

DETECTION OF LANDMINE-LIKE TARGETS USING DATA COLLECTED BY
UNMANNED AERIAL SYSTEMS

by

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(Under the Direction of Marguerite Madden)

ABSTRACT

Scatterable landmines are a recent warfare technology that can be dispersed aerially and quickly render land useless to local populations. This research aims to develop methods for civilian landmine detection and suspected area reduction using readily available unmanned aerial systems (UAS), simulation landmines and very high spatial resolution orthomosaics derived using Structure from Motion from multiple flight dates. This study demonstrated image processing for uniform target detection combined with a multi-temporal analysis, has potential for reducing the search area for landmine detection and making the work of civilian deminers significantly safer. Results indicate it is possible to detect individual landmines, reduce the area needed to search to less than three percent of the original study area, and a multi-temporal process can reduce the number of false positives detected. The best practices for data collection and analysis are reported, and possibilities for future demining methodologies are suggested.

INDEX WORDS: Landmine Detection, UAS, Drone, Multi-Spectral, Multi-Temporal, Uniform Target Detector, Principal Components Analysis, Structure from Motion

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COLLECTED BY UNMANNED AERIAL SYSTEMS

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INTRODUCTION AND LITERATURE REVIEW

A Khmer Rouge General once said, “A landmine is a perfect soldiers; ever courageous, never sleeps, and never misses” (UNICEF, 1996). Landmines are small explosive devices triggered by pressure that can be lethal when detonated and are designed to deny land from enemy combatants (an example can be seen in Figure 1). Landmines are a global



Figure 1: Russian anti-personal landmine in Syria
(“Russian PMN-4 anti-personnel landmines in Syria – Armament Research Services,” 2016)

issue impacting large populations of civilians in many countries. According to the United Nations, 15,000-20,000 people are killed every year by an estimated 110 million landmines placed in or on the ground across 70

countries (United Nations, 1996). Approximately 90% of landmine casualties are civilians, with children most at risk demographic (Achkar & Owayjan, 2012). To make matters worse, impoverished countries are impacted disproportionately by the loss of arable lands, a common location for landmine placement (Paik, Lee, & Abidi, 2002). Efforts associated with demining are numerous, but traditional methods for mine location and deactivation can be highly inefficient, expensive, and physically/mentally taxing. The majority of a deminer’s time is spent on exhaustive demining techniques Maathuis

reports that there are over 100 false alarms per landmine found, Achkar and Owayj have reported the number of false positive per mine is as high as 1000 per min (Achkar & Owayjan, 2012; Maathuis, 2001). Landmines are manufactured in hundreds of different styles and materials making their detection challenging. Antipersonnel (AP) landmines are constructed to be as small as a few centimeters in diameter and blend in with the surrounding environment. They often contain minimal metal content, making detection impossible with traditional landmine detection technologies such as metal detectors.

Geospatial technologies, including geographic information systems (GIS), remote sensing, and image processing, have made mapping landmines easier. Any improvements to landmine mapping efforts can optimize demining, leading to a reduction of demining casualties related to fatigue and further reducing the physical and financial cost of demining (Maathuis, 2001). The introduction of unmanned aerial systems (UAS) into landmine mapping workflows has opened new possibilities for improved detection. The UAS are small, user-operated aerial systems outfitted with sensors for data collection (Marshall, Barnhart, Shappee, & Most, 2016). The UAS enable researchers to quickly and reliably collect data from a safe distance with multiple style sensors at a low altitude. Data collected by UAS have an exceptionally high resolution (<5 cm resolution), and by applying object detection techniques, it could possible to create and implement a low-cost methodology for landmine detection in developing countries.

Literature Review

The Global Problem of Landmines

There are three styles of landmines: antipersonnel (AP), anti-tank (AT), and improvised explosive devices (IED). The placement of landmines is driven by the intent

of whoever is placing them. State actors traditionally use AP and AT landmines in their warfare strategies by placing large numbers of mines in predictable patterns. Guerilla style fighters, such as terror cells or individuals, are much less predictable in placement and mine style. These fighters mainly use IEDs, and occasionally illegally obtained AP or AT mines making their style and placement harder to predict. Most work for landmine detection focuses on traditionally placed landmines as they represent the majority of active landmines and are much easier to detect (Maathuis, 2001).

The primary factors to consider when detecting a landmine are size, shape, material, distribution method, and the time since distribution. The effects of weathering have a substantial impact; the longer a landmine has been in the field, the more difficult is its detection and removal. Weathering causes a landmine's color to fade and shift in the soil, helping to blend the mine with its surroundings (Keeley, 2003). Additionally, landmine casings and detonation systems can start to break down over time making them more unpredictable to handle during the demining process and an accidental detonation more likely (Maathuis & Van Genderen, 2004). To combat common demining technologies such as metal detectors, newer models of landmines are developed with minimal metal content making detection nearly impossible by metal detectors (Maathuis & Van Genderen, 2004).

In 1987, international standards were developed to deter global landmine contamination and aid in demining. In the NATO's International Standardization Agreement known as the STANAG 2045 agreement, all NATO states agreed to place mines in a predetermined arrangement with five antipersonnel mines surrounding one antitank mine in a semicircle (Maathuis, 2001) . Every mine location must be recorded

when placed, however knowledge of these positions can become lost during war, and there is nothing binding non-NATO states to these placement standards. Unfortunately, only some countries and agents follow NATO standards. Terrorist groups have been known to place booby traps on mines to make them more difficult for deminers to detect (Maathuis, 2001). Terror groups are often limited to resources available to them, so they improvise their explosives with materials found in the field, creating hazardous conditions for deminers because there is no sure way of knowing the appearance of an IED.



Figure 2: Ukrainian scatterable mine laying vehicle ("Russian PMN-4," 2016b)

Since World War II, state armies have employed a new class of AP known as the scatterable mine. Scatterable landmines are easily placed by automated systems or vehicles. In the 1980s, both the United States and Russia developed mines designed for aerial distribution

across a landscape via aircraft or mortar. A mortar system attached to the bed of a truck can be seen in Figure 2. Scatterable landmine technologies increase the speed that areas can be mined and rendered useless. Designed to survive a fall through the air and an impact with the ground, scatterable landmines become armed within seconds of deployment and create minefields of very high density. To nullify the lasting effects of minefield contamination scatterable mines are designed to self-detonate after a specified period usually on the order of hours to days to reduce remnants of war. However, there is

a dud rate associated with self-detonation, meaning an area cannot be trusted to be mine-free once it has been sewn with scatterable mines (Pike & Sherman, 2000). This leaves potentially dangerous conditions for locals for years after the end of warfare.

Those who place landmines intend to harm, kill, and induce fear in their enemies, but often end up hurting local populations. For military forces whom often place landmines in strategic defensive locations to protect their flanks, minefields are often left behind when forces leave the area, either out of distress or recklessness (Maathuis, 2001). Because there is no definitive method of detection and landmine presence is often unknown, landmines are incredibly successful at rendering land useless and inducing fear. The physiological effects of landmines cannot be understated leading to widespread use. Unfortunately, those affected by landmines are often different from those initially targeted. Landmines hinder local populations and restrict human movement through mined areas. They are area-denying weapons that can have severe implications for food availability, resources, and the economies of affected nations (Achkar & Owayjan, 2012). Landmine contaminated areas can cause locals to abandon their homes and farmlands until it is proven safe to inhabit once again. Areas impacted by landmines are often impoverished, and at risk of famine. Returning the land to local populations to use for agriculture is a crucial goal for deminers. For those who live off the land, a mine-free field represents their livelihoods and the difference between living comfortably and living in poverty.

To further exasperate the problem, the cost of demining is vast. One study found that “productivity of individual deminers is so low that total labor cost per unit of land cleared remain exorbitant despite minuscule wages in mine-affected countries (Wolf &

Barmazel, 2001).” The persistence of landmines in the environment is second to none, with examples of landmines lasting upwards of 50 years commonplace. In extreme examples, 19th Century Civil War era explosive cannonballs are still being unearthed in the United States (Masich, 2017).

Detection Payloads

Many different types of sensors have helped improve efficiency and safety in landmine detection. These technologies fall into two main categories proximal and remote solutions. Examples of proximal sensors for finding landmines are numerous and include ultrasonic prodders, trained animal sniffers, and mechanical flails (Gasser, 2000). Proximal sensing techniques are generally more accessible to deminers in impoverished countries because of their smaller price tags, but they introduce the possibility of human loss due to the proximity of deminers to landmines during operation. Proximal sensors always have a place in demining because they are needed to deem an area 100% cleared of landmines.

Remote solutions range in detection scale from satellite data to aerial imagery to UAS. To determine the best remote solution, deminers must think about the spatial, radiometric, and spectral resolutions needed for their project. For example in minefield mapping, only environmental context clues are needed to find the presence of minefields, so medium spatial resolutions offered by publically available satellites imagery are satisfactory (Maathuis, 2001). Satellite data offer the advantage of covering large ground swaths (e.g., a Landsat image covers a 185 x 185 km area) in a single collection. Maathuis and Van Genderen (2004) describe specific examples of their work using Landsat scenes (30m resolution) from one area over time to detect potential minefields

using change detection. However, even commercial high-resolution satellite sensors have yet to reach the spatial resolutions necessary to map individual landmines. Currently, the highest ground resolution available is 0.34 meter panchromatic band from WorldView 4 (Digital Globe, 2018).

Generally speaking, minefield detection require multiple bands covering multiple parts of the electromagnetic spectrum, meaning a hyperspectral solution may be necessary. Hyperspectral satellites offer an enhanced spectral resolution to researchers allowing them to leverage spectral characteristics of minefields. Hyperspectral sensors obtain a more complete view of the electromagnetic spectrum collecting tens to hundreds of bands at 10-nm steps or smaller in a range of 400-1100 nm. Hyperspectral data are often referred to as a data cube because of the tens to hundreds of images capturing a single scene. When layers are stacked; they create a data cube. Hyperspectral sensors such as Hyperion a payload of the EO-1 satellite have been used for anomaly detection but space-borne hyperspectral sensors are still limited by spatial resolutions (e.g., 30 m) and not able to detect individual mines typically less than 4-5 cm in diameter (Molero et al., 2011; Ready & Wintz, 1973; Soofbaf, Fahmmejad, Zoej, & Mojaradi, 2007).

For detection of individual landmines, higher spatial resolution data are needed, so data must be collected aurally via aircraft or UAS. Traditionally, manned aircraft were used to collect aerial imagery, but the low cost and the ease of flight have caused a shift towards UAS. Improved spatial resolutions, lower costs, better detection algorithms, and ease of collection has driven researchers to attach many types of sensors to UAS for small object detection. Sensors of many styles have been attached to a UAS and flown for

landmine detection. Examples are cameras, chemical sniffers, metal detectors, and ultrasonic prodders (Gasser, 2000).

UAS Sensors and Structure from Motion

Unmanned aerial systems have revolutionized remote sensing of landmines allowing quick collection of data for large areas at a safe distance. A central consideration for flying UAS mounted sensors, is the target size and the size of the study area. When determining the desired spatial resolution of UAS imagery required to detect the target, the ground sampling distance (GSD) must be calculated. The GSD is the distance between the centers of two adjacent pixels and represents the spatial resolution of an orthorectified image or orthomosaic. Ground sampling distance is calculated with two main factors: focal length of the camera (i.e., the distance between the lens and the focal plane where the image is recorded) and flight altitude above ground. The GSD is derived by dividing the flight altitude by the focal length. In order to achieve higher spatial resolution, the flight altitude must be decreased or the focal length must be increased (Marshall et al., 2016). The tradeoff of flying a UAS at lower flight altitudes is more flight lines are required to cover the study area, thus increasing the number of overlapping images acquired that need to be orthorectified to remove distortions before they can be stitched together into a single orthomosaic. This can be accomplished by computer vision techniques and photogrammetry including multi-image matching, feature extraction by Scale Invariant Feature Transform (SIFT) to create a 3D point cloud in a process commonly called Structure from Motion (SFM) (Vosselman, Sester, & Mayer, 2004). In other words, SFM is a photogrammetric technique that uses mathematical processing to recreate the structure or surface of an object (Cotten et al.).

The resulting 3D point cloud of the landscape can then be used to derive a digital surface model of the ground, which is then used to orthorectify the mosaic of UAS images to create a single orthomosaic of very high spatial resolution.

To increase the quality of the image products resulting from SFM, flights of UAS are planned to cover the entire study area with a high percentage of overlap between images (>70%) and taking the high-resolution images from different look angles. The steps of the SFM process described by (Marshall et al., 2016) are:

- Matching key points between images;
- Creating a 3D point cloud from the key points;
- and draping imagery over the dense cloud.

Landmine Detection Methods

Once the UAS imagery has been acquired and photogrammetrically processed to stitch individual images together in a geometrically correct orthomosaic, the image must be analyzed to detect the landmine targets (i.e., separating the target from the background). Researchers have employed many different methodologies to detect landmines in imagery. It is important for research to understand their targets (i.e. Landmines) to properly detect them. Currently, there are more than 700 models of landmines and even more munitions and IEDs, meaning that detection algorithms have to be robust enough to work with as many styles of landmines as possible. One approach commonly used in detection analysis is to treat landmines as an anomaly in the scene and look for the anomaly. There are two main approaches for anomaly detection depending on whether knowledge of the spectral characteristics of the target are known to the user before detection. If spectral knowledge of the landmine is known, a matched filter

approach is generally used for detection. Matched filter (MF) algorithms use the target spectra to create a filter that enhances the visibility of target spectra and reduces the visibility of background spectra using an unmixing algorithm (Jensen, 2006).

In a U.S. Army-sponsored project, Kenton et al. (1999) attached a hyperspectral sensor to a UAS to detect AT mines using a matched filter (MF) approach. The hyperspectral data were used to detect minefields based on spectral reflectance by features across a wide range of wavelengths that are not inherently visible to the naked eye. Hyperspectral data allowed the mapping of quartz Reststrahlen features to detect soils disturbed by placing the AT mines. Reststrahlen features are unique thermal responses created by minerals that can be detected when looking at their thermal emissions. When the hyperspectral data were analyzed using an MF to enhance the spectral characteristics of the target (Reststrahlen features) and suppress background characteristics, researchers were able to discover areas with large quantities of disturbed soil that indicated a potential minefield. Many researchers have used MF to detect known landmine signatures from background data. (Baertlein, 1999; Reed & Yu, 1990; Soofbaf et al., 2007). However, an MF approach requires prior knowledge of the target being searched for, which is not always the case in demining.

A more likely scenario in demining is an unknown area and unknown target contaminated with landmines. The Reed-Xiaoli (RX) detector (1) has served as the gold standard for detection of unknown anomalies.

$$(1) \quad s_{RXD}(r) = (r - \mu)^T K_{L \times L}^{-1} (r - \mu)$$

Where r is the sample vector

μ is the sample mean

$K^{-1}_{L \times L}$ is the sample covariance matrix.

The RX algorithm detects pixels that differ spectrally from the background pixels. An RX detector can be thought of as an inverse of a principal components analysis (PCA) that looks at the minor components of an image and determines if those components are noise or anomalies by using a covariance matrix (Reed & Yu, 1990).

The U.S. Army created a spectral approach that utilizes the RX algorithm for detecting surface minefields, which troops may encounter during coastal assault missions known as the Coastal Battlefield Reconnaissance and Analysis (COBRA) system (Muisse, Wright, & Holmes, 1996). The COBRA system uses an on-the-fly RX detector and minefield detection algorithm to find potential minefields for multispectral data (Muisse et al., 1996; Stetson et al., 2000). The system uses a stereo camera setup that has bands ranging from deep violet to middle infrared. Not all knowledge of the bands is publicly available, but based on calls for proposals related to the system, at least four of the band centers are in the visible to near-infrared (532nm, 675nm, 810nm, 1064nm) (Almquist, n.d.; Stetson et al., 2000). The COBRA system excels in detecting minefields, but not single mines in littoral environments (Stetson et al., 2000).

Principal Components Analysis and Minimum Noise Fraction Transforms

Image processing methodologies often create multiple sets of data containing different variables that are important in mine detection. In order to efficiently analyze the large amounts of data, a Principal Components Analysis (PCA) can be employed. The

PCA is a multivariate analysis that uses a statistical method of dealing with large datasets that may or may not be correlated (Pearson, 1901). An orthogonal transformation is applied to the dataset to create linearly uncorrelated principal components (PC). The PCs are created so that they preserve as much variance as possible in the first PC with each succeeding PC having less variance than the previous (Pearson, 1901). A PCA creates $n-1$ PCs where n is a total number of datasets. Each PC has an eigenvalue associated with it that indicates the total variance accounted for by the variables contained in the PC. Principal components are unique to each scene and are commonly visually interpreted to see which principal components contain useful data.

