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Disaster Site Structure Analysis: Examining Effective Remote Sensing Techniques in Blue Tarpaulin Inspection

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DISASTER SITE STRUCTURE ANALYSIS: EXAMINING EFFECTIVE REMOTE
SENSING TECHNIQUES IN BLUE TARPAULIN INSPECTION

A Thesis Submitted to the
Graduate Faculty of Jacksonville State University
in Partial Fulfillment of the
Requirements for the Degree
Master of Geographic Information Science and Technology

By
MADELINE GRACE MILES

Jacksonville, Alabama

May 6, 2022

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ABSTRACT

This thesis aimed to evaluate three methods of analyzing blue roofing tarpaulin (tarp) placed on homes in post natural disaster zones with remote sensing techniques by assessing the different methods- image segmentation, machine learning (ML), and supervised classification. One can determine which is the most efficient and accurate way of detecting blue tarps. The concept here was that using the most efficient and accurate way to locate blue tarps can aid federal, state, and local emergency management (EM) operations and homeowners. In the wake of a natural disaster such as a tornado, hurricane, thunderstorm, or similar weather events, roofs are the most likely to be damaged (Esri Events., 2019). Severe roof damage needs to be mitigated as fast as possible: which in the United States is often done at no cost by the Federal Emergency Management Agency (FEMA).

This research aimed to find the most efficient and accurate way of detecting blue tarps with three different remote sensing practices. The first method, image segmentation, separates parts of a whole image into smaller areas or categories that correspond to distinct items or parts of objects. Each pixel in a remotely sensed image is then classified into categories set by the user. A successful segmentation will result when pixels in the same category have comparable multivariate, grayscale values and form a linked area, whereas nearby pixels in other categories have distinct values. Machine Learning, ML, a second method, is a technique that processes data depending on many layers for feature

identification and pattern recognition. ArcGIS Pro mapping software processes data with ML classification methods to classify remote sensing imagery. Deep learning models may be used to recognize objects, classify images, and in this example, classify pixels. The resultant model definition file or deep learning software package is used to run the inference geoprocessing tools to extract particular item positions, categorize or label the objects, or classify the pixels in the picture. Finally, supervised classification is based on a system in which a user picks sample pixel in an image that are indicative of certain classes and then tells image-processing software to categorize the other pixels in the picture using these training sites as references. To group pixels together, the user also specifies the limits for how similar they must be. The number of classifications into which the image is categorized is likewise determined by the user.

The importance of tracking blue roofs is multifaceted. Structures with roof damage from natural disasters face many immediate dangers, such as further water and wind damage. These communities are at a critical moment as responding to the damage efficiently and effectively should occur in the immediate aftermath of a disaster. In part due to strategies such as FEMA and the United States Army Corps of Engineers' (USACE) Operation Blue Roof, most often blue tarpaulins are installed on structures to prevent further damage caused by wind and rain. From a Unmanned Aerial Vehicles (UAV) perspective, these blue tarps stand out amid the downed trees, devastated infrastructure, and other debris that will populate the area. Understanding that recovery can be one of the most important stages of Emergency Management, testing techniques

for speed, accuracy, and effectiveness will assist in creating more effective Emergency Management (EM) specialists.

ACKNOWLEDGMENTS

I'd like to thank the professors of the Department of Chemistry and Geosciences for their guidance and encouragement during my education here at Jacksonville State University. It was a fantastic and beneficial learning experience. I'd also like to express my gratitude to my master's program adviser, Dr. M. Sean Chenoweth, for his advice and skills and to Dr. Daniel McGowin and Dr. Tanveer Islam, members of my thesis committee, for their various contributions to this research. Thank you for proofreading, editing, and supporting my research, Mr. James King, Mr. Montgomery Scott, and Dr. Spencer Reid. My family deserves special gratitude for their suggestion of looking towards the home for research and support during the time it took to make this possible.

Madeline Grace Miles

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INTRODUCTION

The idea of analyzing blue roofing tarps with different methods was conceived while doing personal drone (or unmanned aerial vehicles, UAV) flights over a local neighborhood that had been damaged by an EF4 tornado a month prior. From above, the feature that most clearly stood out was the blue tarps that had been put up over damaged homes. While on the ground it was hard to see the full scope of damage done to the area, from the sky, the large number of homes affected was astounding.

Tornadoes in the United States are measured based on the Enhanced Fujita Scale, or EF Scale, it is used to give a tornado a “rating” based on the apparent sustained winds and damage. Damage from tornadoes is contrasted to a list of Damage Indicators (DIs) and Degrees of Damage (DoD), which help determine the tornado's expected wind speed range. After that, a score (from EF0 to EF5) might be issued. For example, an EF2 tornado can have winds reach speeds of around 111-135 mph and is classified as “Significant” (US Department of Commerce, 2016). When examining damaged structures, a land-based perspective can only offer so much information, as a person is only able to perceive from one vantage point. However, when using an UAV, a complete picture of the damage and devastation done to structures can be clearly mapped.

As mentioned in the abstract of this research, the Federal Emergency Management Agency (FEMA) supplies impacted communities with many resources, such as blue tarps to protect homes. Through Operation Blue Roof, a program started in 2017,

the UASCE installs temporary plastic blue tarps to help reduce further damage to eligible properties. This can help in decreasing water damage and in some cases make homes habitable during repairs. While the ACE processes and plans out blue tarp installations using a geographic information system (GIS) (Army Corps of Engineers n.d.), no follow-up work has been done to track and analyze the locations of the tarps installed by Operation Blue Roof. Remote sensing techniques such as image segmentation, ML, and supervised classification can be beneficial to helping measure the impact a disaster has on a community. This research aimed to find the most accurate remote sensing tool to track blue roofs and determine which one can do so most accurately in the most efficient amount of time for resources at a disaster site. Recognizing that recovery is one of the most critical stages of EM, evaluating strategies for speed, accuracy, and effectiveness will aid in the development of more effective EM professionals' responses.

CHAPTER ONE

LITERATURE REVIEW

IMAGE SEGMENTATION

Using image segmentation, a study in Fuzhou, China aimed to monitor beach trash in data collected by UAVs (Bao et al., 2018). The results of the data analysis demonstrated that by utilizing remote sensing and GIS technology, optical pictures captured by sensors on a UAV may be used to identify and monitor beach trash. The UAV image in the beach region may be successfully segmented using the threshold approach. The researchers found that this method assisted in providing efficient technical support for the investigation and assessment of coastal beach litter by promptly monitoring the distribution of beach litter in the region of interest (Bao et al., 2018). This project serves as a great example of how to apply image segmentation techniques when identifying a determined object against other objects.

When it comes to mapping forest cover and identifying deforestation polygons in multitemporal satellite data, a recent research project was carried out to see how well the U-Net architecture performs (Bragagnolo et al., 2021). To this aim, footage from the Sentinel-2 satellite with a resolution of ten meters was used, which covered parts of the Amazon. With high accuracy (0.9470), precision (0.9356), recall (0.9676), and F1-score

(0.9513), the U-Net was able to recognize and draw polygons of forest regions and forest fragments. This surpassed more widely used and well-known supervised and unsupervised image classification techniques (Bragagnolo et al., 2021). The findings suggested that U-Nets have the potential to serve as the backbone for effective forest cover change monitoring programs and to aid the implementation of near real-time deforestation warning systems.

One important issue in the field of intelligent analysis of remote sensing pictures is semantic segmentation. Due to its strong semantic feature representation, the deep convolutional neural network (DCNN) has become a standard technique in semantic segmentation. The creation of high-resolution remote sensing photography has supplied large amounts of detailed information. However, there are still issues, which is something that a research paper from 2021 aimed to examine (Chen et al., 2021). The authors aimed to examine the differentiating characteristics of geo-object information and offered a new DCNN-based semantic segmentation method. For them to determine the relationship between distinct channels or locations, a cascaded relation attention module was used first. The characteristics of geo-object details were then captured and fused via information connection and error correction. The multiscale feature module provided the output feature representations. The proposed model employed boundary affinity loss to get a precise and distinct geo-object border. The experimental findings on the Potsdam and Vaihingen data sets showed that the proposed model can achieve good overall accuracy and mean intersection over union segmentation performance (Chen et al., 2021).

MACHINE LEARNING

In GIS and remote sensing fields, machine learning has long been seen as a key component of spatial analysis if it is bit complex. The tools and methods have been used to tackle issues in three different areas using geoprocessing technologies. Data processors can use vector machine methods to construct land cover classification layers using grouping. Clustering, which permits users to analyze massive amounts of input point data, allows for the discovery of significant clusters within them and separates them from the sparse noise. Users can represent regionally changing connections using prediction techniques like geographically weighted regression. Data-driven algorithms and approaches that automate data prediction, classification, and clustering are referred to as machine learning (ML). ML is computationally expensive and frequently includes large, complicated data sets. Despite this, it may help solve spatial problems in a variety of applications, including multivariate prediction, picture classification, and spatial pattern recognition. In the project being proposed, ML will be used to detect blue roofing tarps on buildings and structures that are located in post disaster communities.

