0.81**	**102.54**
Max	**95.73**	**76.14**	**106.86**	**16.11**	**0.64**	**0.75**	**-0.01**	**1.02**	**0.99**	**5077.02**
Standard Deviation	**26.01**	**8.01**	**24.10**	**0.45**	**0.29**	**0.13**	**0.26**	**0.34**	**0.07**	**1990.24**

Forest/Trees	Red	Blue	Green	NIR	nDSM	NDWI	NDVI	Z-Dev	Homog	Contrast
1	78.17	66.36	89.25	194.35	9.45	-0.37	0.43	6.81	0.06	1127.96
2	82.07	69.34	90.33	182.81	9.88	-0.34	0.38	7.92	0.054	954.68
3	65.15	60.83	73.59	176.52	11.69	-0.41	0.46	4.89	0.03	1574.15
4	76.06	65.56	84.38	184.15	11.6	-0.37	0.41	6.61	0.05	994.55
5	85.14	69.31	91.95	183.82	4.79	-0.33	0.37	5.5	0.05	805.04
6	82.4	69.14	90.46	186.47	4.44	-0.35	0.39	4.41	0.05	989.91
Mean	**78.17**	**66.76**	**86.66**	**184.69**	**8.64**	**-0.36**	**0.41**	**6.02**	**0.05**	**1074.38**
Median	**80.12**	**67.75**	**89.79**	**183.99**	**9.67**	**-0.36**	**0.40**	**6.06**	**0.05**	**992.23**
Min	**65.15**	**60.83**	**73.59**	**176.52**	**4.44**	**-0.41**	**0.37**	**4.41**	**0.03**	**805.04**
Max	**85.14**	**69.34**	**91.95**	**194.35**	**11.69**	**-0.33**	**0.46**	**7.92**	**0.06**	**1574.15**
Standard Deviation	**7.15**	**3.33**	**6.91**	**5.79**	**3.25**	**0.03**	**0.03**	**1.32**	**0.01**	**265.71**

Grass/Short Vegetation	Red	Blue	Green	NIR	nDSM	NDWI	NDVI	Z-Dev	Homog	Contrast
1	112.2	85.4	117.28	193.45	0.1	-0.24	0.26	0.67	0.17	557.85

2	102.62	77.77	108.04	190.58	1.73	-0.28	0.3	4.97	0.14	509.57
3	113.51	87.69	118.28	193.42	0.13	-0.24	0.26	0.86	0.15	372.55
4	106.98	84.92	114.47	198.57	0.16	-0.27	0.3	0.94	0.2	585.41
5	114.19	88.12	119.16	195.33	0.16	-0.24	0.26	1.05	0.16	660.01
6	115.41	88.97	120.28	192.85	0.42	-0.23	0.25	2.18	0.15	518.46
Mean	**110.82**	**85.48**	**116.25**	**194.03**	**0.45**	**-0.25**	**0.27**	**1.78**	**0.16**	**533.98**
Median	**112.86**	**86.55**	**117.78**	**193.44**	**0.16**	**-0.24**	**0.26**	**1.00**	**0.16**	**538.16**
Min	**102.62**	**77.77**	**108.04**	**190.58**	**0.10**	**-0.28**	**0.25**	**0.67**	**0.14**	**372.55**
Max	**115.41**	**88.97**	**120.28**	**198.57**	**1.73**	**-0.23**	**0.30**	**4.97**	**0.20**	**660.01**
Standard Deviation	**4.97**	**4.09**	**4.48**	**2.69**	**0.64**	**0.02**	**0.02**	**1.65**	**0.02**	**95.91**