Research Questions and Objectives

The overarching research question and goal of this work is to determine if it is possible to reduce the threat of air scatterable surface landmines by accurately locating them using UAS imagery. While solutions like the COBRA system already exist UAS solutions are used to detect minefields for military use, this work aims to detect individual landmines for humanitarian demining missions. To achieve the humanitarian detection goal of 100% clearance, a solution must, practical, and accessible. Two different sensors were compared to determine the optimal combination of bands and spatial resolution for landmine detection.

The findings of this study are reported in a manuscript–style thesis containing four chapters. Following an introductory chapter and literature review, the first article describes the problems of landmines, simulation of a minefield, data collection, the development of landmine detection methods including image dilation and erosion, and PCA thresholding for detection of scatterable landmines. The results of manuscript one

acted as a guide for the research design in manuscript two, which aimed to incorporate multiple sensors and multiple detection dates to detect realistic test landmines. The second article explores improvements in test minefield conditions, simulation landmines, data collection, vegetation suppression, Reed-Xiaoli anomaly detection, and time series analysis for scatterable mine detection. The final chapter offers a review of the successes of the methodology and suggests where future work can further improve the methodology. Specific objectives of this research include:

Manuscript 1:

- I. Create an experimental test area simulating a minefield to test UAS data collection feasibility.
- II. Develop a methodology for acquiring UAS imagery that is representative of recently distributed scatterable surface landmines.
- III. Test PCA as a method for detecting scatterable landmine targets from background vegetation.

Manuscript 2:

- IV. Test Reed-Xiaoli anomaly detection algorithm as a method for detecting randomly scattered landmine targets in an agricultural field site.
- V. Test time series analysis for change detection to indicate landmine locations.
- VI. Develop a methodology that uses statistical thresholding to remove false positives from the results.

Study Site

There are two study areas used in this research one located at the University of Georgia in Athens Georgia, (Figure 3) and one located on private property in Watkinsville, Georgia

(Figure 4). An overview of each study sites location can be seen in Figure 5. Site A is a 0.15-acre plot, primarily grass with a small subsection containing ivy with minimal elevation change. Site B a 1-acre agricultural field that drains towards the center of the study site. The field is used to grow hay that has irregular patches of bare dirt.



Figure 3: Site A located at the University of Georgia, Athens, GA



Figure 4: Site B located in Watkinsville, GA

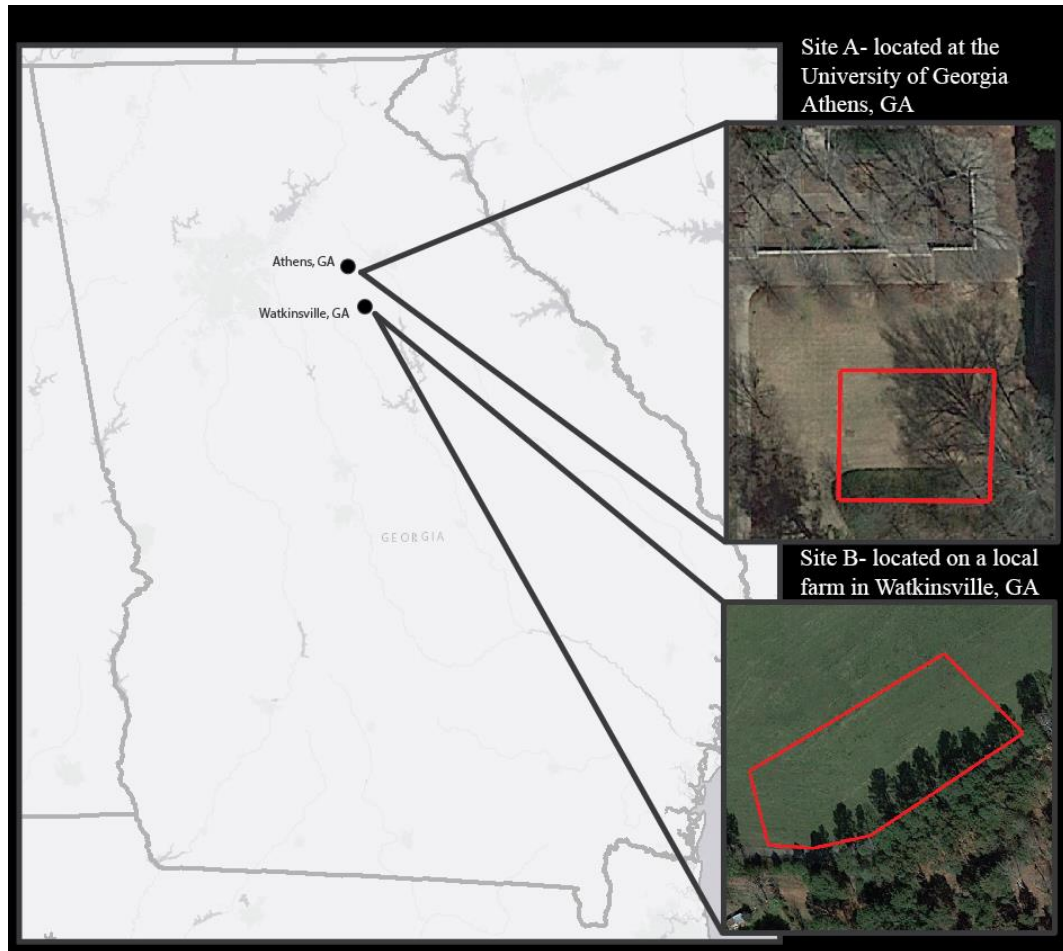


Figure 5: Overview of each study site's location within the state of Georgia

Research tools

A UAS mounted multi-sensor approach was used in this study. Manuscript One used a DJI Phantom 4 (P4) and a stock RGB 12.4-megapixel camera. The UAS used in Manuscript Two is the DJI Phantom 4 Pro (P4P), and the stock camera for this UAS is 20-megapixels. The exact spectral information for the P4 and P4P cameras is not publicly available and therefore data collected with these sensors are only used in a relative sense where bands from the same image are compared with each other. The other sensor used

in Manuscript Two is the MicaSense RedEdge (RedEdge) which is mounted so the P4P camera can also collect simultaneously. The RedEdge multispectral sensor is designed to capture the essential bands for creating broadband vegetation indices (MicaSense, 2018). The RedEdge spectral information can be viewed in Table 1.

Table 1: MicaSense RedEdge sensor specifications (MicaSense, 2018)

Color	Band Center (nm)	Band Width (nm)
Blue	475	20
Green	560	20
Red	668	10
Red Edge	717	10
Near Infrared	840	40

DETECTION OF LANDMINE-LIKE TARGETS USING UAS AND IMAGE ANALYSIS¹

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Introduction

Landmines are small pressure activated explosive devices placed and concealed on or below the ground to destroy or disable enemy targets during wars and conflicts. Landmines are a global issue because of the presence even after warfare has left an area, tragically approximately 90% of those killed by landmines are civilians (Achkar & Owayjan, 2012). According to the International Campaign to Ban Landmines in 2016, yearly landmine-related injuries rose to 8605 people injured and of those injured 2089 people were killed (Landmine & Cluster Munition Monitor, 2017). In most cases, landmines come into contact with civilians as a relic of a past war. Landmines are often hastily placed above ground aerially via mortar or aircraft as area denial weapons to aid in retreat. Aerially dispersed surface landmines are supposed to have an expiration date and self-detonate after a few hours; unfortunately, self-detonation does not always work, and there is a failure rate associated with every style of a landmine. Areas are left contaminated by scatterable landmines that failed to self-detonate for local populations. The human impact of landmine use has been heavily researched but for purposes of this research, landmine detection will be the primary focus (Duttine & Hottentot, 2013; Gasser, 2000; Keeley, 2003).

Many hours of research have gone into military landmine clearance which often employs brute force methods to clear a small linear path for fighters to use. As of 2017, a mine detection system for amphibious assault was declared functional by the U.S. Navy (Almquist, n.d.; Klamser & Boughen, 2015; Muise et al., 1996; Stetson et al., 2000). However, humanitarian demining efforts face challenges in funding demining missions, since a landmine cost less than \$15 to create and can cost up to \$1000 to remove (Paik et

al., 2002). This research aims to create an actionable solution for detecting surface laid landmines with an unmanned aerial system (UAS).

Background

Existing Demining Systems

The problem of landmine detection is nothing new to the geointelligence community, private industry, and international agencies. Systems for mine detection range from the COBRA system created for the US military to hyperspectral minefield detection systems created by humanitarian groups such as the British Find A Better Way Foundation (Almquist, n.d.; Klamser & Boughen, 2015; Muise et al., 1996) (Find A Better Way, 2018). The Marine Corps' Coastal Battlefield Reconnaissance and Analysis (COBRA) was declared mission ready in 2017, twenty-seven years after initial testing began (Klamser & Boughen, 2015; Muise et al., 1996; Witherspoon, Holloway, Jr., Davis, Miller, & Dubey, 1995). The COBRA system is highly successful at detecting mines in littoral zones, the narrow land interfaces such as beaches, dunes, marshes, and mangroves that lie between oceans and dry land. The COBRA mission relies on a multispectral sensor flown from a UAS that operates in six bands and has a Ground Sampling Distance (GSD) of 2.4 inches. Not all knowledge of the bands is publicly available but based on calls for proposals related to the system four of the band centers are in the visible to near-infrared (532nm, 675nm, 810nm, 1064nm) (Almquist, n.d.). The COBRA system does a great job of clearing a path for troop breaches in littoral zones. Anomalies in the scene are detected in COBRA by an RX detector an algorithm that highlights anomalies based on the difference between pixels and the average pixel spectral response of the scene to highlighted potential landmines. The RX detector results

are processed with an algorithm designed to return a probability that the area is a minefield (Earp, Elkins, & Conrath, 1995). The COBRA mission has yet to be proven effective overland missions or detecting individual landmines. It is important to realize that the COBRA system is intended to be used by military personnel for offensive missions, while very little research currently exists for full clearance missions for humanitarian purposes.

Structure from Motion

When detecting individual landmines, it is vital to obtain aerial imagery of extremely high (< 7 cm) spatial resolutions to resolve a landmine from the background. In order to achieve high ground spatial resolution while still covering a large study area, a process called structure from motion (SFM) is often used in conjunction with low altitude UAS imagery (Cotten, Madden, Bernardes, & Jordan, n.d.). Structure from motion uses photogrammetric processes to reconstruct 3D surfaces from multiple images acquired at different angles of one target (McGlone, 2013). During data collection, images are taken in succession so that there is ~80% sidelap ~75% endlap between adjacent photos (Thomas Jordan, personal communication). In each image, key points are found and matched between photos. These matching points become tie points and the basis of a 3D point cloud which is densified and the elevations derived from the point cloud are used to orthorectify the original imagery with the original imagery. The SFM process excels at creating an accurate orthomosaic that reflects accurate geometric and spectral characteristics of the original scene (Marshall et al., 2016).

Morphological Detection

Scholars such as Stanley Grossman (Grossman, 2013) have leveraged shape characteristic for landmine detection by using morphological filters. Many morphological filters exist that can amplify properties such as texture and edges of features. The two filters used in this research are dilation and erosion (similar to low pass, high pass filters). Dilation and erosion are two mathematical operations that when performed on images act to remove noise and enhance edges. Banerji and Goutsias (1998) used dilation and erosion as the leading operator in their methodology to remove noise of background vegetation (Banerji & Goutsias, 1998). By defining the kernel size of erosion filters as the size of the intended target, noise smaller than the target can be filtered out and the edges of the target can be enhanced.

Principal Component Analysis

Of course, the use of morphological filters on data creates multiple sets of data to analyze, thus increasing data complexity and computational times. Extensive datasets created in remote sensing present a large data problem, leading researchers to use principal component analysis (PCA), a solution that reduces the dimensionality of data minimizing noise and enhance key features (Lee, Woodyatt, & Berman, 1990; Pearson, 1901; Ready & Wintz, 1973). A PCA performs an orthogonal transformation to reduce datasets into linearly uncorrelated principal components (PC). The PCs still contain all of the information contained in the original dataset while making it easier to analyze (Pearson, 1901). A PCA creates n number of PCs based on the total input bands with the first PC containing the most variance in the data and each sequential band containing less variance with eigenvalues and factor scores indicating the amount of data contained. A

PCA was used to create intensity bands from PCs of high-resolution data to perform intensity-hue-saturation pansharpening on lower resolution data for minefield mapping. (Maathuis & Van Genderen, 2004).

Relatively few studies have used SFM, morphologic filters, and PCA for landmine detection and this research aims to assess their potential use for humanitarian detection missions. The COBRA system and similar systems work well for military detection but do not reach the standards for humanitarian detection; this research aims to detect individual landmines for humanitarian demining. Specifically, the goals of the research presented in this chapter are:

- Detect individual surface laid simulation landmines with an over the counter UAS solution;
- Determine if morphological data can be extracted and used for landmine detection from just a three-band (RGB) UAS dataset
- Develop optimal data collection methods for future mine detection missions.

Study Site and Setup

The quad behind the Geography building at the University of Georgia in Athens, Georgia was used as a test minefield for this study; the total area was about 1400 square meters (Figure 6). This site had two terrain types: short grass, and low-cut ivy. The ivy area had a small change in relief of about 3 meters. The site is maintained by the University, making it less likely to be similar to a real minefield. However, it was deemed close enough for an initial detection feasibility test. The simulated landmines were constructed from fast-food plastic drink lids painted green and tan to create a semi-realistic target for detection. These simulated landmines were two sizes, either 7.6 cm or

12.7 cm in diameter, in an attempt to simulate both anti-personal (AP) and anti-tank (AT) landmines respectively. The style of the lid is similar to many common types of aerially



Figure 6. Preliminary study area located at the University of Georgia.

dispersed landmines. A comparison between the simulated land mine and an actual landmine is shown in Figure 7. The placement of these simulation landmines was done in a manner as to imitate a real landmine field.

Simulated landmines were distributed on the ground along four transects with one line of five green simulation AP landmines, one line of five tan simulation AP landmines, one line of five alternating colors simulation AT landmines in the grass, and one line of five alternating colors simulation AT landmines in the ivy. All simulation landmines were spaced apart at five paces or approximately five meters apart, as they might be seen on a battlefield.



Figure 7. (Left) Simulation air scattered landmine, (Right) Real air scattered landmine

Methodology

A DJI Phantom 4 was used to fly RGB camera imagery of the study area at approximately 3:30 pm during overcast conditions. The UAS collected a total of 30 photos from a height of approximately 18 m. Of the initial 30 photos, 22 photos exhibited high enough quality for use in the orthorectification process; careful consideration was taken to make sure the scene was fully canvased by the UAS flight path. Ground control points (GCP) were placed on the perimeter of the simulation minefield to perform the orthorectification. The GCPs were approximately 20 cm x 27 cm, and the location of each GCP was recorded with a handheld GPS to an accuracy of +/- 3 m after WAAS differential correction. To prepare the image for use with image processing techniques, a mosaicked and orthorectified image of the scene was produced. The orthorectification process involved multiple steps using Agisoft Photoscan 1.3 (Agisoft LLC, 2018). Each step of the photogrammetry and orthorectification workflow was performed by upscaling each image by a factor of 4 the highest possible settings of Photoscan, resulting in higher overall quality of data; the tradeoff is a longer processing time. A full look at the

processes, parameters, computer specs, and processing time can be seen in Table 2. A three-band orthomosaic (Figure 8) was generated with a 0.7 cm resolution and a digital surface model (DSM) (Figure 9) was created with a spatial resolution of 1.35 cm.