A paper published in 2021 (Avand, Moradi, and Lasboyee, 2021) used machine learning modes to look at the impact of climate change on future flood risk. The researchers wanted to examine how climate and land use changes in Iran's Tajan watershed impact flood susceptibility. To accomplish this, the land change modeler (LCM) technique was used to forecast land use changes from 2019 to 2040 based on

land-use changes during the previous 29 years (Avand, Moradi, and Lasboyee, 2021). Future climate change was estimated for the next 20 using LARS-WG software and two scenarios, RCP2.6 and RCP8.5, based on climatic data from 1990 to 2015 (Avand, Moradi, and Lasboyee, 2021). The geographical distribution of flood vulnerability in the watershed was modeled using 12 variables that impact flooding and 262 sites of historical floods. To forecast flood-prone regions, researchers utilized a random forest (RF) model and a Bayesian generalized linear model (GLMbayes) (Avand, Moradi, and Lasboyee, 2021).

The findings of the models revealed that the most important elements impacting floods in this basin are elevation, distance from the river, land use, slope, and rainfall (Avand, Moradi, and Lasboyee, 2021). The variables were adjusted to account for changes in land use and climate, and the models were then transposed. Land use and climate forecasts in this region show that land-use change, such as reduced forest cover and reduced rangeland along rivers and downstream, is likely, and rainfall is predicted to rise. With these models, they found that flooding would be more likely in the downstream section of the watershed and near the sea as a result of these changes. The random forest model predicted flood probability more correctly than the GLMbayes model.

Another use of ML was performed in landslide susceptibility assessments that in the past have been done with GIS but are now looking for areas of improvement. While there has been the occasional study to have looked into this, few have had such a systematic approach to ML as a study out of Taiwan (Lai and Tsai, 2019). Here they used

ML to establish a systematic strategy for multitemporal and event-based landslide susceptibility evaluations at a regional scale using satellite remote sensing pictures, GIS data sets, and spatial analysis. The landslide susceptibility models were built using the RF technique. In the trials, different ratios of landslide and non-landslide samples were used. The researchers then utilized a cost-sensitive strategy to adjust the decision boundary of the developed RF models with unbalanced sample ratios to improve the prediction results. They used two strategies for model verification: space- and time-robustness. The investigations found that the proposed approach may yield more realistic models, with accuracies of more than 93% and 75% in most cases for space- and time-robustness validations, respectively. Furthermore, the mapping findings indicated that the sample ratios used in the studies did not affect the multi-temporal models (Lai and Tsai, 2019).

As evidenced by the findings of a publication (Jia et al., 2019), advances in machine learning and the availability of earth-observing satellite data can significantly boost people's monitoring capabilities. They found that ML has great potential, but much progress is still required to achieve its full capacity. Machine learning algorithms are beginning to show promise in identifying temporal patterns to produce pixel-level maps of crops; these approaches were intended for remote sensing data that is accessed regularly. However, because such data has a low spatial resolution, it is ill-suited for monitoring small-scale farms, which is one of the more common uses in most regions of the world. As such, using data that is higher resolution such- as that produced via UASs might show greater results.

SUPERVISED CLASSIFICATION

Supervised classification is one of the most common approaches for quantitative analysis of remote sensing images. The notion of segmenting the spectral domain into areas that may be linked with the ground cover classes of relevance to a certain application lies at the heart of it. In practice, these areas may cross at times. A study from 2021 (Wang et al., 2021) applied supervised classification in analyzing the effects of lodging on maize crops. The ability to identify lodging is useful for estimating losses from natural catastrophes, screening lodging-resistant crop varieties, and optimizing field-management techniques. The precise detection of crop lodging is inextricably linked to the exact measurement of the degree of lodging, which aids in crop production field management. To accomplish the study's goal of measuring the degree of lodging with high precision, a method was created that combines supervised and object-oriented classifications on the spectrum, texture, and canopy structure data (Wang et al., 2021).

Wang (Wang et al., 2021) and the other researchers' findings revealed that the object-oriented classification approach utilizing random forest classifiers had the best overall accuracy of 86% when coupled with the original picture, the modification of the digital surface model, and texture characteristics. The best-supervised categorization of the degree of maize lodging at the pixel level was 78% (Wang et al., 2021). This study examined how feature variables impact the degree of lodging by looking at the geographical distribution of the degree of lodging as a function of crop type, sowing date, density, and various nitrogen treatments. These findings enabled them to quickly assess

the degree of lodging in field maize, as well as establish the best sowing date, density, and fertilization strategy for field production. Although the samples were relatively independent of one another when using the supervised classification method to classify the degree of maize lodging, the low discrimination of lodging maize on the pixel scale translated to a large number of nongreen parts in the sample area, leading to misclassification at the pixel level(Wang et al., 2021). They found that removing tiny areas did not enhance classification scores significantly. Furthermore, supervised classification has low classification accuracy; thus supervised classification methods used to high-resolution pictures with considerable variations in category structure and comparable color are only acceptable for broad classification schemes .

Supervised classification is also used in much more large-scale imagery processing, such as detecting land cover changes. A study used this technique to monitor and cover changes in the Bosomtwe Range Forest Reserve of Ghana from 1991, 2002, and 2017 based on satellite imagery (Mensah et al., 2019). To detect land use and land cover changes in the reserve, this study used supervised classification with the maximum likelihood technique in Quantum GIS. The maximum likelihood method is a commonly used statistical sampling-based classification technique that assigns pixels to a specified set of land cover classes using the probability density function. Overall, 72% of the classifications were correct, with a kappa value of 59% (Mensah et al., 2019). According to the findings of this research and their use of supervised classification, land use and cover in the reserve changed dramatically.

The use of UAVs and supervised classification are two concepts that work together in a symbiotic relationship. In a project conducted in 2016, a study of the accuracy of free and open-source methods employed in the geographical object-based image categorization (GEOBIA) of VHR images surveyed by UAVs investigated the rising potential (Heuschmidt et al., 2020). At two separate times during the year, UAV surveys were conducted in a cork oak woodland in central Portugal. A high spatial resolution picture mosaic was used to evaluate the two supervised classification methods: pixel-based and object-based image analysis (OBIA). A UAV with an RGB camera collected the data. Cork oak, bushes, grass, and other plants were identified as four distinct vegetation types (bare soil and tree shadow). The results were compared to data collected in the field using the point-intercept (PI) technique (Heuschmidt et al., 2020). In cork oak woods, data comparison demonstrated the accuracy of aerial imaging categorization systems. Testing the two different methods of supervised classification revealed that cork oak was correctly identified 82.7% percent of the time using the pixel-based approach and 79.5% of the time using OBIA. They found that the OBIA correctly recognized 97.6% percent of bushes, but the pixel method overestimated 22.7%. With OBIA, the grass was overestimated by 21.7%, while with the pixel-based approach, it overestimated by 12%. With this, they (Heuschmidt et al., 2020) determined that the use of only spectral information in the visible range has clear limitations. It can be surmised that as a result, more studies using other bands might lead to a better categorization of land cover types.

UNMANNED AERIAL SYSTEMS REMOTE SENSING FOCUSING ON URBAN AREAS

As of 2020, cities and urban areas accounted for 82.66% percent of the total population of the United States' areas of living (O'Neill, 2021). As the U.S and countries around the world become more and more urbanized, it is important to consider this change when analyzing communities post disaster. Aerial data from an urban neighborhood differs significantly from that of a rural one. It's also probable that the sort of damage detected will be fairly different. Both of these factors result in unique remote sensing experiences and processing. The challenge of merging these techniques and technologies is something that has been looked at in a limited number of studies.

Such a study is one published in 2020 in the *Geoenvironmental Disasters* journal that aimed to demonstrate how several UAV platforms capturing pictures at the same time may produce real 4D or 3D models of geoprocesses; such as riverbed development, rockfalls, and similar events (Gomez et al., 2016). They saw that UAVs are mostly used for mapping geographical characteristics and their evolution over time, mapping risks and catastrophes as they occur, observing human behavior during an emergency or disaster, replacing communications systems damaged by natural disasters, and transporting goods to isolated populations. This study explained that although UAV technology has only been on the market for a few years, its already low cost and widespread availability are expected to accelerate its rapid expansion, allowing communities and emergency services to use this tool in disaster areas, rather than being limited to scientific use. They focused

on examining the use of UAV applications to three of the most serious geo-hazards: earthquakes, volcanic activity, and landslides. These three examples have highlighted the link between survey scales (time and space) and phenomenon scales. The study suggested that the usage of UAV is limited by the predictability and length of occurrences (Gomez et al., 2016). Because earthquakes are very unexpected in terms of time, it has been utilized in the aftermath of earthquakes for emergency management purposes. It has been used in both emergency management, hazards, and risk monitoring on volcanoes since volcanic eruptions are far more predictable and last for longer periods, allowing for the deployment of one to several flights during their active period. Landslides are often slower-onset occurrences, allowing scientists to conduct repeat flights over months or years to observe the evolution of the landslide surfaces.