Roads	**Red**	**Blue**	**Green**	**NIR**	**nDSM**	**NDWI**	**NDVI**	**Z-Dev**	**Homog**	**Contrast**
1	139.37	119.55	137.8	157.37	0.003	-0.07	0.06	0.01	0.04	2052.28
2	139.03	125.08	138.68	134.65	0.21	0.01	-0.02	1.31	0.09	1584.85
3	142.27	126.74	140.74	137.16	0.02	0.01	-0.02	0.19	0.08	2304.66
4	143.71	129.05	142.28	131.56	0.31	0.04	-0.04	1.61	0.09	1731.73
5	146.17	130.26	144.76	139.89	1.97	0.02	-0.02	4.35	0.08	2300.86
6	140.33	127.35	140.11	128.5	0.25	0.04	-0.04	1.39	0.09	1854.43
Mean	**141.81**	**126.34**	**140.73**	**138.19**	**0.46**	**0.01**	**-0.01**	**1.48**	**0.08**	**1971.47**
Median	**141.30**	**127.05**	**140.43**	**135.91**	**0.23**	**0.02**	**-0.02**	**1.35**	**0.09**	**1953.36**
Min	**139.03**	**119.55**	**137.80**	**128.50**	**0.00**	**-0.07**	**-0.04**	**0.01**	**0.04**	**1584.85**
Max	**146.17**	**130.26**	**144.76**	**157.37**	**1.97**	**0.04**	**0.06**	**4.35**	**0.09**	**2304.66**
Standard Deviation	**2.78**	**3.78**	**2.52**	**10.22**	**0.75**	**0.04**	**0.04**	**1.56**	**0.02**	**298.90**

Wetlands/Marsh	**Red**	**Blue**	**Green**	**NIR**	**nDSM**	**NDWI**	**NDVI**	**Z-Dev**	**Homog**	**Contrast**
1	90.9	75.53	92.69	153.42	0.03	-0.25	0.26	0.06	0.04	1264.16
2	84.18	69.4	84.47	139.36	0.05	-0.24	0.25	0.11	0.04	1157.75
3	78.79	68.27	88.68	188.8	0.21	-0.36	0.41	0.21	0.07	1403.93
4	73.22	65.09	77.3	126.77	0.16	-0.24	0.27	0.17	0.05	1363.28
5	74.51	64.93	78.56	137.44	0.24	-0.27	0.3	0.78	0.05	1054.77
6	74.8	62.6	79.04	162.39	0.11	-0.34	0.37	0.72	0.07	705.39
Mean	**79.40**	**67.64**	**83.46**	**151.36**	**0.13**	**-0.28**	**0.31**	**0.34**	**0.05**	**1158.21**
Median	**76.80**	**66.68**	**81.76**	**146.39**	**0.14**	**-0.26**	**0.29**	**0.19**	**0.05**	**1210.96**
Min	**73.22**	**62.60**	**77.30**	**126.77**	**0.03**	**-0.36**	**0.25**	**0.06**	**0.04**	**705.39**
Max	**90.90**	**75.53**	**92.69**	**188.80**	**0.24**	**-0.24**	**0.41**	**0.78**	**0.07**	**1403.93**
Standard Deviation	**6.91**	**4.58**	**6.24**	**22.23**	**0.09**	**0.05**	**0.07**	**0.32**	**0.01**	**256.67**

Bare Soil/Fields	**Red**	**Blue**	**Green**	**NIR**	**nDSM**	**NDWI**	**NDVI**	**Z-Dev**	**Homog**	**Contrast**
1	163.75	126.24	151.54	177.14	0.03	-0.08	0.04	0.42	0.14	561.39
2	149.72	114.85	139.35	169.03	0.01	-0.09	0.06	0.2	0.11	428.78
3	142.41	109.66	133.54	159.36	0.01	-0.09	0.06	0.27	0.11	319.84
4	141.08	107.48	131.98	162.87	0.08	-0.1	0.07	0.76	0.1	463.78
5	131.23	99.02	122.52	150.6	0.01	-0.1	0.07	0.02	0.11	629.47

6	145.2	109.5	136.67	172.29	0.002	-0.11	0.08	0.03	0.1	302.1
Mean	**145.57**	**111.13**	**135.93**	**165.22**	**0.02**	**-0.10**	**0.06**	**0.28**	**0.11**	**450.89**
Median	**143.81**	**109.58**	**135.11**	**165.95**	**0.01**	**-0.10**	**0.07**	**0.24**	**0.11**	**446.28**
Min	**131.23**	**99.02**	**122.52**	**150.60**	**0.00**	**-0.11**	**0.04**	**0.02**	**0.10**	**302.10**
Max	**163.75**	**126.24**	**151.54**	**177.14**	**0.08**	**-0.08**	**0.08**	**0.76**	**0.14**	**629.47**
Standard Deviation	**10.80**	**9.02**	**9.56**	**9.59**	**0.03**	**0.01**	**0.01**	**0.28**	**0.01**	**129.67**