Table 2. Photogrammetry processes and processing time

Computer specifications: CPU – Intel Xeon CPU E3-1270 2 @ 3.50ghz (8 CPUs)

Memory – 16 GB

GPU – NVIDIA NVS 300 4 GB

Process	Quality	Processing Time
Align Photos	High (22 photos)	1 hour
Optimize Alignment	All Properties	2 min
Check Photo Quality	Remove < 0.5 quality rated photos	1 min
Build Dense Cloud	Ultra-High/ Mild Depth Filtering	6 hours
Rectify using GCPs	Handheld GPS Unit	30 min
Build DSM	Use Dense Cloud	30 min
Build Orthomosaic	Use DSM	20 min
Output	DSM 1.35 cm/Pix Ortho 0.7 cm/Pix	8 hours 23 min



Figure 8. Orthorectified mosaic of preliminary study area (0.7 cm resolution)

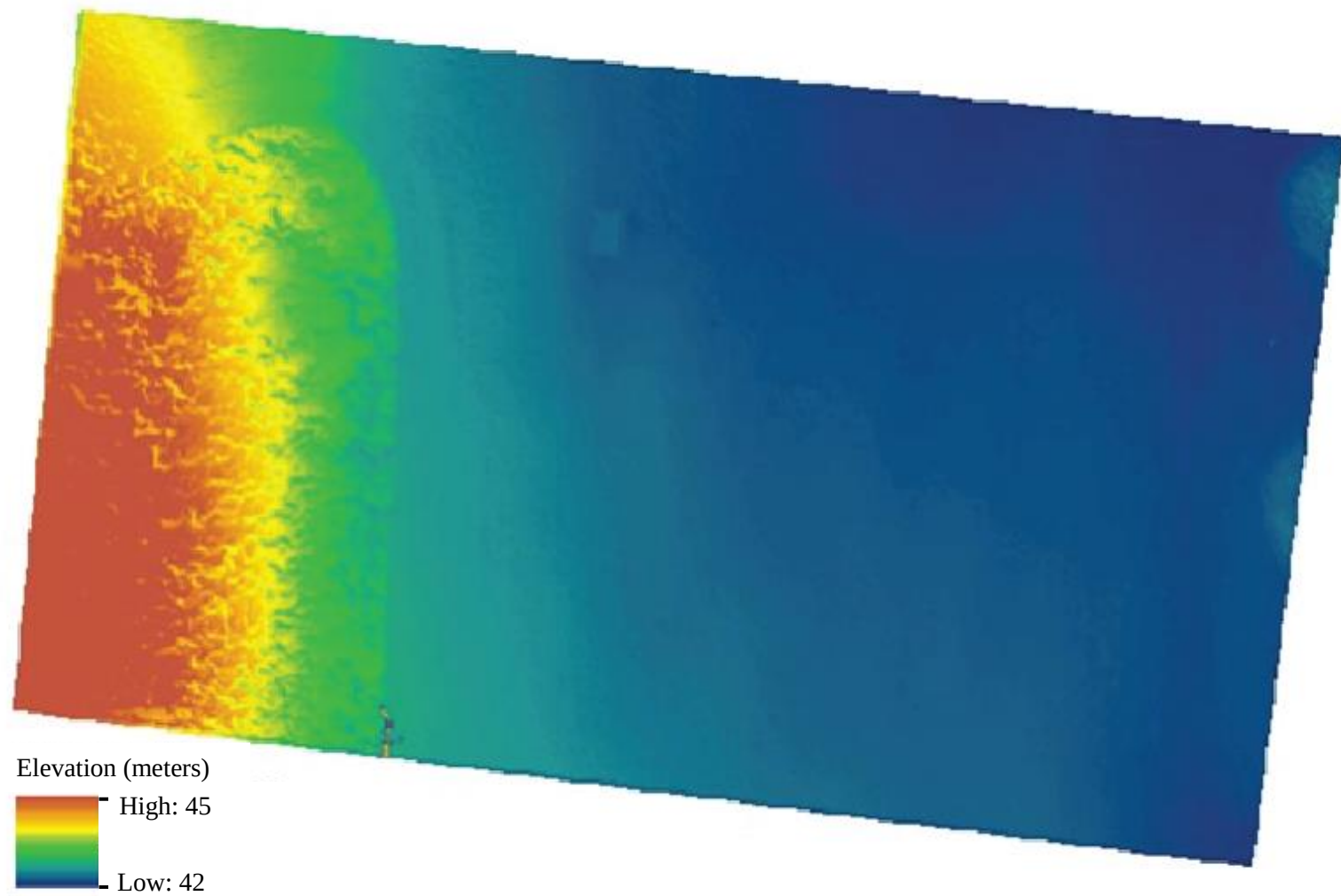


Figure 9. Digital Elevation Model (DSM) of preliminary study area (1.35 cm spatial resolution)

Both the DSM and the orthomosaic were corrected using the GPS locations of the GCPs. The DSM and orthomosaic created from the UAS imagery in PhotoScan were used for a hybrid method of semi-automated object detection with ArcGIS to detect the simulation landmines within the test study site. A 31 x 31 low pass Gaussian filter was used to filter noise and a 31 x 31 high pass Gaussian filter was used to enhance edges that survived the low pass filtering process a process commonly referred to as dilation and erosion. The filtering process was ran to twice to ensure that as much noise as possible was filtered out of the scene. This enhancement smoothed the texture created by the grass and ivy in the scene and brought out the detail of the simulation landmines. A PCA was performed to reduce the dimensionality of the data with the inputs to the PCA being: the original RGB bands, morphologically enhanced RGB bands, and the DSM. The final output of the PCA was constrained to seven total PCs. The PCs were visually interpreted, and the three PCs that best-detected simulation landmine locations were selected for the feature extraction process (An enlarged view of both results, and intermediary products can be seen in Appendix A). The PCs selected were PC1, PC4, and PC5.

At a known simulation landmine location, each component was visually inspected to determine a value to use as a threshold between the simulation landmine and its surrounding vegetation. This threshold was used to remove any pixel below the threshold reducing the suspected area that needed to be processed. The threshold process further reduced the amount of information contained in each PC and helped target the simulation landmines. After applying the threshold to the bands, another edge enhancement filter was applied to group similar pixels with each other and maintain the circular nature of the simulation landmines for distinguishing between the simulation landmines and vegetation

and noise. For the next step, the processed PCs were converted to binary images (background value = 0 and suspected mine = 1) and all three were summed together. The assumption was that a simulation landmine would show up in the majority of PCs and noise would only show up in one PC. Summing the bands removed a majority of remaining noise from the image. For example, if the summed pixel value of all three PCs returned two, then it was likely to contain a simulation landmine and was kept in the final image. If the summed pixel value returned 1, then the pixel was set to null because only a minority of PCs indicated a potential simulation landmine at that location. The final binary images were composited into an RGB image indicating potential simulation landmine locations.

To further discriminate from simulation landmines and noise, knowledge of the simulation landmines circular shape was leveraged; the composite raster objects were vectorized to calculate perimeter and area. With the simulation landmines, geometric properties determining a shape index were derived as the perimeter to area ratio (PAR) for each potential mine. Circles are known to have the lowest shape index or PAR of any shape, therefore objects with the lowest 25% PAR value were kept, and the rest were discarded (Angel, Parent, & Civco, n.d.; ASM International., 2000; Exner & Hougardy, 1988). The remaining identified areas were assumed to be potential landmines. Finally, the resulting vectors were buffered by 1 m to make their locations easier to identify on the original orthomosaic. A visualization of the described workflow is shown below in Figure 10 and Figure 11 and an enhanced view of a single simulation landmine is seen in Figure 12.

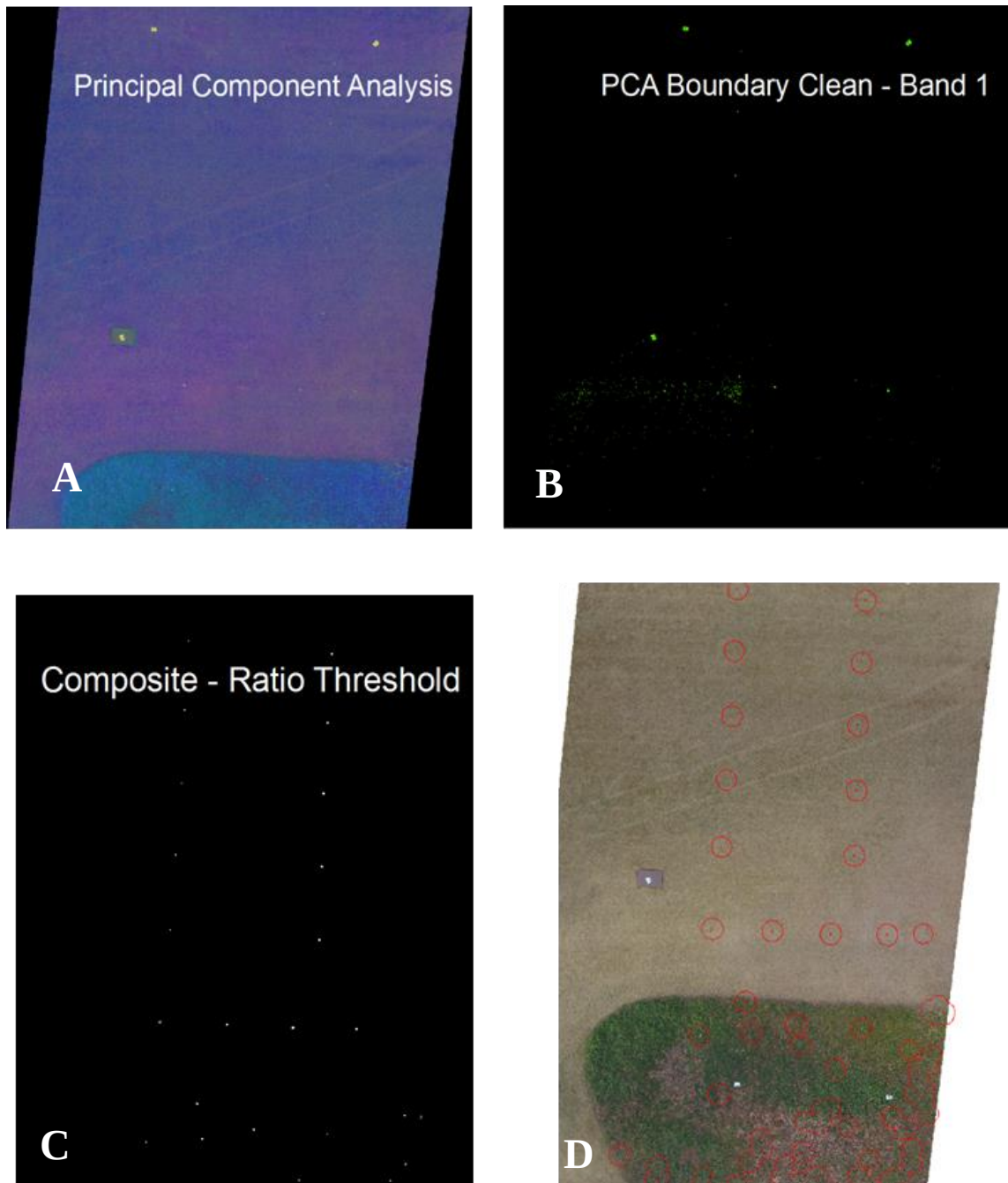


Figure 10. Selected outputs from workflow

- (a) Principal components analysis composite of components 1, 4, 5
- (b) Component 1 Boundary Clean Results
- (c) Composite of PAR threshold
- (d) Final Output of model overlaid onto orthomosaic

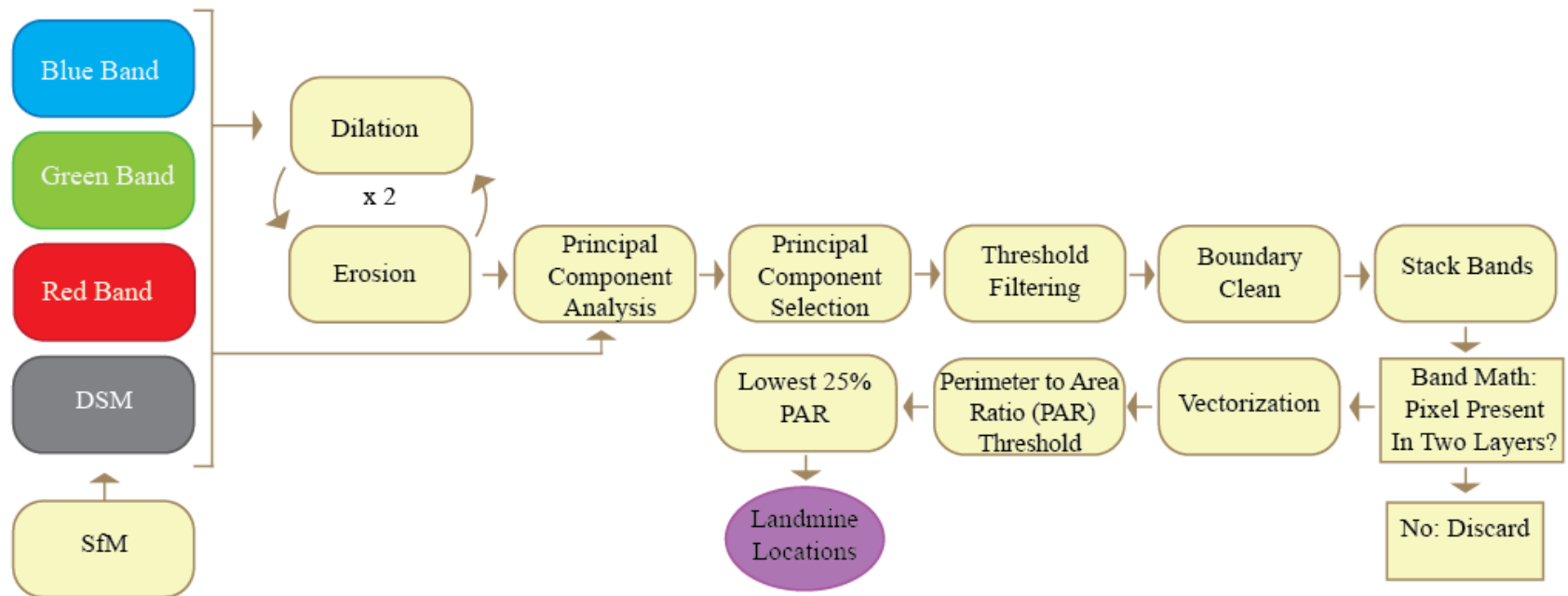


Figure 11: Image processing workflow used for preliminary study

Enhanced view of single mine in field through methodology

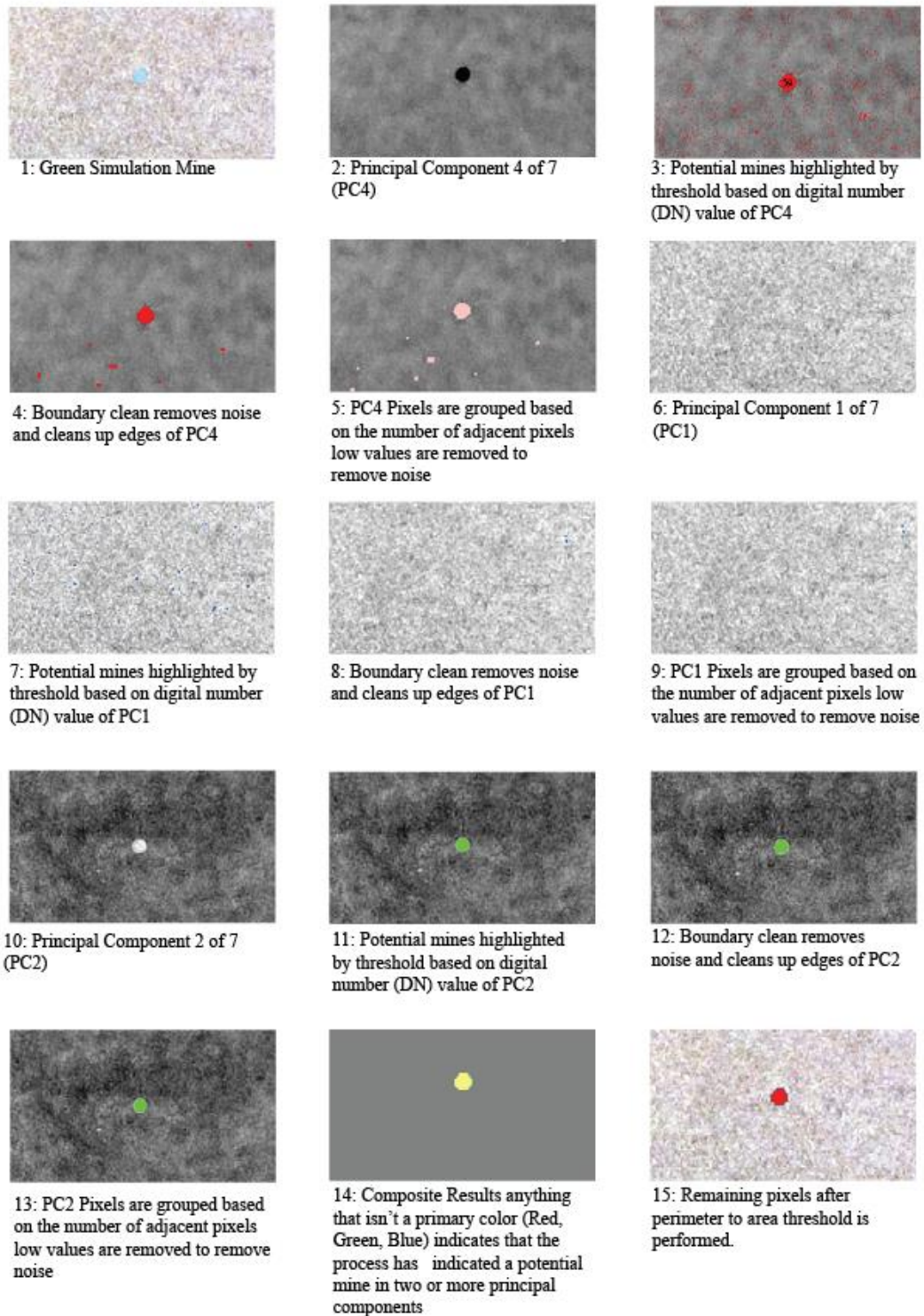


Figure 12: Enhanced view of a single simulation landmine in the field throughout each stage of the methodology

Results

Grass Land Cover

Of the 15 simulated landmines placed in the grass, 100% were found including both sizes and colors in a field of short grass vegetation. The detection success is due to the workflow's thoroughness in differentiating between a mine and a homogeneous land cover. The initial threshold of each principal component worked well in significantly reducing general background noise like vegetation. The noise that made it through the threshold step was removed by the boundary cleaning and compositing steps. These steps minimized noise of vegetation that was too similar in value to the landmines to be removed using the principal component threshold. Noise like shadows, mixed stems, rocks, and soil in the grass was much smaller in area and differed in shape from a simulation landmine, so they were easily detected with the PAR analysis.