A study from Canada evaluated pre-disaster 3-D data correctness in terms of geographic accuracy and building depiction. This was to provide a case study of developing a pre-disaster 3-D map of downtown Victoria, British Columbia, Canada, utilizing drone-based data (Kucharczyk and Hugenholtz, 2019). The photographs were taken with a fixed-wing drone equipped with real-time and post-processed kinematic capabilities. Although the drone's spatial accuracies allow sub-meter building collapse identification, their non-gimbaled camera was unsatisfactory for recording building facades. When used for building assessment with drone-derived 3-D textured meshes, it was discovered that a high-resolution mesh, with up to 96% more vertices and faces than a moderate mesh, visually improved design geometry and texture, especially for

historical buildings with complex geometries and small architectural features. However, both mesh resolutions were unable to cope with large point cloud gaps on facades. The model's data gaps were discovered to be linked to significantly distorted building geometry and texturing. As a result, alternative technology will be necessary for future drone-based pre-and post-disaster 3-D mapping of towns. When it comes to recreating building facades, the capacity to acquire extremely oblique pictures is critical. A multi-rotor drone with a gimbaled camera is one option. However, due to regulatory constraints, lightweight multi-rotor drones may be more difficult to use for large-area mapping missions in big cities in the near future. As a result, they recommend doing follow-up research with a fixed-wing drone equipped with oblique image acquisition capabilities (Kucharczyk and Hugenholtz, 2019).

To respond quickly and correctly to hydrometeorological risks, it is important to estimate the damage to the affected region. This is typically accomplished by conducting time-consuming reconnaissance visits to gather extensive field data. By comparing pre- and post-event data, a paper published in *Geomatics, Natural Hazards and Risk* proposes a methodology for rapid urban flood damage assessment and estimation of the number of houses washed away, or with a total or partial roof collapse, using

- i) High-resolution satellite and RGB images from unmanned aerial vehicles (UAV)
- ii) Digital elevation models (DEM)
- iii) Object-based image analysis (OBIA) (Jiménez-Jiménez et al., 2020).

The findings show that the three-pronged strategy described here may distinguish between changes before and after an incident and enhance picture categorization of washed-away or damaged buildings. The suggested automated categorization derived using UAV data has an overall accuracy of 97.4% and the Kappa coefficient was 0.954. This research, however, did not look at structural damage that may have been caused. The team determined that if UAV data is available, the methodology can be implemented in one of three ways:

- i) Using before (satellite) and after (UAV) image information
- ii) A GIS vector of houses obtained from census information
- iii) Analysis of changes between the GIS vector and the classification (Jiménez-Jiménez et al., 2020).

CHAPTER TWO

METHODOLOGY

The research proposed here took place across four different stages. Errors and complications that took place, especially during Stage Three, were recorded. The first part was data collection from areas that experienced a disaster causing roof structure damage. UAS has more small-scale commercial uses than satellite photos, which have more large-scale scientific applications. The relationships between components of landscapes are difficult to notice from the ground using aerial images. Drones, which fly closer to the ground than satellites, give a comprehensive and high-resolution perspective from above, revealing previously overlooked details or uncovering hidden relationships. For most personal or commercial needs, aerial photography is still a superior option to satellite images. Because many accessible satellite maps are often more than a year old and most do not represent recent changes or advancements, UAS is less expensive and, in some situations, more up-to-date. Individuals and small businesses may hire a licensed UAV operator more readily and have greater control over the process. The resolution and clarity of the photos will likely be improved as well, making them easier to grasp and obviating the need for additional analysis. It is for all these reasons that UAV imagery was collected and used for research.

For the purpose of repeatability, and ease of use as well as accessibility, all data was processed in Environmental Systems Research Institute’s (ERSI) ArcPro and Drone2Map. This software is both easy to use and a standard across the field of both geography and emergency management for its data processing uses.

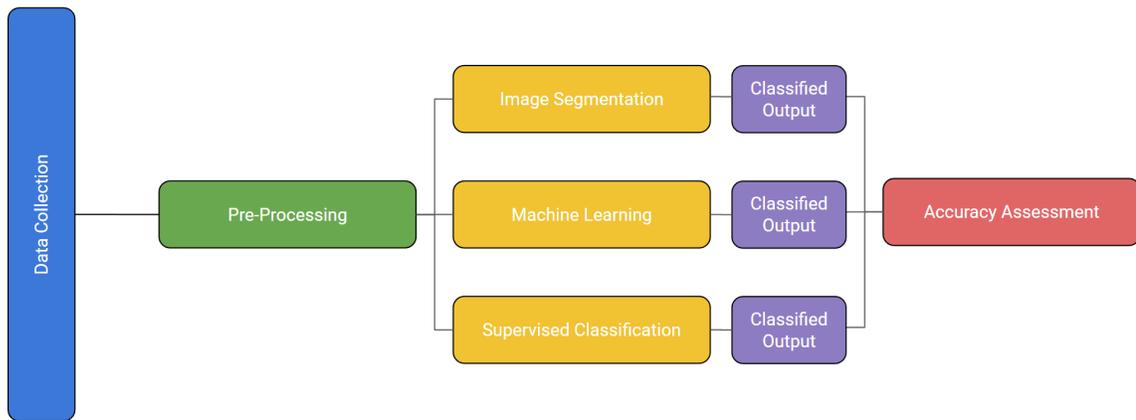


Table 1. Depicting the workflow of data from start to finish.

COLLECTION OF UNMANNED AERIAL VEHICLE DATA

The data will be of communities that experienced a disaster that caused roof damage. It will be best to collect within a few weeks of the disaster occurring, but this was not necessary. The reasoning behind this is that blue tarps should be placed on structures as soon as safely possible in order to prevent further damage, and in many cases can make homes habitable once more. Data collection immediately following a disaster is unsafe both to the UAV operators and those around them. The FAA has

advised drone operators that using an unlawful drone might disrupt local, state, and federal rescue and recovery operations. Without authorization, flying a drone in or near a disaster zone might be a violation of federal, state, or local laws and ordinances. Allowing first responders to rescue lives and property without being hampered in their efforts is of higher priority.

When safe and legal to operate the UAV in the chosen disaster site, the data was be collected. The UAV was flown at an AGL (above ground level) of 150 feet. It was proposed that the Jacksonville State University Department of Chemistry and Geosciences' DJI Phantom 4 drone would used in the collection. This UAV represents a good entry point for EMAs looking to get into the UAV side of disaster management. Emergency Management Agencies or EMAs, are municipal, tribal, state, national institutes in charge of thoroughly planning for, reacting to, and recovering from all types of catastrophes, both man-made and natural. It is most common for local EMAs to be the first to respond to disasters and the last to leave disasters sites. While grants and federal funding are available to these local smaller scale organizations, drones can pose an expensive barrier in both technology and training cost.

Sensor	1/2.3" CMOS Effective pixels:12.4 M
Lens	FOV 94° 20 mm (35 mm format equivalent) f/2.8 focus at ∞
ISO Range	100-1600 (photo)
Mechanical Shutter Speed	8 - 1/8000 s
Photo	JPEG, DNG (RAW)
Image Size	4000×3000

Table 2. Key DJI Phantom 4 technical specifications.(DJI Official., n.d.)

While the flights can be flown manually, to keep a standardized approach to each site, Pix4D Capture App was used in assistance. This application allows for the flights to be planned before going out into the field and the UAV to fly itself while the pilot maintains a visual line of sight (VLOS) and obeys all FAA UAV regulations. Overlap of the imagery collected will be 70% to ensure smooth orthomosaicing.

DATA PREPROCESSING

Once the data was collected and stored, it will be processed using Esri's Drone2Map application. Individual, overlapping picture frames captured by drones were processed to provide orthorectified images, digital surface models (DSMs) and digital terrain models (DTMs), point clouds, and textured meshes, among other 2D and 3D outputs. For the study, only orthorectified images were needed. While this can be a costly application, its simplicity is what is important as many EMAs lack trained operators. Creating orthomosaics in this way is quite simple and a matter of adjusting settings to create the most complete picture. All three methods were tested in ArcGIS Pro, a software also operated by Esri. This was to keep all software under the same umbrella to keep things simple for those who have little to no experience in GIS.