Pavement	Red	Blue	Green	NIR	nDSM	NDWI	NDVI	Z-Dev	Homog	Contrast
1	186.35	169.61	183.81	185.47	0.27	-0.004	-0.002	1.07	0.19	1178.16
2	170.99	143.89	164.85	185.86	0.05	-0.06	0.04	0.23	0.1	1533.51
3	196.76	177.59	192.38	194.93	0.06	-0.006	0.004	0.19	0.2	1639.54
4	183.98	164.85	179.94	184.29	0.39	-0.01	0	1.65	0.18	987.64
5	184.37	166.64	180.74	185.25	1.12	-0.01	0.002	2.65	0.15	1376.34
6	171.39	147.93	165.67	172.39	0.01	-0.02	0.004	0.02	0.06	1869.92
Mean	**182.31**	**161.75**	**177.90**	**184.70**	**0.32**	**-0.02**	**0.01**	**0.97**	**0.15**	**1430.85**
Median	**184.18**	**165.75**	**180.34**	**185.36**	**0.17**	**-0.01**	**0.00**	**0.65**	**0.17**	**1454.93**
Min	**170.99**	**143.89**	**164.85**	**172.39**	**0.01**	**-0.06**	**0.00**	**0.02**	**0.06**	**987.64**
Max	**196.76**	**177.59**	**192.38**	**194.93**	**1.12**	**0.00**	**0.04**	**2.65**	**0.20**	**1869.92**
Standard Deviation	**9.79**	**13.09**	**10.74**	**7.19**	**0.42**	**0.02**	**0.02**	**1.03**	**0.06**	**319.42**

Table 1: Imagery Interpretation Data for Segmented Objects

The Red, Blue, Green, and NIR bands represent the spectral reflectance values for each object. Next, the nDSM values indicate each object's height above the ground level. NDWI values reflect water content, with negative values suggesting non-water surfaces. Additionally, NDVI values indicate vegetation density and health, with higher values indicating denser vegetation. Furthermore, Z-Deviation represents each object's height deviation from the mean. Homogeneity measures the uniformity of spectral values within each object's area. Finally, contrast indicates the variation in spectral values within each object's area.

The table also includes summary statistics such as mean, median, minimum, maximum, and standard deviation for each parameter across all objects within each landcover type. These statistics provide insights into the overall distribution, variability, and typical values for the spectral and derived metrics among the objects in the dataset.

The final piece of the current process is the identification of the land cover objects whose measurements fall within specific ranges associated with water levels observed through the NDVI and NDWI measurements per object. These indices provide valuable insights into the environmental conditions and vegetation health across different regions. EOS Analytics (n.d.) outlines that the NDVI ranges from -1.0 to 1.0, with negative values primarily indicating areas covered by clouds, water bodies, or snow. Values between 0.2 and 0.3 typically represent shrubs and meadows, while the range of 0.6 to 0.8 indicates temperate and tropical forests. NDVI is essential because this measurement, plus a higher nDSM measurement, indicates vertical hazards like trees and tall grass that can potentially mask other hazards to a landing helicopter.

On the other hand, the NDWI offers insights into water-related features, ranging from 0.2 to 1.0 for water surfaces and 0.0 to 0.2 for areas affected by flooding or high humidity. Negative values ranging from -0.3 to 0.0 suggest moderate drought or non-aqueous surfaces. In contrast, values from -1.0 to -0.3 indicate severe drought or non-aqueous areas. These indices are crucial in delineating water bodies, assessing moisture levels, and identifying areas experiencing varying degrees of water stress or inundation. These are all potential hazards to lacking helicopters. Areas with water stress and low moisture levels, like bare fields that lack vegetation to mitigate dust, are the most likely to produce a "brown-out" condition as a helicopter comes into land.