Ivy Land Cover

The simulated landmines in the ivy vegetation cover were much harder to detect due to the landmines being 20% covered by overhanging foliage. Some of the landmines were intentionally covered to test the capabilities of detection. The detection accuracy of landmines in the ivy was 2/5 (40%). The results for the ivy were expected to be poor because of poor visibility of the simulated landmines within the ivy vegetation, but the relatively high detection rate was encouraging for preliminary results. One positive part of this methodology was that the boundary clean algorithm was still able to detect the circular edge of the partially exposed mines in the ivy, making the PAR ratio low enough to differentiate the mine from the ivy leaves. It seems that as long as part of the perimeter of the mine was visible the PAR was able to detect its circular nature.

Full Simulation Minefield

In total, the preliminary test detected 17 of 20 simulated landmines (85%). These results were derived from UAS aerial imagery obtained from a height of approximately 18 m with a flight time of fewer than 5 minutes to cover an area of 1070 square meters. By calculating the area of all suspected pixels, it was determined that the detection method reduced the search area to less than 1 square meter or 0.85% of the original area. In a real situation, potential landmines locations would be given to deminers preparing them when entering a minefield.

Conclusion and Future Work

The initial RGB simulation landmine detection results were promising towards developing a robust workflow for detecting surface simulation landmines. This research showed that with relatively little time and money invested, it is possible to create a methodology that has 85% success in detecting objects similar to circular landmines. The primary aspect of demining that this research attempted to improve was the time deminers spend exposed to potential landmine laden areas. The results showed that with roughly 10-12 hours of processing a deminer could reduce the area to be searched by 99%.

Two human factors in the methodology, however, should be removed with future research. First, the user should not have to select the best PCs to represent simulation landmines; making the workflow more applicable to different land covers. Second, a user should not be required to possess knowledge of physical traits of landmines in the area like size, shape, and color in order to determine the threshold value between landmine and background pixels. Thresholding can be problematic because a scenario

where deminers have existing knowledge of a minefield is unlikely to occur in a real-world field situation. Overall, the research has helped determine that it is feasible to use an off the shelf UAS; with a standard three-band camera almost all simulation landmines were detected. With the improvement of technical aspects of the methodology like the inclusion of a sensor that is sensitive in the near-infrared (NIR) portion of the electromagnetic spectrum, vegetation could be identified in the scene to separate target from the background and further improve results. Finally, even with only three bands, useful morphologic data can be extracted and used to tease out the simulation landmines from background scenes. The morphological data retrieved from the PCs showed that a combination of both spectral and morphological characteristics should be used for detection. Finally, the appropriate flying heights were determined along with overlap of flight lines for best Structure from Motion results saving time and energy for future research.

**DETECTION OF SIMULATION SCATTERABLE LANDMINES USING UAS
DATA AND TEMPORAL ANOMALY ANALYSIS²**

² Knight, A., Madden, M. Bernardes, S., Mishra, D., Morgan, N, Neel, N., Detection of Simulation Scatterable Landmines Using UAS Data and Temporal Anomaly Analysis, 2018, To be submitted to *Photogrammetric Engineering and Remote Sensing*

Introduction

Landmines are pressure activated explosives that vary in size based on the intended target. Anti-personal (AP) mines that are designed to kill or injure people are the most common form of landmine and can be as small as a few centimeters in diameter. A common style of AP mine is the scatterable mine that is designed to be placed by an aerial drop either from mortar or aircraft. Scatterable mines can render land useless by quickly deploying hundreds of landmines to an area, leaving behind a highly dense minefield for humanitarian deminers to clean up. Multiple methods exist for deminers to find landmines, ranging in scale from the use of satellite imagery to find suspect fields to metal detectors to find individual landmines. In order to detect individual mines, ground-based methods that use metal detectors and prodders that put deminers in harm's way have proven most effective. Instances of imagery acquired by unmanned aerial systems (UAS) have proven to be successful in military operations for individual landmine detection, and humanitarian applications are also becoming more common. This research will focus on analyzing orthomosaics derived from UAS image data analyzed using Structure from Motion (SFM) with anomaly detection and multi-temporal methods.

Background

Scatterable Landmines

To understand the global landmine problem, one must first understand what a landmine is and what makes them so dangerous. Merriam-Webster's dictionary defines a landmine as "a mine usually placed just below the surface of the ground and designed to be detonated usually by the weight of vehicles or troops passing over it." This definition attempts to categorize the over 700 different types of landmines in existence into one

group, but, the problem is much more complicated. There are three main styles of landmines: the most common and oldest style is buried landmines, the second style is improvised explosive devices (IED) which can be made from random materials and placed or buried, and the third style is scatterable landmines which will be the focus of this study. The common goal of all three of these styles of landmines is to induce fear in anyone who encounters them or learns about their deployment. Landmines are designed for one of two targets either vehicles or people. Anti-Tank (AT) mines target vehicles and are typically at least 30 cm in diameter and are capable of piercing armored vehicles when activated. Anti-personal target individuals and are smaller, ranging in size from as little as three to fifteen centimeters in diameter. Landmines are specifically designed to blend in with their surroundings; they are colored with camouflage paints or manufactured from camouflage-colored plastics. As time passes landmines become more dangerous as colors begin to fade further into the background and the mine's internal structure begins breaking down becoming more unpredictable (Keeley, 2003). These two characteristics, small size and blending in with their environment, make AP landmine detection using remote sensing techniques especially difficult.

Surface landmines are an important subset of the global landmines problem. Scatterable landmines are landmines that are designed to be strewn across the surface of the land quickly by mechanical methods. Airplanes or mortars are the primary distribution method for scatterable landmines and can quickly disperse hundreds of landmines across a landscape. During the placement process, landmines are sent flying through the air until they impact the surface of the ground where they become active. Scatterable mines are designed to render an area utterly useless with the density of

landmines in a field ranging from one to four mines per 32 x 32 square meters (Pike & Sherman, 2000). The time per mine it takes to deploy scatterable landmines is considerably less than those placed by hand and has caused an increase in scatterable mine usage. The increased number of landmines entering the environment adds to the already significant global landmine problem. To reduce the risk of mine contamination, scatterable mines are designed to self-detonate between 4 and 48 hours after becoming active, however, each mine has a dud rate of self-detonation failure.

Much of the information known about scatterable landmine dud rates comes from US reports on past conflicts. In a report to Congress, the U.S. The General Accounting Office states in its report, “GAO/NSIAD-93-212”, that the dud rate for the M77 scatterable mine used in the Gulf War ranges from 2- 22% (U.S. General Accounting Office, 1993). GAO-02-1003 further reports on U.S. landmine use, and states of the U.S. 20 million landmine stockpile, approximately 2 million mines were taken to the Gulf War where munitions saw a 12% higher dud rate than reported (U.S. General Accounting Office, 2002). It can be assumed that the same trend exists globally for other state forces, increasing the need for scatterable mine detection strategies as this technology proliferates.

Demining Operations

Two groups are combating landmine contamination with demining missions: military forces and civilian programs. In most military circumstances, only a partial clearance of the environment of landmines is necessary, just enough space to clear a path for troop and vehicle movement (Gasser, 2000). Humanitarian demining action works towards a different goal of 100% clearance to return the land to local populations since

roadways and agricultural fields are broadly used by many over time. Humanitarian groups face substantial funding challenges. Since the estimated cost of removing one mine is up to \$1000 with millions of landmines already in the ground the cost of demining quickly becomes exorbitant (Duttine & Hottentot, 2013). Further exaggerating funding issues is the estimated cost to demine an area is almost always much higher than the estimated economic yield of the land (Wolf & Barmazel, 2001). Despite funding issues, humanitarian groups still work towards a mine-free world.

Humanitarian demining missions designate the demining workflow into three levels (Wolf & Barmazel, 2001). Level 1 is a general surveying stage where the local populations are interviewed, and the information provided is used to delineate likely minefields and identify the types of landmines that are likely to be found. In Level 2 surveys, deminers use previously gathered Level 1 survey data to inform deminers where to start demining. The goal of a Level 2 survey is to discover an adequate number of mines around the border of the suspected minefield to statistically delineate the boundaries of the minefield for a future full clearance mission. The third and final level of a humanitarian demining mission is an exhaustive clearance that requires the field to be cleared to a nearly 100% clearance rate (Maathuis & Van Genderen, 2004). Wolf & Bamazel (2001) point to Level 1 surveys being the least costly but least reliable and Level 3 surveys being the most expensive but the most extensive and reliable. They theorize that any improvements to Level 2 surveys can be the most economically efficient and viable for future implementations. Any improvements to the Level 2 survey can be hugely beneficial in reducing the overall cost to demining groups.

There are many different military solutions for detection and mine clearance, examples include specialized metal detectors and rocket-propelled explosive ropes for lane clearance. There are presumably more solutions internationally and, in the U.S. classified space. One current detection technology used by the U.S. Army is the Coastal Battlefield Reconnaissance and Analysis (COBRA) system. The COBRA system is used by U.S. forces in advance of offensive beach breaching missions to detect minefields in the littoral zone (shallow water to the beach). The system works by using two sets of passive sensors recording spectral reflectance ranging from deep violet to middle infrared to detect spectral anomalies. The six-band data set is collected by two Xybion™ CCD video cameras equipped with filter wheels that spin in sync with the camera's frame rate to produce five images per band per second (Holmes, Schwartz, Seldin, Wright, & Witter, 1995). The images gathered by the two cameras are registered and use the Reed-Xiaoli (RX) constant false alarm rate algorithm (Reed & Yu, 1990). The formula to calculate RX is seen in Formula 2.

$$(2) \quad s_{RXD}(r) = (r - \mu)^T K_{L \times L}^{-1} (r - \mu)$$

Where r is the sample vector
 μ is the sample mean
 L is the number of spectral bands
 $K_{L \times L}^{-1}$ is the sample covariance matrix.

The RX detector works by using two concentric sliding windows to calculate the spectral mean of the inner smaller window centered within the outer bigger window and the spectral mean of the outer window. The Mahalanobis Distance of both the spectral means is calculated, and the difference is used to create an eigenvalue representing the difference in values. Large eigenvalues are more likely to be anomalies. Any resulting eigenvalue from the RX detector that exceeds a noise threshold has its magnitude

calculated and reported as a proxy for confidence in the anomaly results reported by the COBRA system.

The COBRA system is designed for on-the-fly minefield detection, but not for single-target mine detection. The results of the RX algorithm are returned for further analysis with a minefield detection algorithm that analyzes the pattern of anomalies with a log sum of confidence scores and returns a confidence score if the area is a minefield (Muisse et al., 1996).

Joseph Harsanyi, enhanced RX results by using a uniform target detector (UTD) given by Equation (3) to reduce the impact of background noise (Harsanyi, 1993).

$$(3) \quad S_{UTD}(r) = (1_{L \times 1} - \mu)^T K_{L \times L}^{-1} (r - \mu)$$

Where r is the sample vector
 μ is the sample mean
 L is the number of spectral bands
 $K_{L \times L}^{-1}$ is the sample covariance matrix.

A UTD subtracts the spectral mean of the background from one instead of subtracting the target spectral mean causing the UTD to act as a target detector looking for anomalies in background noise (Harsanyi, 1993). The UTD method offers enhanced results and is suitable for images with large volumes of background noise.

Structure from Motion

Structure from Motion (SFM) offers a single image analysis alternative to the image-by-image analysis done in the COBRA workflow. Structure from Motion uses multiple overlapping images taken from many different angles to create a 3D point cloud of the surface used to orthorectify or remove the distortion effects of image perspective

and terrain relief. The orthoimages are then mosaicked together to create a single seamless orthomosaic. The SfM process is as follows (Marshall et al., 2016):

- 1) Find distinguishable features to use as tie points in each image;
- 2) Identify tie points that are the same in multiple images to use as tie points;
- 3) Create a point cloud from the matched tie points of all images;
- 4) Use camera GPS metadata to scale point cloud;
- 5) Create a dense point cloud by filling gaps between tie points; and
- 6) Create an orthomosaiced image using elevation data from dense the point cloud and original images.

Orthorectified images generated by the SfM can be used for spectral analysis as long as an interpolation method that preserves original sensor recorded values is used; nearest neighbor interpolation is one example of a suitable interpolation.

Based on the results from manuscript 1, this study aims to follow Marshall et al. (2016) to analyze UAS image data with SfM and spectral anomaly detection to detect scatterable landmines and assess the potential use for humanitarian detection missions. The goals of the research presented in this chapter are:

- Test Reed-Xiaoli anomaly detection algorithm as a method for detecting randomly scattered landmine targets in an agricultural field site.
- Test time series analysis for change detection to indicate landmine locations.
- Develop a methodology that uses statistical thresholding to remove false positives from the results.

Study Site and Simulation Landmines

Study Site

The study site (pictured in Figures 13, 15, 14, and 16) was set up on a local farm in Watkinsville, GA simulating farmlands that are often strategically mined. Examples of similar land with minefields include Germany's Iron Curtain in World War II and Croatian farms during the 1995 Croatian war of independence from 1992-1995 (Maathuis, 2001). A closeup of the land cover seen in Figure 14, shows ants commonly created circular ant hills out of dirt and circular grass clumps were common and could be confused with scattered simulation landmines.



*Figure 13: Watkinsville, GA Test site from eye level perspective
(July, 2018 after mowing)*



Figure 14: Overhead perspective of test minefield with 10 simulation landmines placed. Field located in Watkinsville, GA. Photo acquired February 2018



Figure 15: Close-up of study site B taken from April 20th orthomosaic - Grass clumps are common and occur as circular features. Red -Dirt features can occur as circular or linear.



Figure 16: Overview of the study site taken from a nadir perspective. Taken from April 20th Orthomosaic. Red Honda Cr-V and Mercury Mountaineer in bottom right for scale

Simulation Landmines

Simulations landmines were created to replicate live scatterable landmine likely to be found on a battlefield like the one pictured in Figure 17. Simulation landmines were 7.5 cm in diameter and colored either tan or green. The simulation mines were made using quickcrete poured into a two-piece 3D printed mold. The molded quickcrete was coated with plastidip a conventional rubberized paint to give the simulation landmine a spectral response as similar as possible to a real plastic landmine. The spectral comparison seen in Figure 18 shows the simulated mines are similar in spectral response, the only

significant differences being between 720 nm and 850 nm. The most substantial difference is seen between the tan simulation mine and the tan plastic mine.