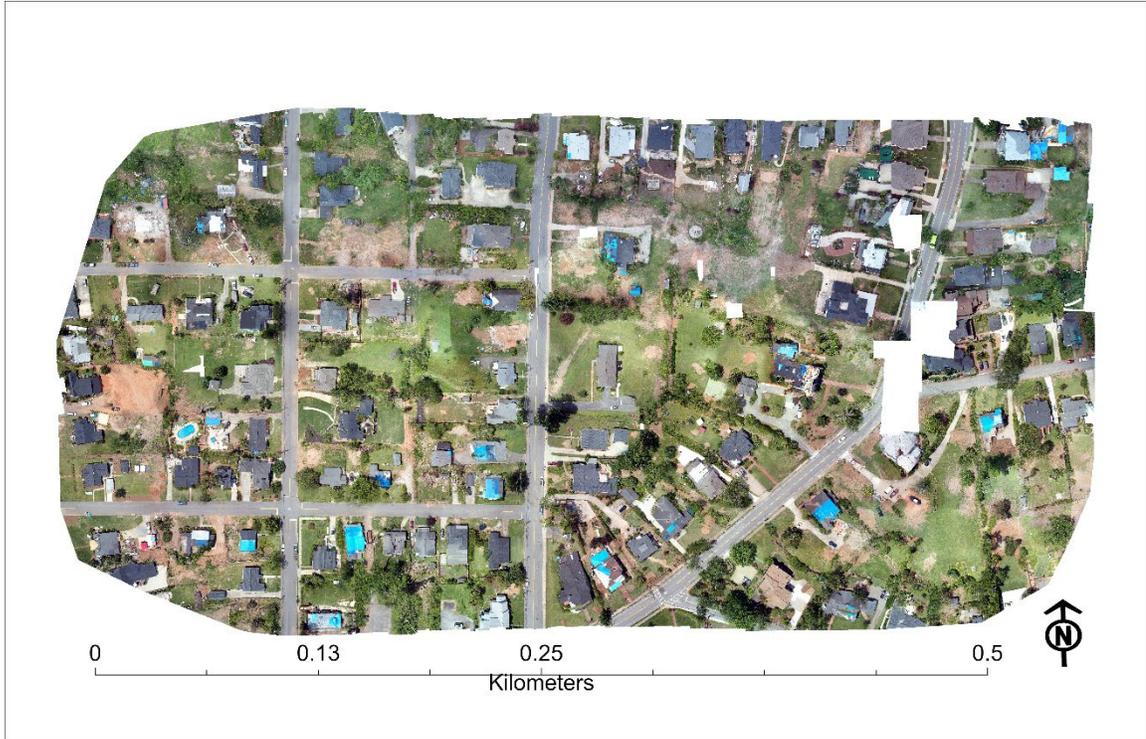


Figure 1. 0.58 by 0.30-kilometer orthomosaic.

Processing in Drone2Map resulted in roughly 0.58 by 0.30-kilometer orthomosaic land cover area. The Average Ground Sampling Distance (GSD) or spatial resolution of this 1.21 cm per a pixel. The holes in the image are likely due to a lack of usable imagery as the weather at the time of collection was unexpectedly windy.



Figure 2. Drone2Map view site showing flight path and imagery points.



Figure 3. UAS failed to stitch areas or holes compared to ArcGIS Pro satellite images.

Looking at the process report generated by Drone2Map the areas that holes and other errors occur in line with a lack of overlapping images. For each pixel of the orthomosaic, the number of overlapping pictures is determined. The red and yellow spots suggest low overlap, which might lead to unsatisfactory outcomes. For each pixel, green patches show an overlap of more than 5 photos. As long as the number of key point matches is adequate for these locations, good quality results will be provided. Figure 4 shows how the holes seen in Figure 3 line up with the lack of overlapping images. Out of the 219 images collected, 213 were able to be calibrated for orthomosaicing, the missing 6 images were disabled or uncalibrated images, which means they were likely taken at an angle of which was unusable for the software.

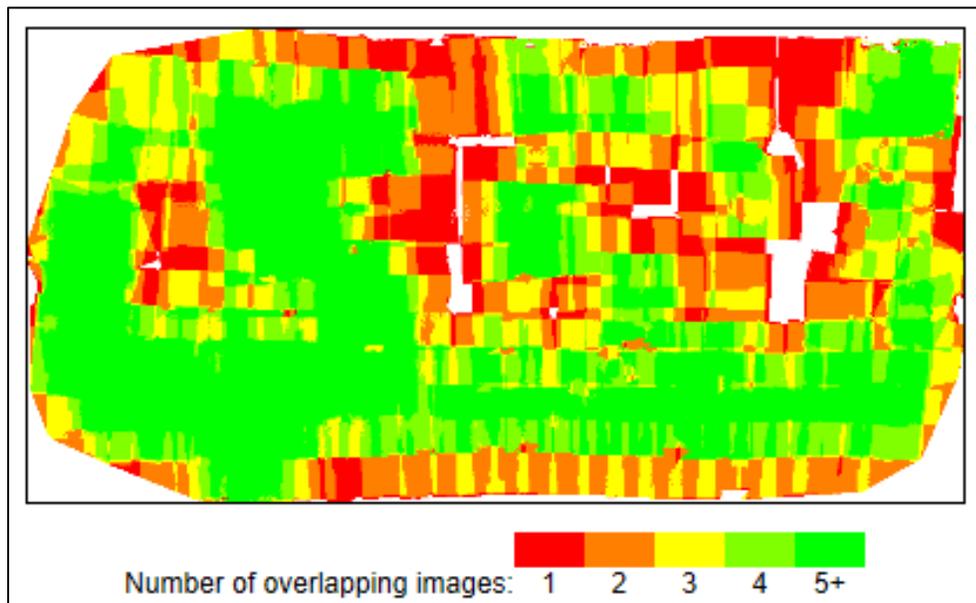


Figure 4. Overlap report.

CHAPTER THREE

TESTING METHODOLOGY

IMAGE SEGMENTATION

The object-based categorization method relies heavily on segmentation. This method brought together pixels that are similar in hue and have comparable form properties, in this case, blue roofing tarps. These objects are made using an image segmentation technique that divides pixels into segments based on their proximity and spectral properties. Objects formed from segments with certain forms, spectral, and spatial properties. The items will then be classified into classes that correspond to real-world ground characteristics, the classes proposed will be “blue roof” and “non-blue roof”.

The object-oriented feature extraction technique is a workflow that includes tools for picture segmentation, segment derivation, and classification. The data from one tool is fed into the next, with the objective of creating a meaningful object-oriented feature class map.

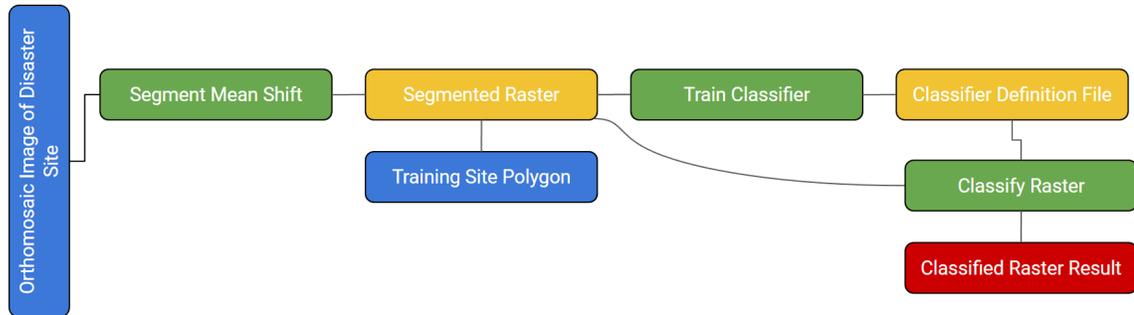


Table 3. Workflow of image segmentation.

Mean shift is a method used to segment the images. To select which pixels should be included in each segment, the method employs a moving window that produces an average pixel value. The value is continually recalculated as the window travels over the image to ensure that each segment is appropriate. As a consequence, picture pixels were grouped into a segment with an average color. Collecting training sample data entails identifying a collection of pixels that correspond to specific characteristics in a picture. After that, all of the pixels in the image were statistically compared to the class description that has been supplied, and a class was assigned.