Of note is that the Normalized Difference Moisture Index (NDMI), again not used here, provides further granularity in assessing vegetation health and moisture content. Ranging from -1.0 to 1.0, the NDMI distinguishes between bare soil, different levels of canopy cover, and water stress conditions. Understanding these ranges enables precise mapping and monitoring of environmental conditions, aiding in decision-making processes related to land use, agriculture, and water resource management. However, this index calculation requires the Short-Wave Infrared (SWIR) band, and the appropriate imagery data was unavailable. The utilization of NDMI would be beneficial for follow-on research.

V. RESULTS AND FINDINGS

The following is a summary of the NIR, NDVI, NDWI, and nDSM measurements of the land cover classifications that indicate "brown-out" potential or water-inundated areas as well as additional land cover types not feasible for landing, i.e., open bodies of water, tall grass, and forest, are also summarized.

Comparing these results to the NVDI and NDWI ranges provides insight into the terrain and the potential for the stated hazards. The NDWI values Range: 0.2 – 1 – Water surface, 0.0 – 0.2 – Flooding, humidity, -0.3 – 0.0 – Moderate drought, non-aqueous surfaces, and -1 – -0.3 – Drought, non-aqueous surfaces. The NDVI value Range: 0.1 or less - empty areas of rocks, sand, and snow; 0.2 to 0.3 - shrubs and meadows; 0.6 to 0.8 - temperate and tropical forests. (EOS Analytics, n.d)

Data for Wetlands/Marsh objects indicates significant variations across different metrics. The NIR values range from 126.77 to 188.80, with an average of 151.36 and a standard deviation of 22.23. The nDSM values vary between 0.03 and 0.24, averaging 0.13 with a standard deviation of 0.09. The NDWI ranges from -0.36 to -0.24, with a mean of -0.28 and a standard deviation of 0.05. These objects Mean borders the Flooding and Moderate Drought ranges for NDWI. Lastly, the NDVI spans from 0.25 to 0.41, averaging at 0.31 with a standard deviation of 0.07 bordering between meadows and tropical forests. This is expected for these areas as plants in meadows and tropical forests typically have high measurements of NDVI due to ample water content, like marshes and wetlands.

The data for Bare Soil/Fields reveal distinct characteristics compared to other land cover types. NIR values range from 150.60 to 177.14, with a mean of 165.22 and a standard deviation of 9.59. The nDSM values are relatively low, ranging from 0.00 to 0.08, with an average of 0.02 and a standard deviation of 0.03. NDWI values for this land cover type vary between -0.11 and -0.08, averaging at -0.10 with a standard deviation of 0.01.

This NDWI range, which indicates moderate drought and non-aqueous surfaces, could indicate rainfall just before the imagery acquisition date or humidity in the air settling on the terrain and not fully absorbed. Imagery interpretation of the imagery identified objects within the bare soil and fields landcover that were darker in color than the others. This is assessed to be areas possibly containing higher water levels and which are not absorbing as quickly as the surrounding objects. This assessment is made on the fact that bare fields should have low NDWI and NDVI measurements. This assessment is supported by the low NDVI values ranging from 0.04 to 0.08, with a mean of 0.06 and a standard deviation of 0.01, indicating rocks, sand, or snow based on the predetermined ranges. Moderate drought conditions and low NDVI measurements could be associated with "brown-out" conditions, even more as the NDWI measurements near -1.

Water bodies exhibit distinct spectral signatures in the imagery data. NIR values range from 15.00 to 16.11, with a mean of 15.20 and a standard deviation of 0.45. The nDSM values range from 0.00 to 0.64, averaging 0.31, with a standard deviation of 0.29. NDWI values span from 0.36 to 0.75, with a mean of 0.60 and a standard deviation of 0.13. NDVI values vary significantly from -0.73 to -0.01, with a mean of -0.53 and a standard deviation of 0.26. These readings align with NDWI and NDVI ranges. These ranges also provide a comparative variable by knowing how bodies of Water, Wetlands, and Little/No Water land cover classes present via object-based classification.