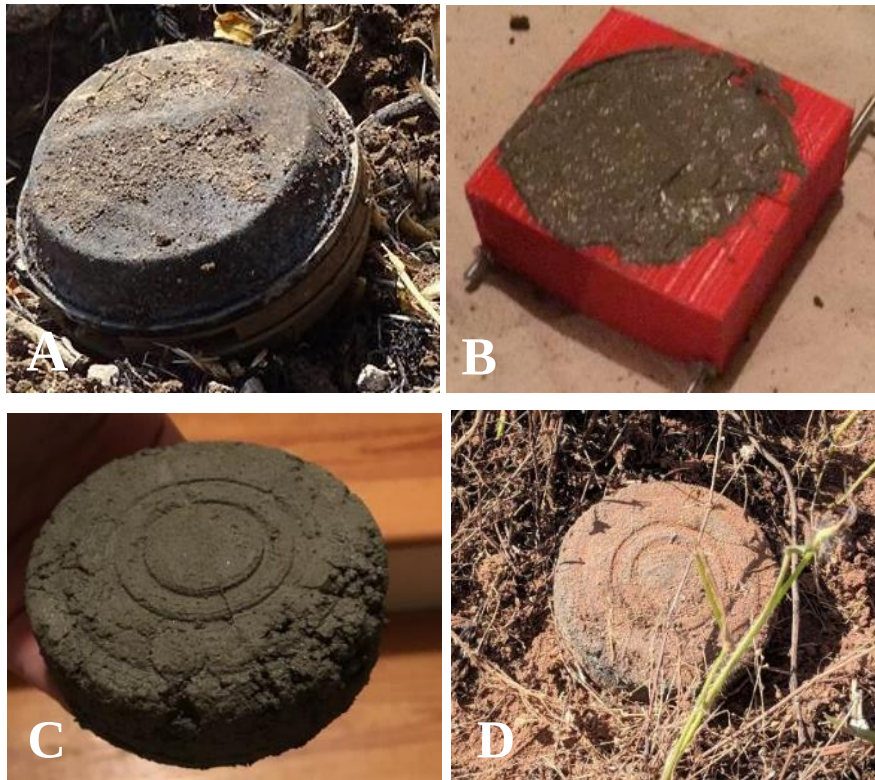


Figure 17: A. Russian scatterable landmine found in the field
 B. 3D printed landmine mold filled with quickcrete
 C. Quickcrete mine coated in Plastidip
 D. Simulated mine six months after placement

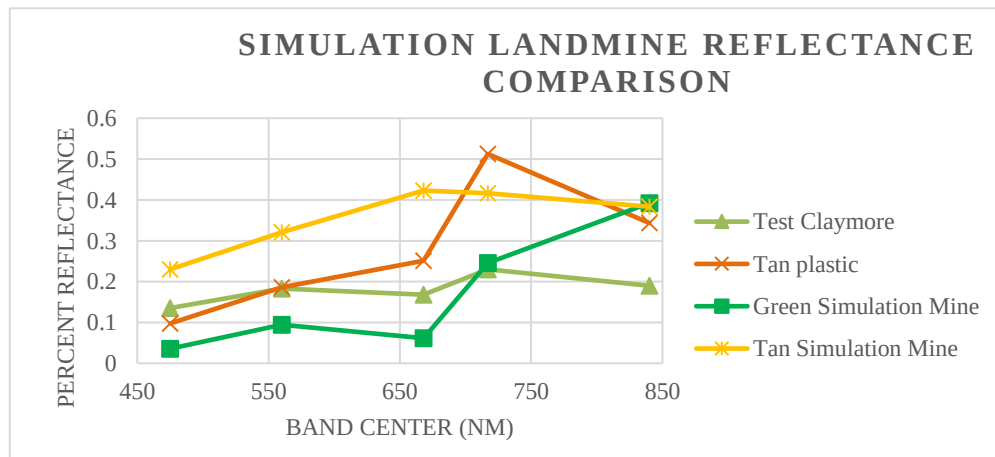


Figure 18: Simulation Landmine Reflectance Comparison

Minefield Layout

The mines were placed during December 2017 by a third party to ensure that any detection results were unaffected by the bias of previous knowledge of simulation landmine placement. Green simulation landmines were provided to the third party with no requirement for the number of mines to be placed. After all analysis detection was complete, and the simulation landmines identified in the workflow were recovered, the original placement information was shared by the third party. In total, there were ten mines placed on the test site with eight recovered after the study. The two mines that were not recovered are assumed to have been accidentally removed by farm equipment used after the study.

Methodology

Data Collection

A DJI Phantom 4 Pro (P4P) quadcopter was used to collect imagery during this study. Data were collected with a dual sensor approach employing both the stock P4P camera and a MicaSense RedEdge (RedEdge) multispectral sensor attached so data from both sensors could be collected in tandem. The P4P is equipped with a 20-megapixel RGB camera that can attain extremely high spatial resolution imagery from a moderate UAS flying height (e.g., with a flying height of 15 m, the spatial resolution of resulting imagery is 0.41 cm). The RedEdge sensor has a reduced spatial resolution (e.g., flying height of 15 m yields imagery of 1-cm spatial resolution) and is designed to collect data that are relevant to vegetation health. The RedEdge sensor collects five bands of data, ranging from visible to near-infrared, that are useful in creating vegetation indices. The

wavelength of the band center and bandwidth of the five RedEdge bands are listed in Table 3.

Table 3: MicaSense RedEdge sensor specifications (MicaSense, 2018)

Color	Band Center (nm)	Band Width (nm)
Blue	475	20
Green	560	20
Red	668	10
Red Edge	717	10
Near Infrared	840	40

Ground control points (GCPs) that are targets of known geographic locations were evenly distributed around the perimeter of the study area, and their locations were recorded using a Trimble GPS unit within a +/- 1 to 3 m accuracy. The GCPs allowed datasets from different dates to be correctly georeferenced; as the UAS GPS is not accurate enough to use for the pixel-to-pixel alignment required for temporal comparison. The PIX4D smartphone app was used to create the flight plan and pilot the P4P during all three flights. Figure 19 shows the flight plan used on each flight. Flight lines have 90% overlap and sidelap for the P4P camera and 80% sidelap and 80% endlap for the RedEdge camera. The section highlighted in red in Figure 19 was too close to the tree line for autopilot, so it was flown manually with the same altitude and similar sidelap, endlap as the automated flight.



Figure 19: Flight plan in PIX4D interface using an iPad as flight controller for Phantom 4 Pro. The portion highlighted in red was flown manually due to proximity of trees.

Three sets of data were collected to provide an opportunity for multi-temporal analysis of the study site. The dates were roughly one month apart although the range was not exact because weather conditions forced flight delays and acquisition dates to change. The dates of UAS image acquisition were: February 27th, 2018; March 23rd, 2018; and April 20th, 2018. The data collection dates coincide with the region's growing season meaning that for each date the study area had seen progressively more rain than the prior date. Conditions during each flight were clear to avoid shadows from clouds and within two hours of solar noon to ensure enough radiance reached the RedEdge Sensor. Flight times were between 11am and 2 pm.

Flight altitudes were determined by calculating the minimum ground sampling distance needed for the RedEdge to attain imagery of the desired spatial resolution for this study. During the February 27th flight, the altitude of 33 meters was chosen because it would give a spatial resolution of 2 cm, small enough that the simulation landmine (7.5 cm diameter) would be represented by multiple pixels. The March 23rd and April 20th

flights were flown at 15 m altitude for approximately 1 cm spatial resolution based on information gained from initial processing results and flight observations.

Before and after each flight, images of a calibration panel were collected and used to calculate a calibration factor for each band with specialized software (Bernardes, 2018). The before and after calibration factors were linearly scaled using the time of acquisition for each calibration panel's image. A unique time-adjusted calibration factor for each image was used to convert the imagery from radiance to reflectance. No atmospheric corrections were needed due to the low flight altitude. Data from the P4P camera were not converted to reflectance because the sensor was not designed for scientific measurements and therefore was not used in any spectral analysis.

The SfM program Agisoft Photoscan 1.4 was used to create orthomosaics for each date from the calibrated images (Agisoft LLC, 2018). The calibrated photos were aligned at the highest processing setting, meaning that each image was upscaled by a factor of four before key points were detected. Upscaling each image helps to pinpoint the location of the key points within the image and can increase the overall accuracy of the point cloud. The point cloud was filtered using the mild setting to remove any extraneous points while preserving small details. Based on the photo-alignment step and GPS metadata, a depth map of each image was generated and used as a guide to densify the original point cloud into a dense point cloud. From the dense cloud, an orthorectified image mosaic (i.e., a seamless mosaic of the individual orthoimages "stitched" together) was generated by orthorectifying the original images using elevation derived from the dense point cloud.

Four orthomosaics in total were created; the orthomosaic created from the P4P data on April 20th can be seen in Figure 20; all other orthorectified mosaics can be seen in Appendix B.

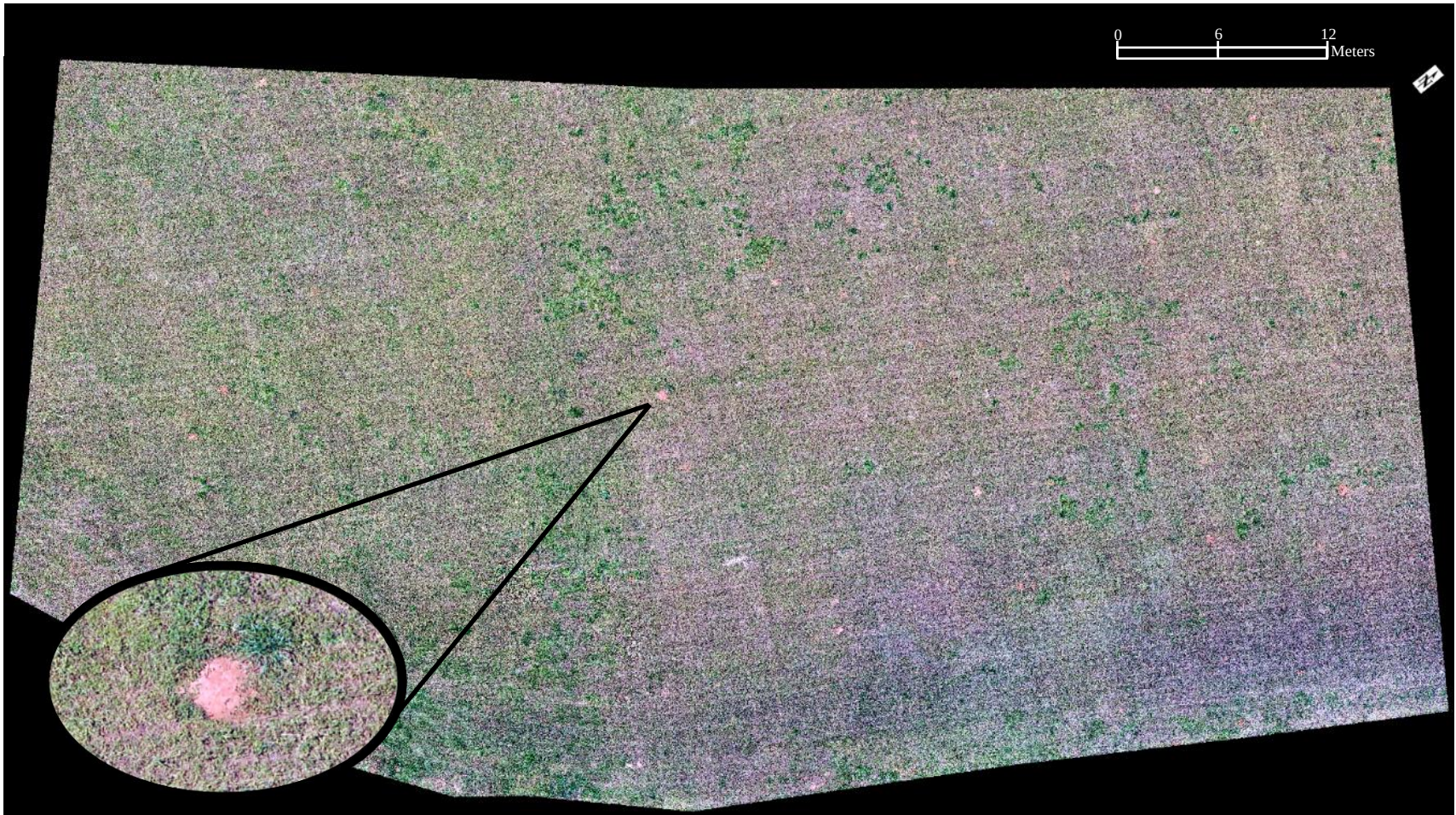


Figure 20: Orthorectified mosaic created with Agisoft Photoscan using stock Phantom 4 Pro camera data from April 20th.

The map callout highlights an anthill which was a common feature in this scene

With SfM complete, all further image processing of the orthomosaics used Harris Geospatial Solutions ENVI 5.4 program. For multi-temporal analysis, each image needed to be aligned as close to pixel to pixel registration as possible. Because there was an error in the image GPS location metadata (1-3 m), georeferencing was necessary to align each image. The P4P stock camera orthomosaic taken during April 20th was chosen to be the base image to reference each of the five-band RedEdge orthomosaics. First, the location of each GCP in the base image was corrected by using the previously collected GPS data. When referencing the orthomosaics, at least ten tie points were distributed across the scene, and a second-order polynomial transformation was used. The average root mean square error (RMSE) for each image was less than four meaning the error in registration was up to four pixels. This RMSE was deemed acceptable, and later in the workflow, a small correction buffer was applied to negate any issues that might arise from the registration error.

With all the orthomosaics prepared and aligned, a UTD kernel was used to process each image. A UTD kernel the size of 31 x 31 pixels was chosen because it was roughly three times the width of a simulation landmine, ensuring that background pixels would always be considered by the UTD filter. Using the results of the UTD for each date, pixel value frequency statistics were calculated, and a threshold representing the pixel values of the top three standard deviations or higher (0.05%) was used to remove noise lower than this threshold and leave only significant UTD results (Figure 21-23).