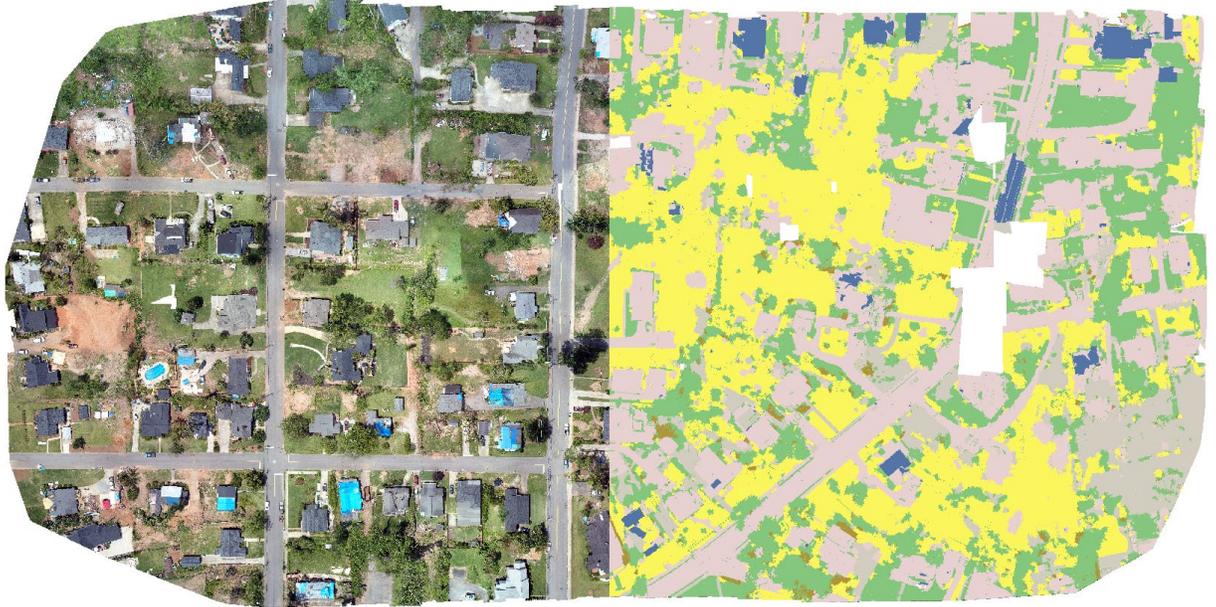


Figure 5. Image showing classification following training samples. Blue Tarps (blue), Developed (pink), Barren (tan), Forest (green), Shrubland (brown), and Planted/ Cultivated (yellow).



Figure 6. Example of two areas that were falsely classified as blue tarp roofs. Left is planters on the front steps of a house. Right is appearing to be the shadow on a cupola.

Note the lack of a blue tarp.



Figure 7. Examples of correctly identified blue tarp on a roof. Note the shape of the area aligns with the typical roof structure and covers the whole area as well as the presence of the color blue.

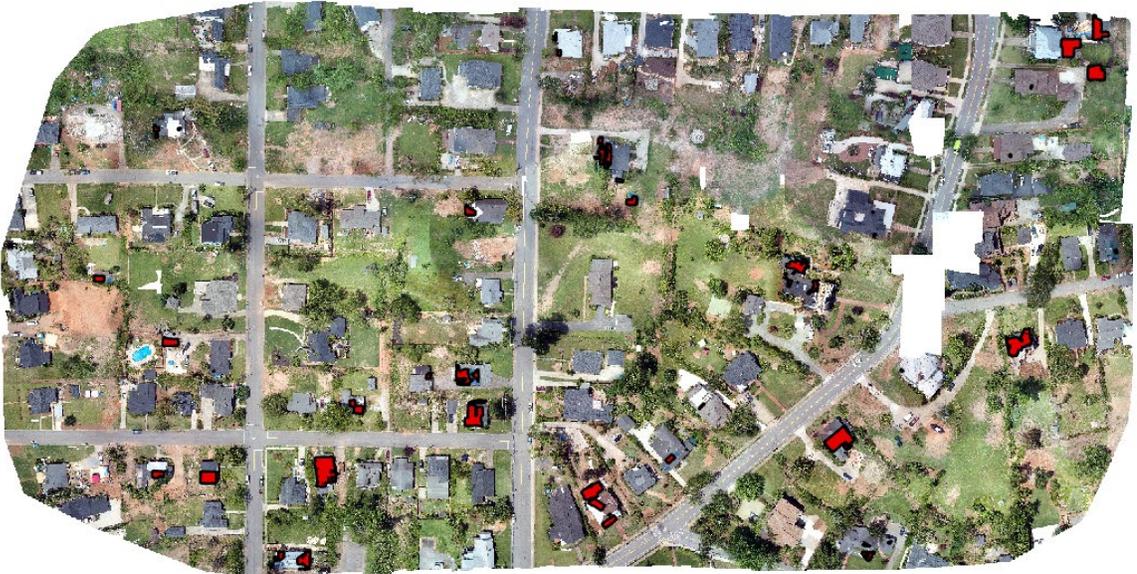


Figure 8. Initial classification and post classification. Yellow areas are classified as a blue tarp. Bottom: red classified as blue tarps after removing falsely classified areas.

The final image only reveals blue tarps set on top of roofs after categorization and correction. Blue tarps account for 1286.128 pixels out of 156112.739 pixels, or 0.823% percent of the image. Before removing incorrectly classified objects, 2482.307 pixels total were classified as blue tarps, with the modify vertices tool 1196.178 of those could be removed.

MACHINE LEARNING

To test ML, there first needed to be training samples. This was done in ArcPro by creating training samples in the Deep Learning pane, which were then be converted to deep learning training data. To create an output, the analyst used the trained model to execute the Classify Pixel; if done correctly this will highlight areas that contain blue roof tarps. While this method might sound simple, it will likely take much trial and error to adjust the samples to get an accurate estimate of the tarp locations.

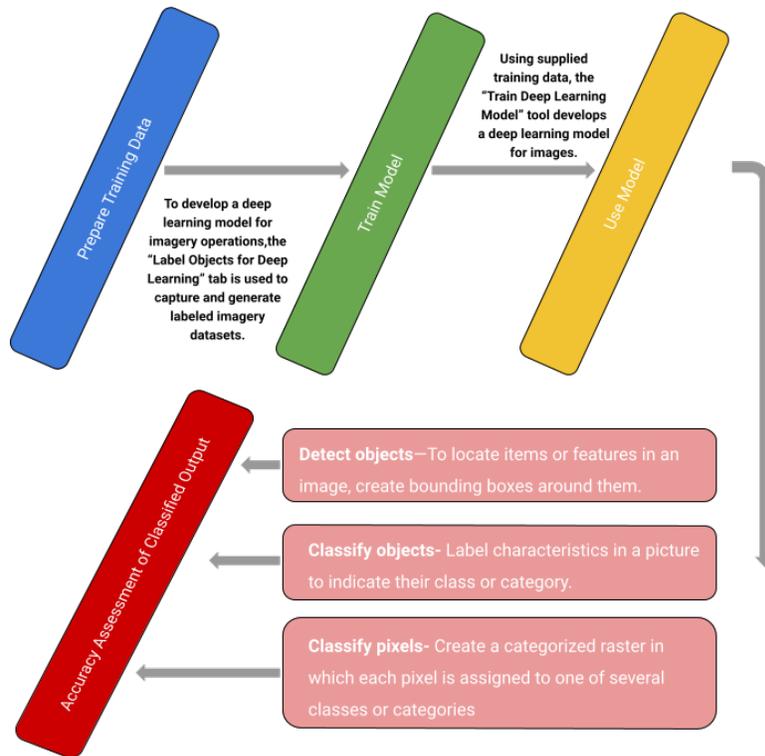


Table 4. Machine Learning Workflow outline.

The training data was the initial stage in machine learning. “Export Training Data For Deep Learning” is a tool that uses a remote sensing picture to transform categorized vector or raster data into deep learning training datasets. The result was folder containing picture chips and a folder containing metadata files in the format provided. This program also generated training datasets for third-party deep learning programs. Deep learning class training images were based on picture chips, which are sub-images that include the feature or class of relevance.

Using the results from the Export Training Data for Deep Learning tool, the "train deep learning model" tool was utilized in this study. This tool uses deep learning frameworks to train a deep learning model. A deep learning framework for ArcGIS must be installed and put on to ArcPro to set up the machine to utilize deep learning frameworks in ArcGIS Pro. PyTorch is the suggested framework by ESRI but other third-party deep learning frameworks do work here as well. This is a free download, that does not take much computing power to download and use. This tool may also be used to fine-tune an already trained model in a close enough model that already exists.