Forests and tree-covered areas demonstrate specific spectral characteristics in the imagery data. NIR values range from 176.52 to 194.35, with a mean of 184.69 and a standard deviation of 5.79. The nDSM values range from 4.44 to 11.69, averaging 8.64, with a standard deviation of 3.25. NDWI values are relatively stable, ranging from -0.41 to -0.33, with an average of -0.36 and a standard deviation of 0.03. NDVI values range from 0.37 to 0.46, with a mean of 0.41 and a standard deviation of 0.03.

The critical takeaways from the measurements for the Forest and Tree covered are the nDSM and the NDVI. Trees are inherently tall, so their nDSM is a great way to segment and classify them as hazardous to aircraft. Coupling their nDSM with their high NDVI metrics, it is easy to identify them as tall – plants, more than likely trees. Trees also indicated a low NDWI. The assessment is that these low metrics result from any water not being held in the vegetation due to gravity and absorption.

A similar assessment is made with the Grass/Short Vegetation data. NIR values range from 190.58 to 198.57, with a mean of 194.03 and a standard deviation of 2.69. The nDSM values range from 0.10 to 1.73, averaging 0.45, with a standard deviation of 0.64. NDWI values are within the Moderate Drought Range, varying from -0.28 to -0.23, with an average of -0.25 and a standard deviation of 0.02. NDVI values range in the Shrubs and Meadows, with a range of 0.25 to 0.30, with a mean of 0.27 and a standard deviation of 0.02.

These output ranges can be used to establish rulesets that exclude land cover with those ranges on follow-on datasets or symbolize them accordingly for a mission planner to know to avoid. As a result, a table of measurements or index ranges starting points for future ruleset development that identifies hazardous areas based on the ranges associated with each landcover classifications. In general, an analyst could reference the graph below, and the NDWI/NDWI ranges for quick decision-making.

	High/Med NDVI	**Low NDWI**	**Low/Med nDSM**
Low NDVI		Fields/Dirt, "Brown-Out" Potential	
High/Med NDWI	Marsh/Wetlands, "Soft Ground"		Bodies of Water or Grass/Shrubs
High nDSM	Trees "Vertical Hazards"		

VI. DISCUSSION AND CONCLUSION

In conclusion, terrain analysis is critical in identifying safe and suitable helicopter landing zones based on various operational and safety factors. Traditional in-person reconnaissance and GIS-based approaches have long been used to assess terrain suitability for landing operations. However, these methods often lack integration with non-visible regions of the electromagnetic spectrum, which can provide valuable insights into land cover characteristics and moisture content crucial for HLZ determination.

This capstone project aimed to bridge this gap by exploring object-based imagery segmentation and classification using spectral measurements, explicitly focusing on the red, green, blue, and near-infrared bands. By leveraging Trimble's eCognition software, alongside LIDAR data and imagery from the NAIP, the project successfully identified terrain features suitable for helicopter flight operations. Through a comprehensive methodology involving LIDAR data processing, digital elevation modeling, and image segmentation using multiple algorithms like quadtree segmentation, multi-resolution segmentation, and spectral difference segmentation, the project extracted meaningful insights regarding terrain suitability for HLZs.

Incorporating indices such as the NDVI and NDWI provides valuable metrics related to vegetation health, water content, and moisture levels. These metrics and terrain slope data derived from LIDAR contribute to a holistic assessment of terrain conditions impacting helicopter operations. While this study does not utilize the NDMI due to data limitations, its potential significance in assessing vegetation health and moisture content underscores avenues for future research utilizing Short Wave Infrared (SWIR) imagery.

Overall, this capstone project contributes to advancing the understanding of terrain analysis techniques for helicopter landing zone suitability assessments, integrating remote sensing data and object-based classification methodologies to enhance safety and operational efficiency in helicopter flight operations.