Figure 21: Top 0.05% Uniform Target Detector (UTD) results for February 27th

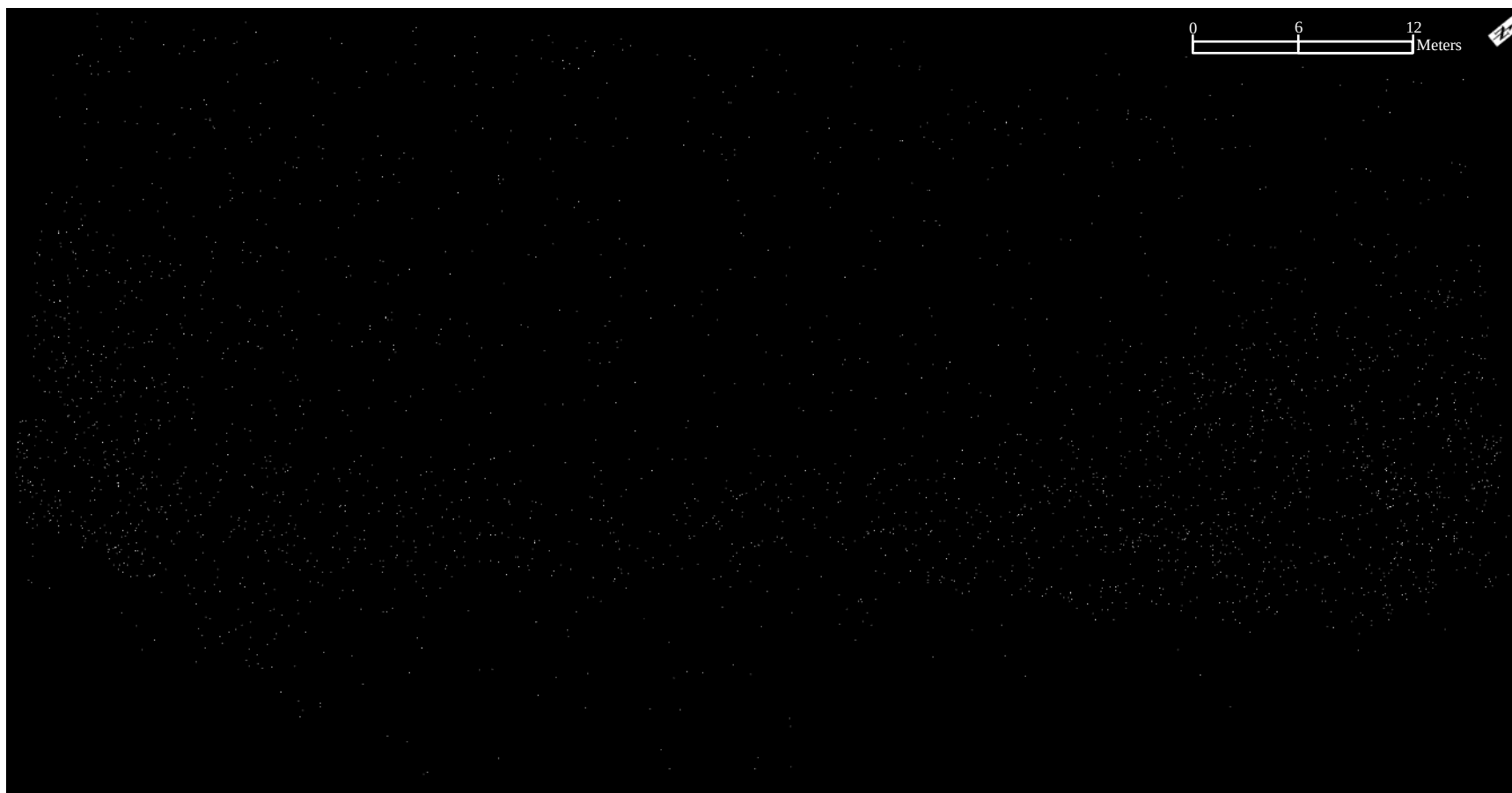


Figure 22: Top 0.05% Uniform Target Detector (UTD) results for March 23rd

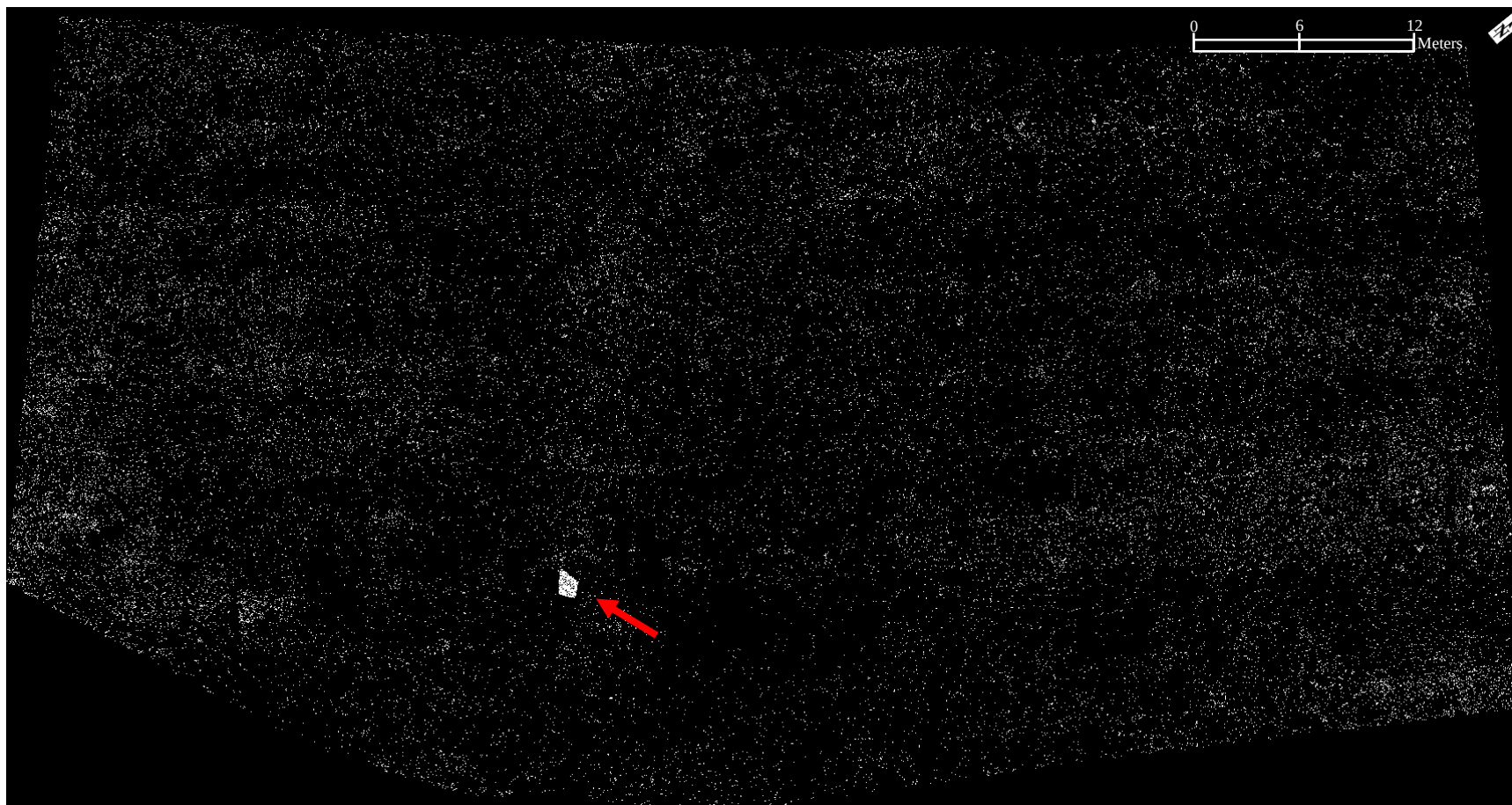


Figure 23: Top 0.05% Uniform Target Detector (UTD) detector results for April 20th. Artifact of SfM indicated by red arrow

To further enhance the UTD results, a Normalized Difference Vegetation Index (NDVI) was calculated for each original orthomosaic. Each orthomosaic was visually inspected to find a conservative NDVI threshold (0.5) that would eliminate very healthy bright green vegetation from the scene. Any pixels removed by this threshold were removed from the significant UTD results. The final results of the UTD were converted into a binary image.

The binary image for each date's significant UTD results was buffered by eight pixels to negate any misalignment issues from referencing the five-band imagery. The buffered results were added together (Figure 24) to remove outlier results that only appeared in one of the three dates. Based on the sum of the UTD results any pixel with a value of two or more was identified as an anomaly in at least two images and was considered a possible positive result (i.e., possible simulation landmine), pixels with a value of three were identified in each date and considered a high confidence positive result. The results were overlaid onto the April 20th P4P orthomosaic to leverage its high spatial resolution and lack of shadows from the adjacent tree line. This image was visually inspected, and erroneous UTD results were removed based on the viewer's interpretations of the scene and the results. An overview of the entire methodology can be seen in Figure 25.

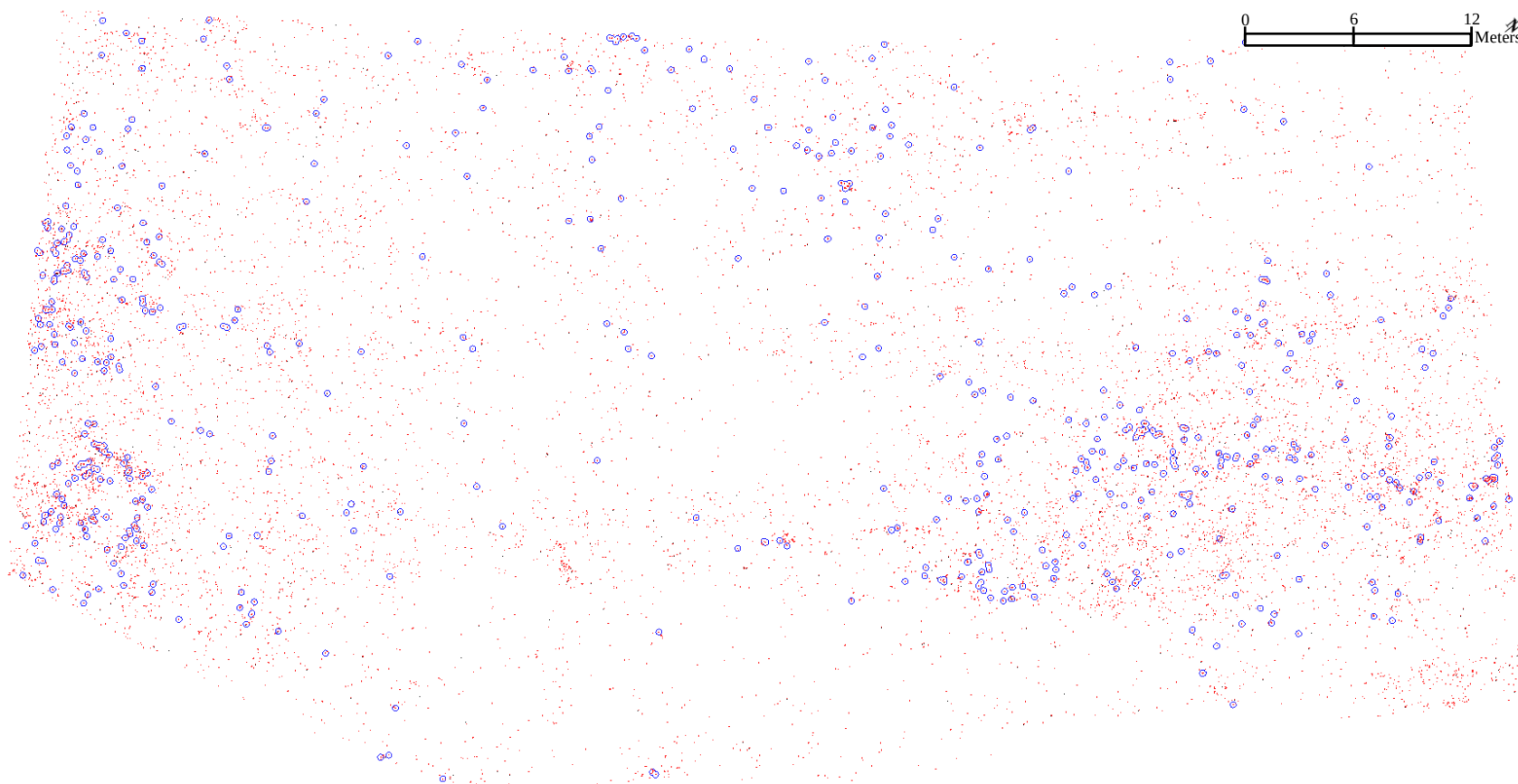


Figure 24: Results of multi-temporal Uniform Target Detector (UTD) analysis. Red indicates pixels detected in two dates, Blue circles indicate pixels detected in all three dates.

MicaSense RedEdge Datasets collected on: 2/27/2018, 3/23/2018, 4/20/2018

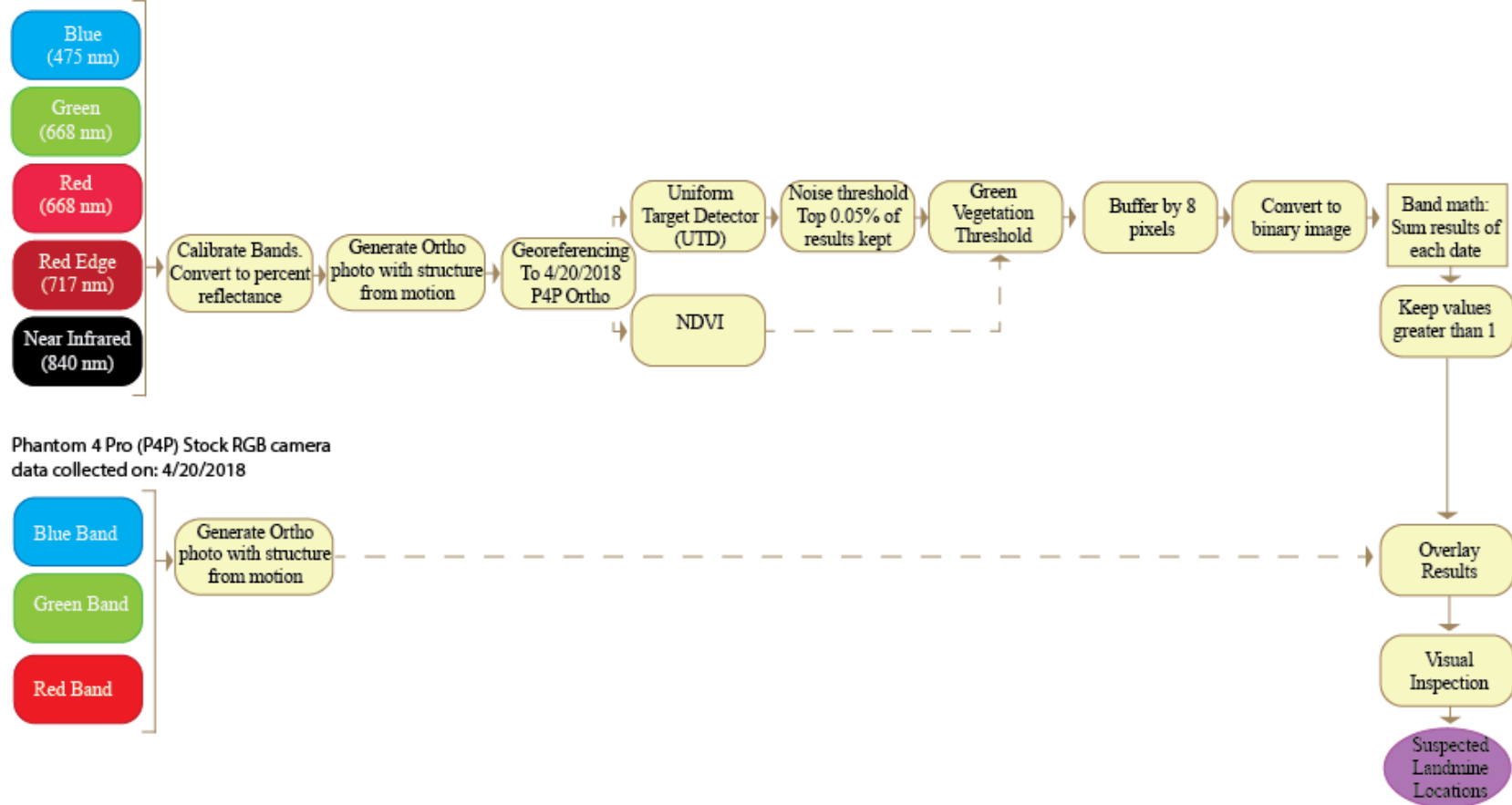


Figure 25: NDVI assisted Uniform Target Detector (UTD) multi-temporal methodology

Results

The UTD results had an unusually high number of false positives (i.e., predicted landmines that were not actual simulation landmines) with roughly 33,000 in total. However, based on visual interpretation, a majority of false positives were removed from consideration in the final results. Most of the false positives were dirt clumps, grass shoots that were not removed with the NDVI assisted temporal anomaly detection.



Figure 26: Left - Examples of grass shoots and dirt patches that were incorrectly identified as anomalies and possible simulation landmines. Right - April 20th P4P orthomosaic overlaid anomaly detections showing grass and dirt have been incorrectly identified.

A smaller portion of the false positives was caused by the buffering required to align each date, it is impossible to quantify the percent of false positives caused by the buffering, but slivers (an indicator of the buffer) are visible throughout the UTD results.

In terms of area, the total area covered by the UTD results was roughly 65 square meters or 2.2% of the original study area, but the results were spread across the study site. After a visual inspection, twelve anomalies were identified as potential simulation landmines, and the locations were recorded on the April 20th image indicated by squares in Figure 27. A GPS was used to navigate to the exact location of the potential simulation

landmines, but because of the GPS accuracy (approximately +/- 3 m), a 3-m search radius around the GPS location was searched to negate any location errors.

Of the twelve suspected simulation landmines, only two simulation landmines were confirmed after a physical search of the location; their positions are indicated by the red stars in Figure 27. A close-up of landmine 4 (Figure 28) and landmine 8 (Figure 29) are pictured below. The multi-temporal UTD was able to detect two of ten (20%) placed simulation landmines. Additionally, the April 20th P4P image which was overlaid with the methodology results and used for visual inspection only had 2 of 10 simulation landmines were visible.