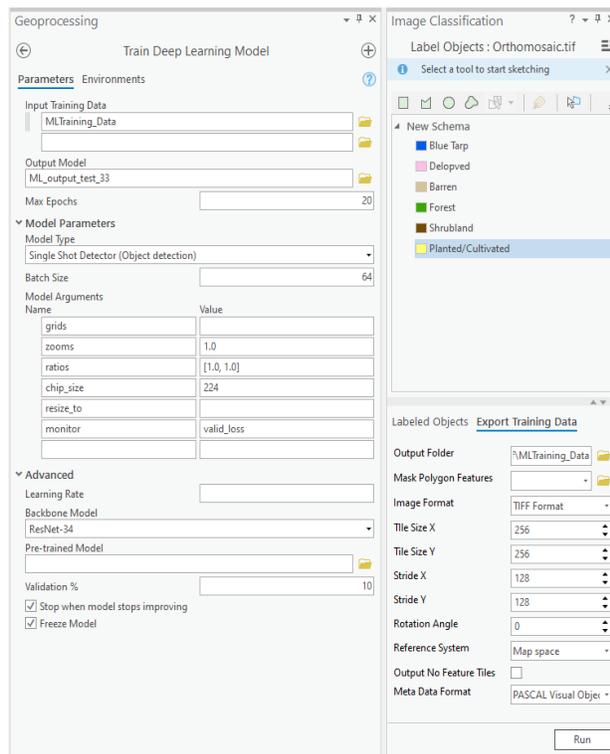


Figure 9. Illustrates the layout and input of data for the training of and exporting of ML

data.

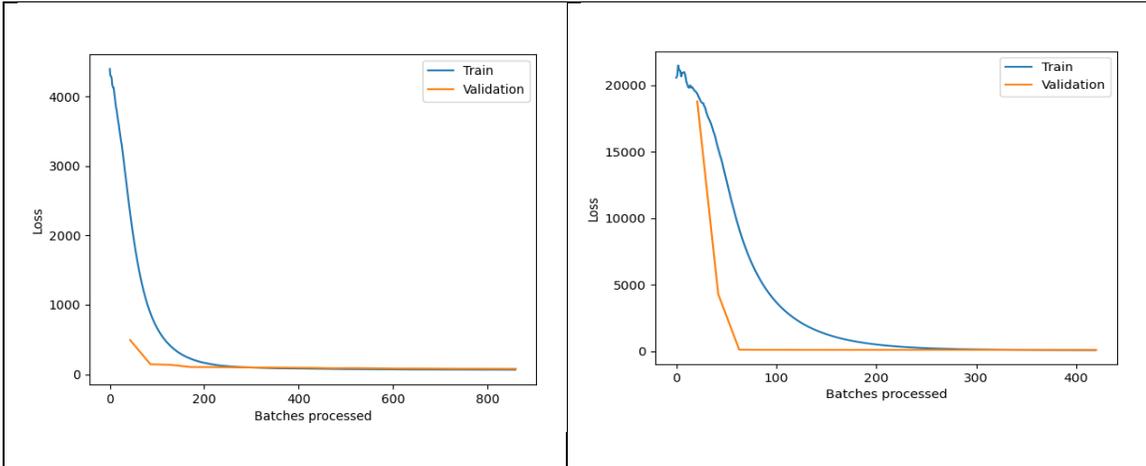


Figure 10. Loss graphs from ML.

The purpose of the training algorithm was to find a decent match between an overfit and an underfit model. A training and validation decline that lowers to a point of stability with a limited difference between the two ultimate loss values is indicative of this. On the training dataset, the model's loss is usually always smaller than on the validation dataset. This implies that a difference between the training and testing data loss learning curves should be expected. The plot of training loss declines to a point of stability, whereas the plot of validation loss drops to a point of stability and has a tiny gap with the training loss, indicating a good match. In figure 10, these can be seen as a good fit after looking at the train and validated lines.

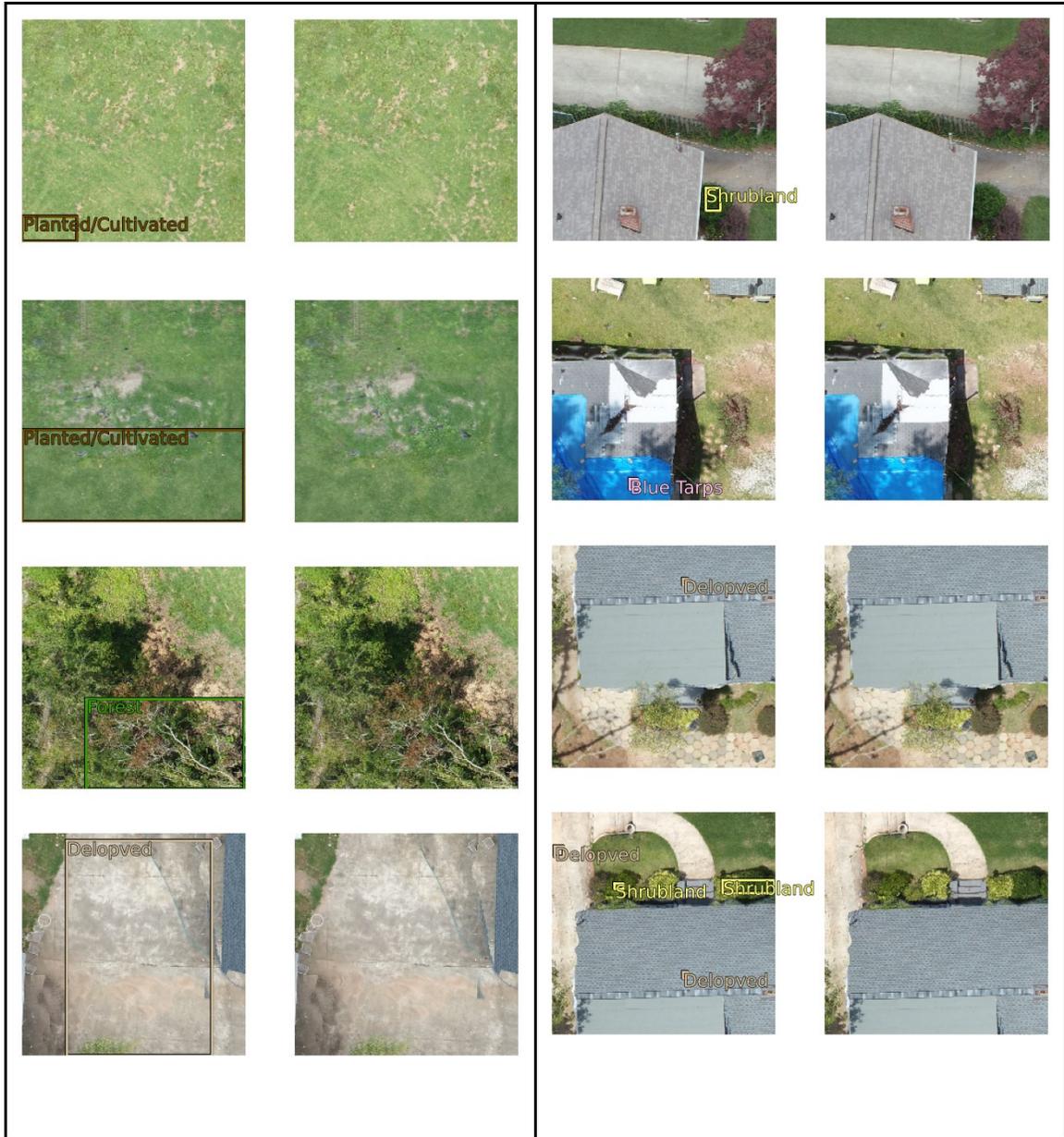


Figure 11. Ground Truth/ Predictions from ML.

Following the training of the deep learning model, it was attempted to use the model to use to create an output to execute the Detect Objects Using Deep Learning, Classify Pixels Using Deep Learning, or Classify Objects Using Deep Learning tools.

After attempting to run, all of these have failed to run and give a meaningful result or correctable error.

SUPERVISED CLASSIFICATION

In keeping things simple, the Classification Wizard tool in ArcPro was used to do supervised classification. This interface walks users through a guided process that includes best practices and a streamlined user interface so that it is user-friendly and easy to follow. The accuracy of the outcome was determined by the training samples given. These sites can be generated or selected based on our human understanding of the source data and expected outcomes, and they are recorded as a point or polygon feature class with matching class names for each feature. The training samples' features were used to classify all other pixels in the picture. Classification in this project were done on a per-pixel basis, with the spectral properties of each pixel determining which class it belongs to.

Because a supervised classification was utilized, the classification's outcome is determined by the training samples provided. Training samples are illustrative sites for all of the categories that need to be classified, most notably blue tarps in this case. These sites are developed or selected based on user understanding of the source data and expected results, and they are saved as a point or polygon feature class with class label

names for each feature. The training samples' features are used to classify all other pixels in the image, which runs reasonably quickly because of the image size.



Figure 12 . Supervised Classification. Blue Tarps (blue), Developed (pink), Barren (tan), Forest (green), Shrubland (brown), and Planted/Cultivated (yellow).