This research furthers the discussion and serve as an initial step towards refining and enhancing the application of the discussed techniques for future use, specifically focusing on creating eCognition rulesets to identify land cover-specific measurements based on distinct requirements. This advancement is crucial for enabling planners, whether in military or civilian contexts, to effectively utilize tools like ArcGIS or eCognition to identify potential hazards as part of established methodologies. It lays the groundwork for a more targeted and precise approach to land cover analysis, contributing to improved decision-making processes related to terrain suitability and safety considerations.

It is imperative to acknowledge that while these remote sensing methodologies provide valuable insights, no single method can offer a definitive and flawless solution. Analytical judgment and imagery interpretation remain paramount, especially when considering dynamic factors such as weather conditions over specific time frames and diverse terrain compositions, including clay, dirt, or sand. Weather patterns and rainfall, for instance, are crucial in dust mitigation, impacting mission planning and operational outcomes significantly. Understanding the interplay between weather events and terrain characteristics is essential for mitigating dust-related hazards and overall mission success, weather intelligence gathering, and operational logistics such as ingress and egress strategies, especially those on foot. Moreover, considerations such as the geological features of the area and other operational limitations further underscore the complexity of terrain analysis and the need for a multifaceted approach to decision-making in mission planning and execution.

VII. REFERENCES

Bradley, L., Gonzales, J., Schroeder, M., Roy, B., Packard, A., Mbony, M., & Bilek, C. (2022, March 23). An in-depth analysis of Helicopter Landing Zones (HLZ). ArcGIS StoryMaps. https://storymaps.arcgis.com/stories/7ceede7001ad424dae480f72aeb1ce7a

Campbell, J. B., Wynne, R. H., & Thomas, V. (2023). *Introduction to Remote Sensing: Fifth Edition.* The Guilford Press.

EOS Data Analytics. (2024). Satellite band combinations: Analytical methods for imagery. EOS Data Analytics. https://eos.com/make-an-analysis/

Gao, B. (1996). NDWI—a normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58(3), 257–266. https://doi.org/10.1016/s0034-4257(96)00067-3

Headquarters, Dept. of the Army. (2006). FM 3-21.38 - *Chapter 4: Helicopter Landing Zones. Pathfinder Operations.*

Javed, T., Bhattarai, N., Acharya, B. S., & Zhang, J. (2023). Monitoring agricultural drought in Peshawar Valley, Pakistan using long-term satellite and Meteorological Data. Environmental Science and Pollution Research, 31(3), 3598–3613. https://doi.org/10.1007/s11356-023-31345-3

Kaljahi, M. A., Shivakumara, P., Idris, M. Y., Anisi, M. H., Lu, T., Blumenstein, M., & Noor, N. M. (2019). An automatic zone detection system for safe landing of UAVs. Expert Systems with Applications, 122, 319–333. https://doi.org/10.1016/j.eswa.2019.01.024

Kroh, P. (2020). Identification of landing sites for rescue helicopters in the mountains with the use of Geographic Information Systems. Journal of Mountain Science, 17(2), 261–270. https://doi.org/10.1007/s11629-019-5805-0

McFeeters, S. (2013). Using the normalized difference water index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. Remote Sensing, 5(7), 3544–3561. https://doi.org/10.3390/rs5073544

Mertova, E., & Bures, M. (2021). Helicopter landing site identification depends on slope, landing site dimension, and Shape. *AGILE: GIScience Series*, 2, 1–7. https://doi.org/10.5194/agile-giss-2-35-2021

Olson, Charles E. (1979). Elements of Image Interpretation. University of Michigan School of Natural Sciences.

U.S. Geological Survey (2018) National Agriculture Imagery Program. Accessed July 7, 2023. https://earthexplorer.usgs.gov/

U.S. Geological Survey (2023) USGS 3D Elevation Program Digital Elevation Model. Accessed June 17, 2023. https://apps.nationalmap.gov/lidar-explorer/#/

University of Vermont. (n.d.). Object-Based Feature Extraction Lesson. Rise 360. https://rise.articulate.com/share/8kXDel4obrJUdiFb1D5LzReIb8LkuuEm#/lessons/TI9WcvkGgTrE5iZw_2IN5wwgfRGDUllz