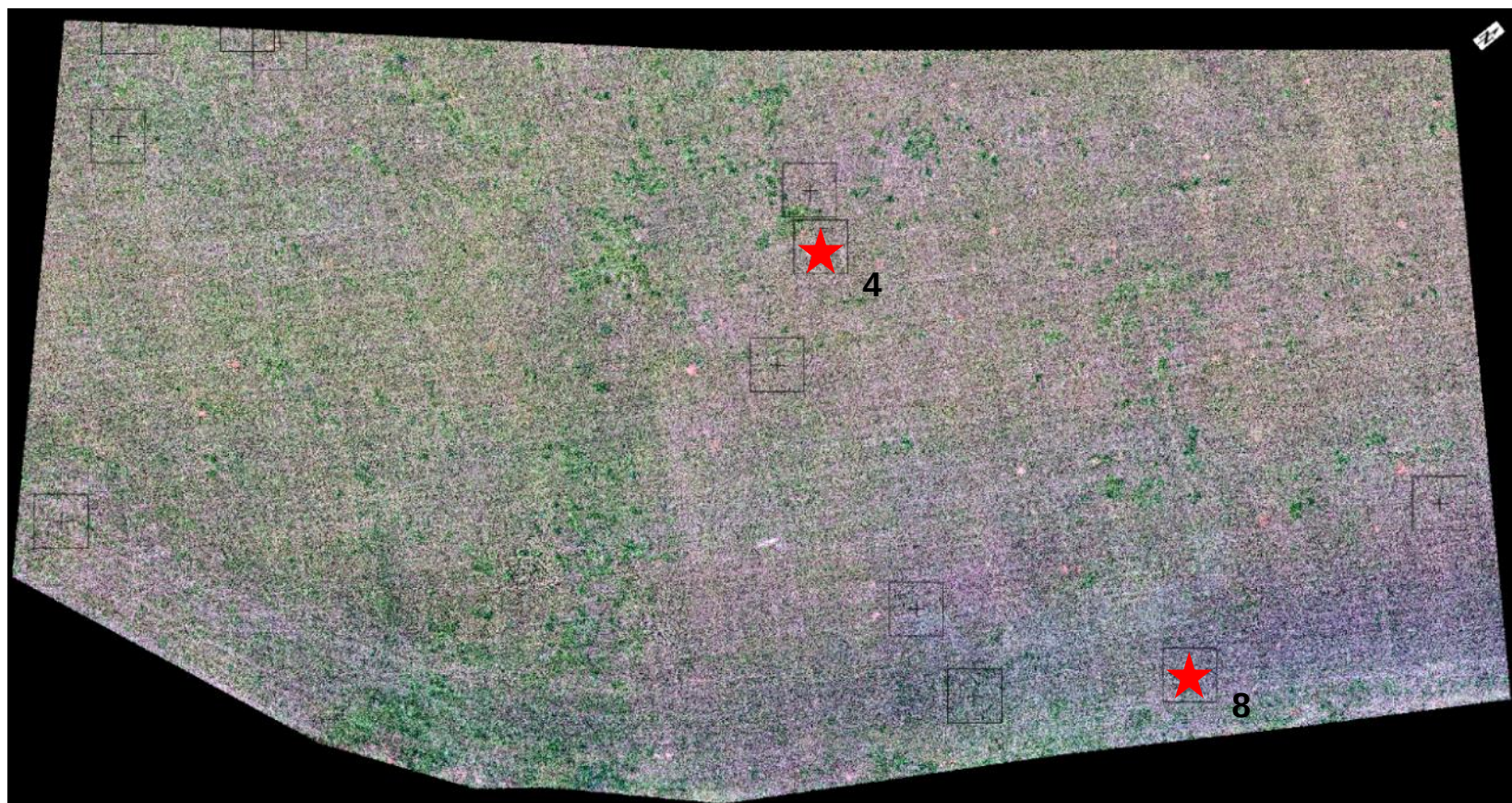


Figure 27: Potential simulation landmine locations (Black Squares) based on UTD. Red stars are confirmed simulation landmines



Figure 28: Confirmed green simulation landmine 4, six months after placement



Figure 29: Confirmed green simulation landmine 8, six months after placement

After simulation landmines 4 and 8 were found, a post-detection survey was performed and using location information for each simulation landmine, eight of the total ten simulation landmines were found, and locations are plotted in Figure 30.

After the post-detection survey, it became clear that only 6 of 8 simulation mines were visible during February and March and 4 of 8 simulation mines were visible during April. This limited the full detection possibilities of the UTD. It is interesting to note that the February image had the worst spatial resolution of any image but still had the most simulation landmines visible, the image with the highest spatial resolution image (April 20th P4P) had the least simulation landmines visible. This is a major indicator that time since placement is the number one factor in simulation landmine visibility. Likely another factor that impacts visibility is the quality of the imager; the P4P experienced contrast issues which made the simulation landmines blend in with the environment.

For the eight known simulation landmine locations, Table 4 shows the percentage their surface visible in each image. There is a clear seasonality in the results showing that as the growing season began less of the mines became visible leading to reduced average visibility over time. February and March both had 6 of 8 simulation landmines visible and April only had 4 of 8 simulation landmines visible. Table 5 shows the percent of each mines visible surface that is detected by the UT results. Unlike the visibility results, the UTD results seemed to be uninfluenced by seasonality with average UTD detection of roughly 60% for each month. These were promising results showing that if a landmine was visible in a real situation, it could be detected by the UTD. Figures 31 and 32 show a close-up of each simulation landmine by date with associated statistics. Ground-based images of each mine take from the field can be viewed in Appendix C.

Table 4: Percentage of simulation landmine visible in the image by date

Mine #	Feb. 27 th	March 23 rd	April 20 th
1	67%	78%	59%
2	40%	96%	26%
3	0%	22%	0%
4	100%	63%	77%
5	45%	0%	0%
6	58%	15%	0%
7	0%	0%	0%
8	100%	76%	66%
Average	51%	43%	28%

Table 5: Percentage of simulation landmine visible in the image detected using UT detector by date

Mine #	Feb. 27 th	March 23 rd	April 20 th
1	98%	100%	34%
2	50%	4%	100%
3	NA	100%	NA
4	100%	42%	41%
5	45%	NA	NA
6	11%	10%	NA
7	NA	NA	NA
8	95%	87%	66%
Average	64.8%	57.16%	60.25%

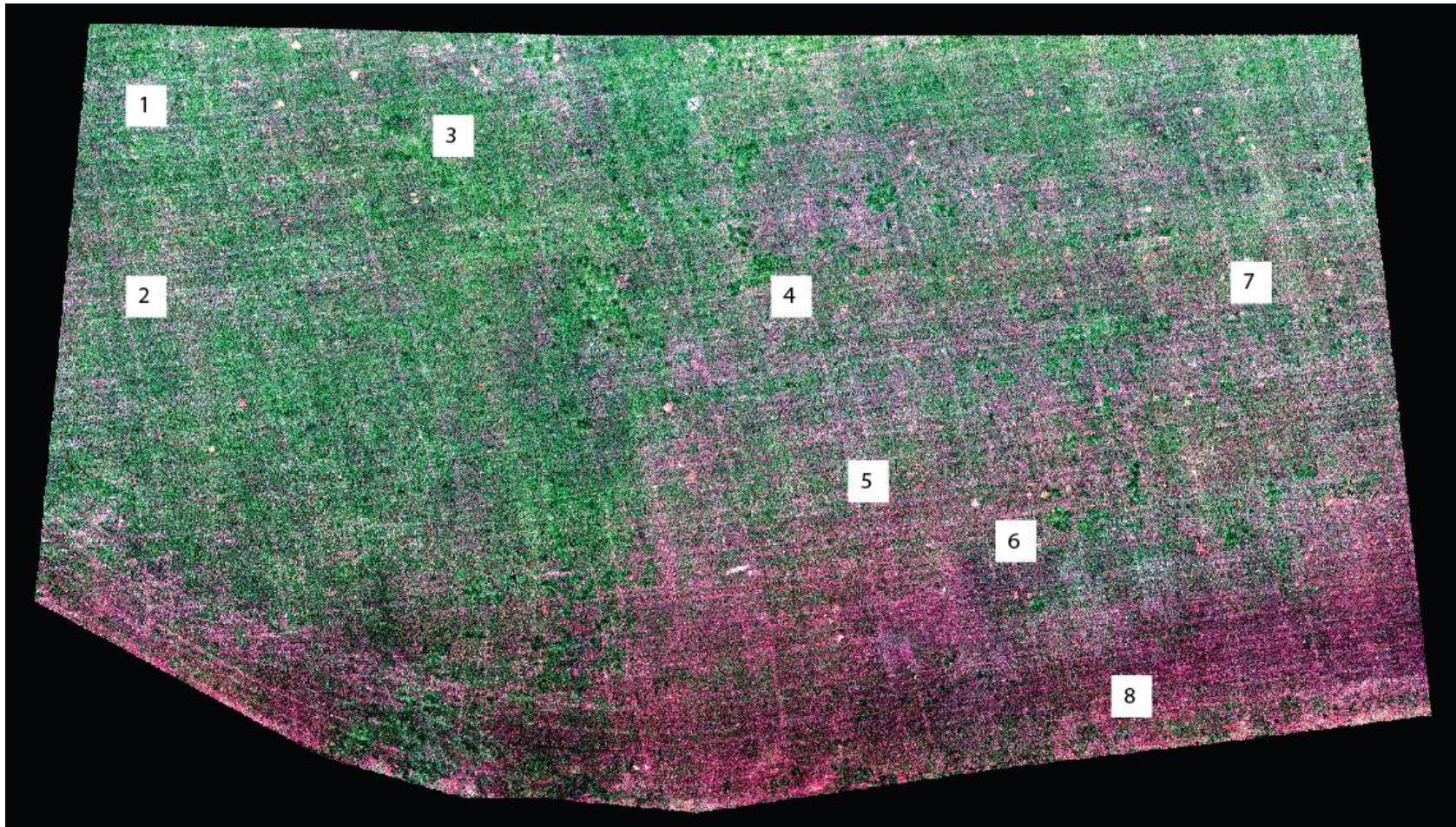


Figure 30: Location of each simulation landmine within the scene

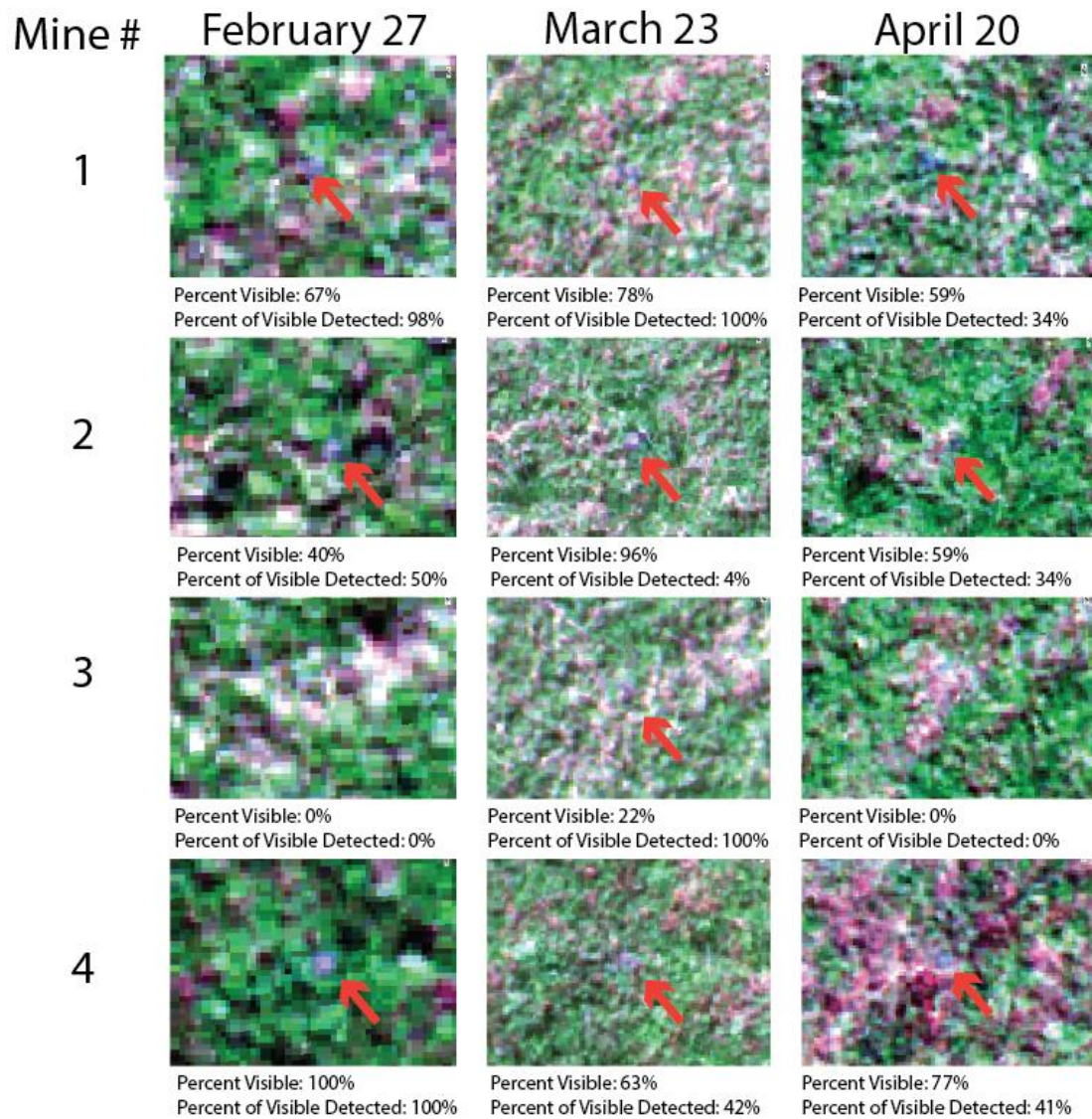


Figure 31: Simulation landmine locations (1-4) indicated by red arrows. Percent of simulation landmine surface visible in image. Percent of visible simulation landmine that is detected by Uniform Target Detector (UTD)

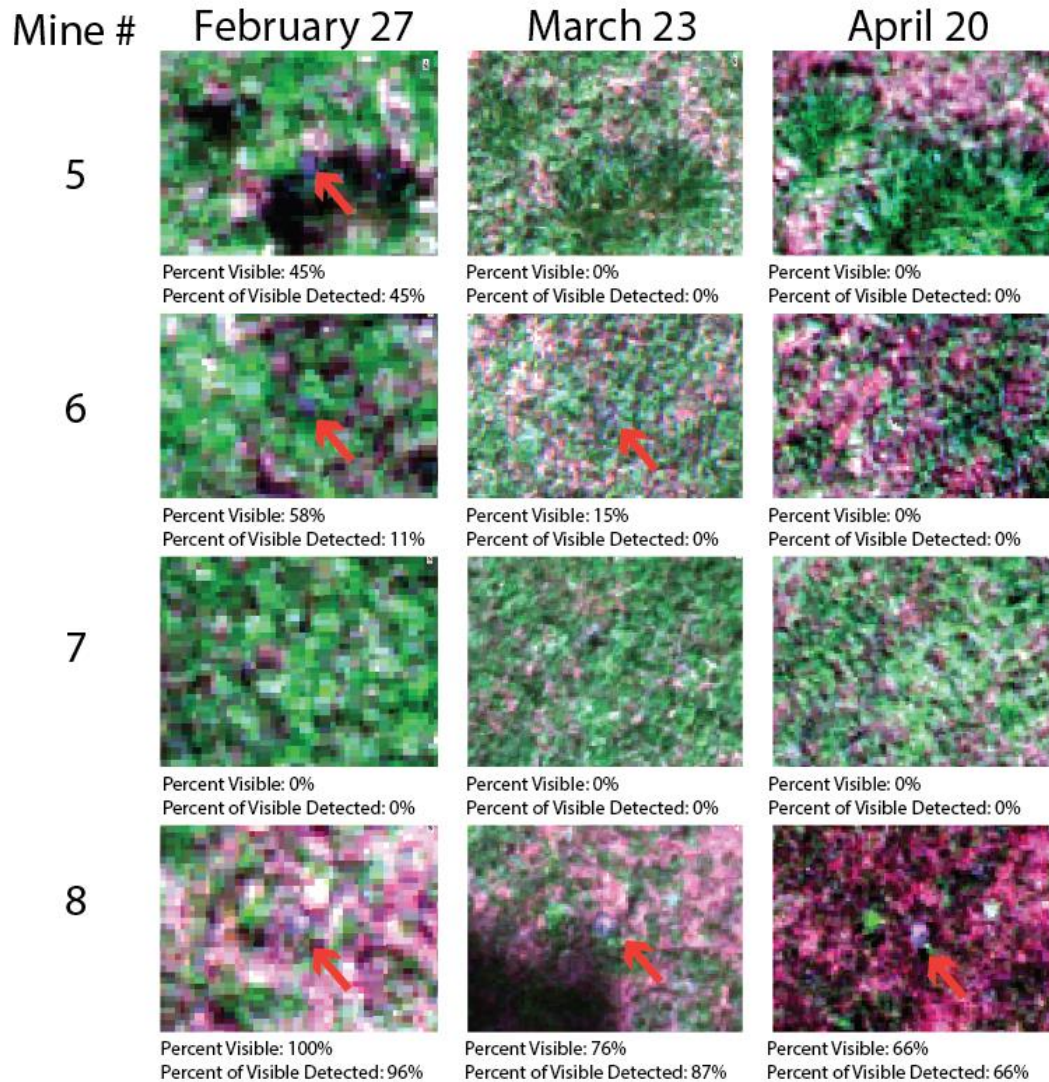


Figure 32: Simulation landmine locations (5-8) indicated by red arrows. Percent of simulation landmine surface visible in image. Percent of visible simulation landmine that is detected by Uniform Target Detector (UTD)

After the post-detection survey, an NDVI threshold including all of the mines (0.12 - 0.45) was used to see if a simple threshold could give similar results to the UTD results. The image was thresholded, and a total area of 1171 m² was still considered a potential simulation landmine. If this study had access to real landmines, the suspected area could most likely be reduced further because the NDVI values of the mines would be lower due to their lower NIR response than the simulation landmines. Even considering this there was still a significant amount of noise that survived the threshold which included dirt and browning vegetation indicating that a more sophisticated response needs to be taken in detection. These results indicated in Table 4 indicated that greening vegetation did not improve detection possibilities. The results of post-detection NDVI also showed that a detection method based purely on the greenness of vegetation was ineffective and a more complex method like the UTD results was needed for detection.