This supervised classification resulted in the imagery highlighting blue tarps into their class, however, the edges of the raster and its groups are rough so a Boundary Cleaning Tool was applied twice. By smoothing the borders between zones, this tool normalizes or simplifies rasters. The tool allows for selecting how the cells in the input zones influence the flattening and how much smoothing is applied. Following this, the raster was turned into a polygon so that incorrectly classified objects such as trash bin

lids, windows, and pools could be removed. This resulted in a much clearer image showing the active blue traps on roofs.



Figure 13 . Example of two areas that were falsely classified as blue tarp roofs. Left is a child's play area, Right is grey-blue toned shingles on the roof. Note the shape is different from than typical roof shape and the classification is spotty.



Figure 14. Correctly identified blue tarp on a roof via Supervised Classification. Note the shape of the area aligns with the typical roof structure and covers the whole area.

After classification and correction were finished, the resulting image showed only blue tarps placed on top of roofs. It is important to note that not all blue tarps from the first classification were onto roofs as some were over supplies, car windshields, tools, or placed otherwise. Out of 156112.715 pixels, 1212.287 can be classified as blue tarps or about 0.776% of the image. Before removing wrongly classified objects, 1602.351 pixels were classified as blue tarps, later 390.063 of those pixels had to be removed.



Figure 15 . Initial classification and post classification. Top: yellow areas are classified as a blue tarp. Bottom: red areas classified as blue tarps after removing falsely classified areas.

CHAPTER FOUR

ACCURACY ASSESSMENT

Once all three methods were tested across each disaster site an accuracy assessment was run on the results to gauge the correctness of the classification of blue roofs. To assess the correctness of the categorized results a reference dataset was created using the classification wizard. This reference dataset's values must match the schema. The schema used is simply a reference to the objects being classified. It is a way for the program to recognize what is being classified and what is not. This reference data was put in raster format. The randomized equalized stratified technique was employed. This means that the program created a random distribution of points inside each class, with each class having the same number of points. These points will be what is used for future analysis of the sites that are desired to fit into the schema. Accuracy is measured on a scale of 0 to 1, with 1 representing perfect accuracy. This is done using the kappa statistic, which compares observed accuracy to expected accuracy. The greater the kappa number, the more closely two datasets agreed. High accuracy and kappa number will indicate a successful method of finding blue roofing tarps. For reference, should an accuracy analysis be done, and the accuracy fall somewhere below 0.5, this would mean that the accuracy of the image falls more than halfway below the expected, and would

need to be re-referenced. For the purposes of this image, a Kappa of 1 was successfully achieved.

OBJECTID *	ClassValue	C_1	C_20	C_30	C_40	C_50	C_80	Total	U_Accuracy	Kappa
1	C_1	10	0	0	0	0	0	10	1	0
2	C_20	0	135	0	0	0	0	135	1	0
3	C_30	0	0	91	0	0	0	91	1	0
4	C_40	0	0	0	126	0	0	126	1	0
5	C_50	0	0	0	0	29	0	29	1	0
6	C_80	0	0	0	0	0	113	113	1	0
7	Total	10	135	91	126	29	113	504	0	0
8	P_Accuracy	1	1	1	1	1	1	0	1	0
9	Kappa	0	0	0	0	0	0	0	0	1

Table 5 . Confusion Matrix of Supervised and Segmentation Classification.

As seen in Table 6, the after finishing an Accuracy Assessment on both the Classified Image and the Segmented Image, it can be possible to understand how accurate the information presented was compared to actual physical locations (in this case, Newnan, GA). Geo-referencing is possible, but is time-consuming and instead achievable by using tools in modern geospatial programs. For this data, the Kappa value for both of these images was 1. This result was due to the fact that the data used to classify these images was properly georeferenced, allowing for accurate use of the data and properly located classifications.

The accuracy column displays false positives, or omission mistakes, in which pixels are wrongly classified as a recognized class when they should be classed as something else, in this case blue tarps placed on roofs. Mistakes of omission, or type 1 errors, are often referred to as user accuracy. The data used to calculate this error rate was taken from the table's rows. According to the reference data, the Total row reflects the amount of points that should have been categorized as a certain class. The accuracy column displays false negatives or commission mistakes. The data used to calculate this error rate is read from the table's columns. The Total column corresponds to the number of points that were classified as belonging to a specific class.

RESULTS

With the ML failing to run in its last stage it was hard to recommend this process to EMA and other agencies looking to track roof damage via blue tarps. However, supervised and segmentation both ran without major issues or technical errors. In applying the Supervised Classification 1212.287 pixels were found to be blue tarps placed on roofs. Of the original 1602.351 pixels were classified as blue tarps, 390.0637 of those pixels had to be removed due to not being blue tarps on roofs. This means that they represented pixels that made up objects such as water hoses, trash bin lids, pools or blue tarps that were not installed on roofs.

The correctly classified blue tarps as seen in Figure 12, showed the successes of Supervised classification in that the blue tarps on roofs were correctly classified and done so in that the whole area of the tarp was identified. The pixel-based classification used in supervised classification is done on a per-pixel level, with the spectral properties of each pixel determining which class it belongs to. The pixel-based technique ignored the characteristics of nearby pixels which led to a better more complete classification of the blue tarps.

With the Segmentation method blue tarps after categorization and rectification, the final image only shows blue tarps placed on top of roofs, Figure 7. Blue tarps made up 1286.128 pixels of the image's total of 156112.739 pixels, or 0.823 percent. Before eliminating erroneously categorized items, a total of 2482.307 pixels were classified as blue tarps, of which 1196.178 could be eliminated due to not being blue tarps on roofs.

This method brings together pixels that are similar in hue and have comparable form features. The Mean Shift method is used to segment the images. To identify which pixels are included in each segment, the approach employs a moving window that generates an average pixel value. The value was iteratively recalculated as the window advances over the image to ensure that each segment was appropriate. As a result, image pixels were grouped together into a segment with an average color as seen in Figure 6.

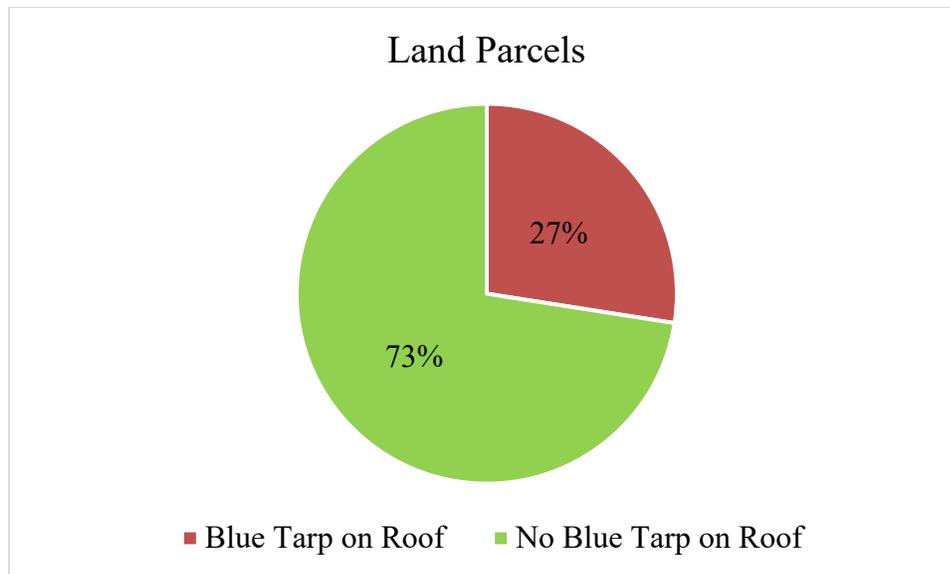


Table 6 . Showing the breakdown of land parcel blue roof tarp presence.

Out of the 91 land parcels with a structure that fell within the 0.58 by 0.30-kilometer orthomosaic land cover area, 25 had a structure with a blue tarp on a roof when overlaid with the Supervised Classification image. Of the 91 parcels, about 73% did not have a blue tarp on a structure's roof within parcel's boundary area. All 91 land parcels are classified as RU_1 zoning allows for higher density house development in Newnan's historic residential zones. Single-family houses and accompanying recreational, religious, and educational institutions are the primary uses of property in this district, which are typically expected to provide a balanced and organized neighborhood. The use of public water and sewer infrastructure is needed for all permitted purposes within this zoning. Low-density non-residential development and the encroachment of conflicting uses are avoided in high-density residential zones.



Figure 16. Locations of land parcels with blue tarp on roof structure. Red crosshatching indicates blue tarp on roof within boundary. Green simple hatching indicates no blue tarp on roof within boundary.

Working with FEMA, the US Army Corps of Engineers is in charge of Operation Blue Roof. The goal of Operation Blue Roof, as mentioned earlier in this project, is to supply blue tarpaulin or similar fiber-reinforced sheeting to homeowners in recent disaster zones to cover damaged roofs until permanent repairs can be done. This is a no-cost service for homeowners. One major benefit of Operation Blue Roof is that it helps to preserve property and allows residents to stay in their house as repairs can be done. This

program is for main residences or rental properties that are permanently occupied and have less than 50% structural damage. Most of the structures seen in the Newnan data would fall under the criteria needed for Operation Blue Roof as most are less than 50% structural damage, are occupied by main residences or rental properties that are permanently occupied.

CHAPTER FIVE

DISCUSSION

This data showed that between the two methods that made it to completion, Supervised and Segmentation based off using the Newnan data they are yield nearly identical results, only different by about 73 pixels different between them in their final forms. The Segmentation required more manual correction than the Supervised Classification by 806 pixels, a quite minor difference when compared to the image as a whole.

However, since Supervised Classification runs faster and is a simpler process, for newcomers and those looking for an accelerated process of examining blue tarps on roofs it is a better tool to employ. This method along with the initial data collection, was simplified into a 6 steps procedure. The time it would take to process data using this procedure is hard to quantify as computer operating systems and output power vary.

Across all methods there were several objects that caused issues with processing complications. This was likely due to similar pixels colors and has an impact of accuracy along with adding extra time to the image processing. Due to these objects sharing such similar features to blue tarps, it was difficult to work around them making editing the vertices the most straightforward method of editing errors such as these.

Alternately FEMA, EMA, NGOs and other emergency aid organization could supply tarps of a distinct color such as bright pink or yellow. This would allow for quick visual confirmation of the use of resources as well as improve remotely sensed classification as bright colors are less common in nature. Tarpaulin being a cheaper plastic material is easily mass produced and can come in many different colors. Moving to a color such as bright yellow eliminates most of the errors seen in this project. Any bright colors can be considered as long as the environment it will be used in is considered. For example, a neighborhood damaged by a tornado with many pools would have a more difficult time tracking blue tarp due to there visual similarities. Where as if a bright pink tarp was distributed for residents to used in the same neighborhood it would make Supervised Classification a much smoother and dynamic process.





Figure 17. Objects that caused issues in classification across all methods. From top left to right; trampoline, garden hose, pool with pool furniture, car window with sunshades, blue tent, trash piles with blue tarp, blue trash bins, blue car, green roof child's play structure.

COLORED TARPAULIN ANALYSIS AND RECOGNITION PROCEDURE

The Colored Tarpaulin Analysis and Recognized Procedure (CTARP) following is the standard procedure for technicians looking to track colored roof tarpaulin on structures in post disaster areas. In this example the color tarp is blue as this is currently the most common color. The instructions call for the use of: a UAV with RGB sensor, UAV flight application (such as Pix4D Capture), and analysis software for processing and analyzing images such as Drone2Map and ArcGIS Pro (Spatial Analyst License). It is important to check your computer's ability to run Esri products. At the time of writing this, ArcPro 2.8 and Drone2Map 2020 are the two main software that are most commonly used. For most mapping and remote sensing projects, certain technical specifications must be met. These include: 32 GB of free space for storage purposes, a CPU of at least 2 cores and a RAM minimum of 8 GB is needed. Additionally, understanding the level of operating system is also needed. Windows Server 2012 Standard and Datacenter (64 bit) is the oldest Microsoft Windows operating system that can run Esri products, with Windows 11 Home, Pro, and Enterprise (64 bit) being the most recent Windows operating system at the time of this writing.

STEP 1: Study Area Data Collection

The very first step in CTARP is to first determine the area to be analyzed. If collection is done with a UAV, pre-program the flight according to the area that is to be surveyed.

Collect imagery while maintaining a consistent AGL and obeying all local and FFA UAV regulations. It is best to have more than 70% of your imagery to have overlapping images and to fly on a cloudy day to reduce atmospheric interference.

STEP 2: Creating an Orthomosaic

After data of the selected site is collected, the technician must load images into Drone2Map using the “2D Rapid” option. Following this, within the Home frame, navigate to Processing and explore Options. Not many of these settings need to be changed depending on the flight. Be sure that under Initial, “Run Initial” and “Aerial Grid or Corridor” are checked off. It is also important to check the Coordinate System to make sure that the local or best coordinate system is selected for the area being analyzed. The coordinate system used for the data collected by drone is typically WGS84, as drone data is collected using GPS coordinates. Once finished with the Options menus click apply, and this will start the orthomosaicing process. Once the orthomosaic is finished, it can be exported as a tiff file and opened in ArcGIS Pro. Tiff files are preferable due to their ability to maintain the high-quality detail that is capable of being collected by drone cameras, as drones are able to see an incredible amount of detail due to their much closer proximity to the ground than airplanes or satellites.

STEP 3: Begin Classification

Once the technician has opened the tiff in ArcGIS Pro, select it in the Contents pane and navigate to Imagery, and then to the Classification Wizard. Configure the settings as follows:

- Classification Method – Supervised
- Classification Type - Pixel Based
- Classification Schema – Default (NLCD2011)
- Output Location – Insert location on D: drive to save file to

Click Next and collect samples to train the data. You will need to add a field for blue tarps on roof using the Add New Class tool. Be sure to have 25 at minimum samples per class as this will ensure more accurate classification. After this, click Next again. The following page is the Train page in which the input for Classifier is Support Vector Machine and Maximum Number of Samples per Class is 500. Click Next.

STEP 4: Complete Classification of Selected Image

Following the resolution of Step 3, it will result in a preview of the classified image. If it looks accurate, click Next. If the image seems to not have classified correctly, or you find that certain objects are not being classified in accordance with what you wish, go back and review training samples, perhaps adding more classes to assist in a better

classification. Once happy with the classified image, click Next. Before hitting Run, name the Output Classified Dataset. This will result in complete classified image.

STEP 4.5 (OPTIONAL): Boundary Cleaning

Using the Boundary Clean tool, by smoothing the edges between classes it simplifies rasters. This is a recommended step but not required, if using this tool, run it twice for best results.

STEP 5: Selecting Tarp Roofs

To simplify the raster to only show blue roof tarps, go to the Attribute Table of the layer and make the blue roof tarps class its own layer by selecting all rows that make up the blue roof classification. This will highlight only the blue roof tarps and make editing the layer much easier.

STEP 6: Remove Image Errors

To remove errors, use the Raster to Polygon tool and leave the autogenerated settings.

After clicking Run the result will be editable using the Edit Vertices under the Edit pane, this will make the vertices moveable and removeable. Use the original orthomosaic as a reference to the location of blue roof tarps. When finished it is very important to click Save under the Edit pane. This will result in a final image overlaid with the highlighted locations of blue roof tarps to indicate damaged but potentially salvageable structures.

CONCLUSION

This thesis aimed to improve and support EMA's GIS ventures when it comes to locating damaged structures with blue tarps. The objective was to evaluate which approach is the most efficient and accurate for identifying blue tarps by comparing picture segmentation, ML, and supervised classification. FEMA's mission comprises supporting people in the aftermath of catastrophes, thus disaster victims received government cash to help with temporary housing, emergency house repairs, personal property loss, funerals, and other expenditures. Observing communities from an elevated aerial perspective can give more insight into the damage done to homes and communities, allowing resources to be effectively directed to aid those in need. By locating structures with blue roofing tarps, EMAs and NGOs can get a more accurate number of those impacted by disasters who are likely still in dangerous areas. Disaster assistance is costly, logistically difficult, and largely reliant on public support, and the rising number of natural catastrophes associated with climate change has prompted researchers to study more about disasters. Ultimately, any research done in proximity to disasters should aim to lessen the effects of those most impacted by them. Finding the most effective way to observe these disaster areas with UAVs and track roof damage is the first step in creating a solid recovery for communities of future disasters.

This research has evaluated three methods of analyzing blue roof tarps and concluded that Image Segmentation and Supervised Classification yield nearly identical

results. While Machine Learning has a great deal of potential, it is still a very new and complex technology that has a way to go until it can be effectively used for quick disaster recovery efforts. Although Image Segmentation and Supervised Classification's final results were much the same, Supervised Classification is a much more accessible and established method that has a higher rate of success when finding blue roof tarps. Comparatively, it is also a faster tool to run, requiring little computing power.

Thus, with these results, it is the Supervised Classification method that will be fundamental to CTARP. The processing of tarp locations can be used in a variety of different post disaster areas that sustain structural roof damage. This is the ultimate goal of this project: to produce a method that is applicable to studying the interactions between GIS and disaster recovery. This may be more easily facilitated by the deployment of tarps that have a markedly distinct color, such as yellow or bright pink. By implementing these changes and procedures, as well as progressing the development of CTARP, it can then be possible to better allocate resources to people and communities in need.

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