Conclusions

This study set out to determine if the use of anomaly detection algorithms (i.e., RX and UTD) were useful in detecting individual scatterable simulation landmines using visible – NIR data collected with a UAS. Of the ten simulation landmines blindly placed in an agricultural pasture, two were found (20%). Although the detection rates of this methodology were low, they could be greatly improved with better spectral resolution. Many false positives from the UTD were dirt that could not be removed from the scene in the way vegetation was with NDVI. With the addition of a middle infrared/thermal band soil indices could be used to remove the false positives created by dirt based on soil

moisture differences with the dry simulation landmines assuming they do not become covered by soil.

In addition to spectral resolution, a camera that is capable of higher spatial resolution from higher altitudes could provide better results. The increased footprint size covered by each of the images would allow the study site to be captured at the same or higher spatial resolution with fewer images. With fewer data pixels to process, SfM would be less intensive and prone to errors like the one seen in Figure 22 and would reduce the errors when georeferencing the imagery. By improving the SfM results, there would be fewer alignment issues eliminating or reducing the size of the buffer needed to align UTD results for a multi-temporal analysis. Eliminating referencing errors would enable the use of new processes to enhance UTD results like morphology filters and edge detection filters.

Time since placement proved to be an essential factor. As a general trend, most of the simulation landmines became less visible with time as vegetation surrounding the simulation landmine targets grew, and weathering occurred making the sections of the simulation landmines less visible and less likely to be detected. The consistent reduction in simulation landmine visibility over time suggests that flying UAS imagery should take place as close to the time of placement as possible to provide optimal results. It may not be possible to fly an area immediately after placement, but once an area is suspected of containing landmines and is safe to fly it should be done so immediately. Many suspected areas are large and take time for deminers to work through. By collecting UAS aerial image data from the beginning, deminers may be able to identify landmines in the central regions of suspected areas that could be covered by growing vegetation by the

time human deminers reach them. Even without 100% clearance of the landmines from the surrounding vegetation, this methodology reduces the risk posed by a mine-affected land by removing some of the landmines, making the job of demining safer. The methodology still is useful as an initial step in the demining process and serves as a launching point for future projects.

CONCLUSION

Throughout the flight collection and preprocessing stages in manuscript 1, many lessons were learned that informed the study design for manuscript 2. Two main changes involved flight planning. The UAS imagery acquired for the Site A test site in Athens, GA and the results of the PCA image processing it was determined that there was a need for greater image overlap to attain the highest levels of SfM image processing quality in Agisoft PhotoScan. By implementing 90% overlap for the RedEdge sensor, the SfM results achieved a much higher 3D point cloud spatial resolution, which allowed the methodology to detect small features such as simulation landmines. There was also a greater understanding of how filtering in the dense point cloud impacted the results of the orthomosaic. The second study of Site B in Watkinsville described in manuscript 1, used mild depth filtering instead of aggressive filtering, which removed erroneous tie points but left small details in the dense cloud. Both changes, along with a lower flying altitude led to the creation of a higher quality orthomosaic for the second study described in manuscript 2.

Between the UAS flights of Sites A and B, a redesign of a commercial RedEdge mounting solution designed for a P4P was required. The mount was changed so that the RedEdge sensor could be used with a P4P so not to block down-looking sonar sensors used by the P4P (to detect the distance to the ground) and still allow the P4P camera to

operate simultaneously. The mount (see Figure 33), allows both the RedEdge sensor and the P4P camera to simultaneously collect data from a nadir perspective while maintaining a full range of motion for the P4P camera and used by the flight operator for manual navigation, if necessary. Creating a dual mount solution was essential to the study because having simultaneously collecting data made the datasets comparable between one another.

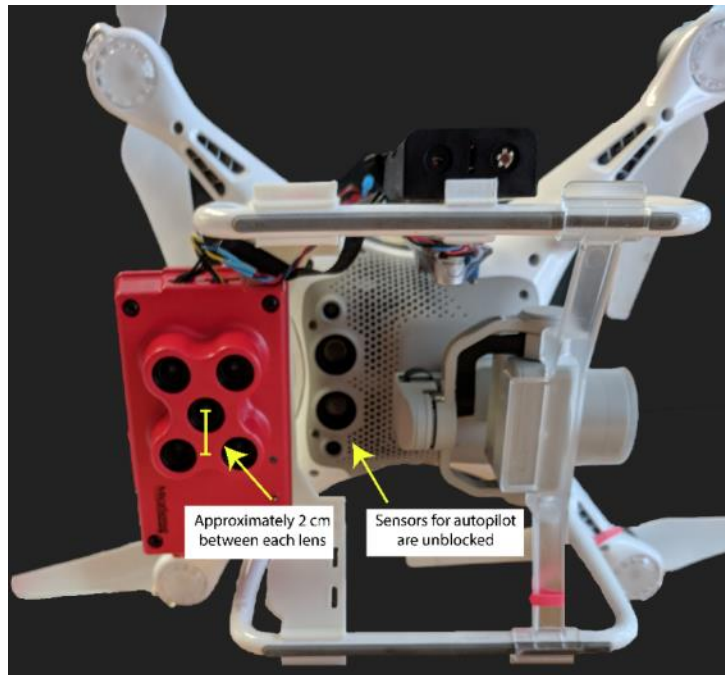


Figure 33: MicaSense RedEdge mounted to Phantom 4 Pro

An excellent example of the benefits of the dual sensor approach was in the last step of the methodology, where the UTD results of all dates were overlaid on the P4P leveraging each datasets strengths, spatial resolution (P4P) and spectral resolution (RedEdge).

Processing of April 20th P4P camera data was completed using the highest possible settings in Agisoft PhotoScan operating on a computer with an AMD Ryzen Threadripper 1950X/RE CPU, 3 ASUS GeForce GTX 1080 11GB GDDR5X graphics

processing units, 128 GB of DDR4 memory. Even with the considerable processing power, processing still took approximately a day. In future studies, a significant amount of processing time could be saved by processing with “high” settings (vs. “highest”) and this alone would cut processing time by 75% because images would not be supersampled (x4) and instead be processed using the native resolution.

Flying at a lower altitude would offset losses in spatial resolution caused by processing with lower settings. However, because of the slight offset between each lens of the MicaSense RedEdge, the sensor requires a minimum flight altitude to avoid image processing errors caused by differences in parallax. The minimum flight altitude suggested by MicaSense was 15 m which was used in manuscript 2. Based on the results of both study sites and additional GSD calculations, the target spatial resolution should be below 0.5 centimeters to ensure that each mine is 14 pixels in diameter. This target altitude can be achieved using the stock P4P camera, but the camera itself cannot be converted to reflectance and had contrast issues which caused only 2 of 8 confirmed mines to be visible in the April 20th orthomosaic for manuscript 2.

A multispectral sensor that is capable of imaging the multiple bands from a single lens is an ideal solution for detection so that a lower flight altitude and spatial resolution can be achieved in the detection methodology. If a rolling filter wheel sensor similar to the COBRA sensor were to be used with the UAS, a higher spatial resolution could be achieved by flying at a lower altitude. One caveat of a filter wheel style sensor is that the UAS would have to pause for one second per image to account for the filter wheel spin time so that each band can be collected at the same location and not have issues with parallax.

When designing future simulation minefields to test detection methodologies, a blind setup should be replaced with a GIS solution that randomly generates simulation landmine locations. The goal of the blind setup was to avoid a bias in placing mines and removing the ability to use thresholds in the methodology. Placement bias is avoided by using a GIS, and any additional thresholding is now based on statistics of the image, so it is no longer an issue. With initial knowledge of simulation landmine placement, the researcher can more effectively test the effects of false positives in future studies.

One possibility for detection that was explored and not reported in manuscripts 1 or 2 was the use of change detection. Ultimately, because the simulation landmines are only roughly 15 pixels in diameter and a pixel-to-pixel registration was not attainable, change detection analysis did not return useful results but are instead corrupted by noise from registration issues. A change detection using fully aligned data that has greater spectral and spatial resolution could highlight unchanging areas in the image that have a higher likelihood of being a simulation landmine.

This study's overall goal was to determine if it is possible to reduce the threat of air scatterable surface landmines by accurately locating them using UAS imagery. The results from Site A (Athens, GA) showed that using RGB image data alone it is possible to detect recently placed surface simulation landmines. The methodology developed in the first study reported in manuscript 1 also demonstrated that extra information extracted from the original dataset such as dilated and eroded spectral bands and a DSM could add to results. The extra processing time incurred by using more data can be negated by using a fusion technique such as PCA. The PCs selected from the PCA for detection showed lower variance and factor scores demonstrating the analysis viewed the simulation

landmines as noise. The low factor scores indicated that more focus should be put on anomaly detection for landmine detection.

The methodology of the first study (manuscript 1) was highly reliant on the previous knowledge of at least one simulation landmine position to develop a filtering threshold for each PC to remove noise from vegetation. The need for thresholds was significantly reduced in the second study (manuscript 2) by using statistical means to derive threshold values. One noise reduction technique that showed promise in the first study of Athens Site A was the removal of noise and reduced false positives using a PAR test to remove non-circular features and significantly reduce the number of suspected simulation landmines detected. Most of the remaining false positives in the first study's results were leaves in the ivy, which showed that in the right conditions vegetation could pass a PAR test. The results of this study also demonstrated that the focus of future work should be selecting the time for UAS image acquisition to reduce the influence of vegetation on results and eliminate the need for thresholding.

In study two, the decision to move away from PC thresholding was made based on the insights gained from study one and a UTD was used to find spectral anomalies instead. The results of the UTD had the same effect as PC thresholding in study one while removing the need for previous knowledge of simulation landmine location. In fact, by using only the top 0.05% of UTD results, results could be trusted to be significant and more likely to be an anomaly within the scene. Unfortunately, because of the need to buffer each date's UTD results a PAR test would not have worked in study two but could in the future with a reduced need to buffer results.

The temporal analysis of superimposing potential targets derived from different dates of UAS orthomosaics served the same purpose of the PAR test by eliminating small noise and returning results that could be trusted to be anomalies because they were identified in multiple images. In the two examples of positive identification of simulation landmines, only a few interior pixels of the interior survived the UT threshold and were not circular, therefore, likely would have failed the PAR test. The inability to use a PAR test seems to be the tradeoff of using a strong threshold of 0.05% for the initial UT test and multi-date temporal analysis.

A difficulty encountered in this research were the dirt anomalies which spectrally matched the simulated landmines and became problematic to remove from the scene. There was not a significant difference between dirt and simulation landmines spectral responses making common differentiating techniques such as band ratios ineffective. A simple solution would be to ignore dirt features in future studies by adding another middle infrared/thermal band to the data collection. This could allow for more discrimination between spectral responses of the dry landmine target and moist background soil. An added middle infrared/thermal band would also aid the UT detector in finding anomalies within the scene. With the addition of more bands and higher resolution data, the UT detector may have an easier time identify the whole landmine.

Overall, this study was successful in developing a method to detect and reduce the threat of scatterable simulation landmines remotely. An improvement to the testing of the methodologies would be the use of a GPS of higher positional accuracy to determine the locations of randomly distributed landmine-like targets that can then be used to compute the percentage of correctly detected targets resulting from the image analysis. In this

study, a high detection rate was not achieved, but 20% of the mines were still found, and, in a real situation, this would mean an increase in safety to deminers. The results of the first study of Site A in Athens, GA helped to improve the methods used in the second study of Site B in Watkinsville, GA. In the same way, both studies can help improve future results by highlighting successful and unsuccessful strategies. With improved UAS flight planning, sensors, and test site set up, a detection methodology could conceivably detect more scatterable mines and significantly reducing danger to deminers and local populations exposed to abandoned simulation landmines following times of conflict.

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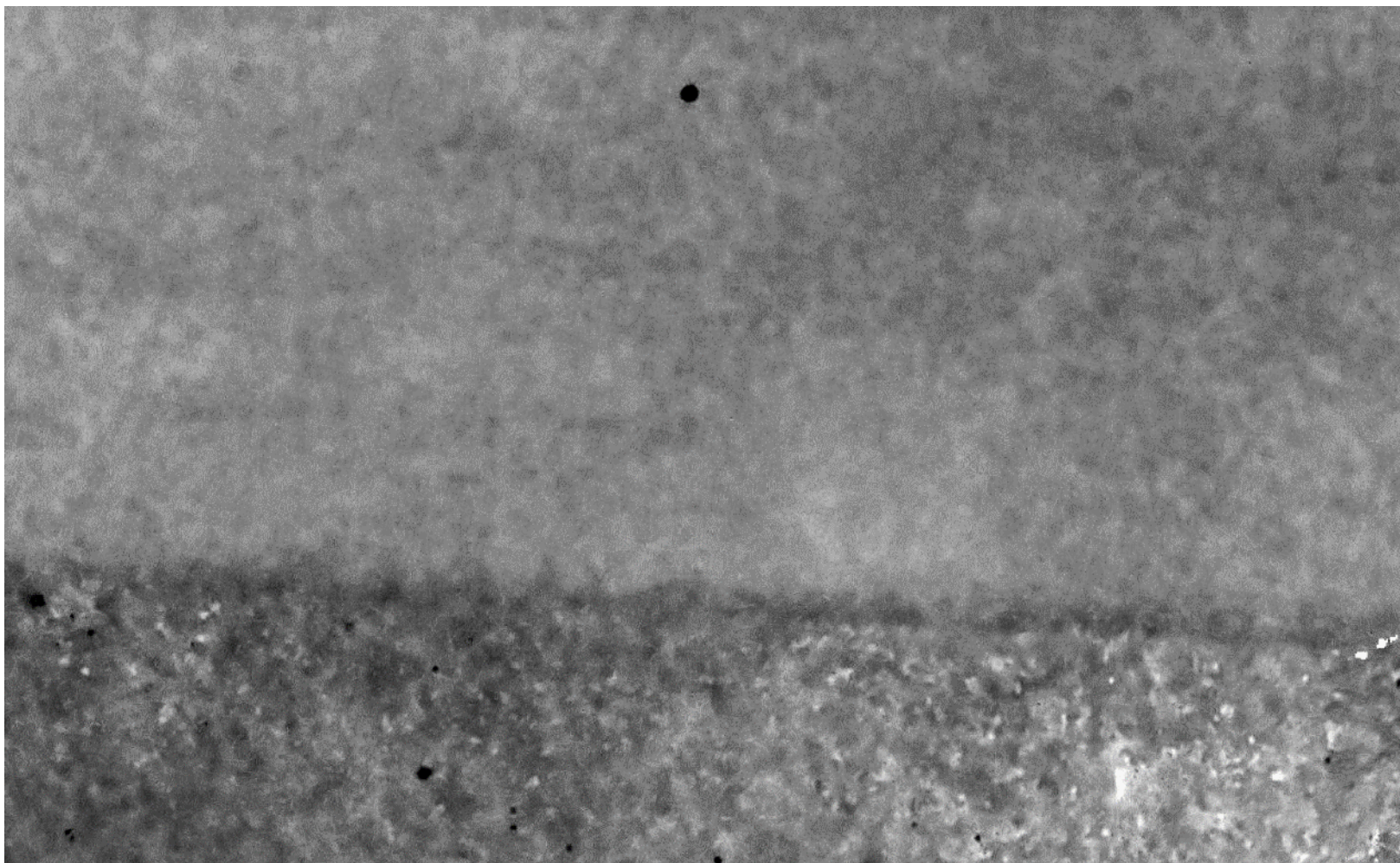
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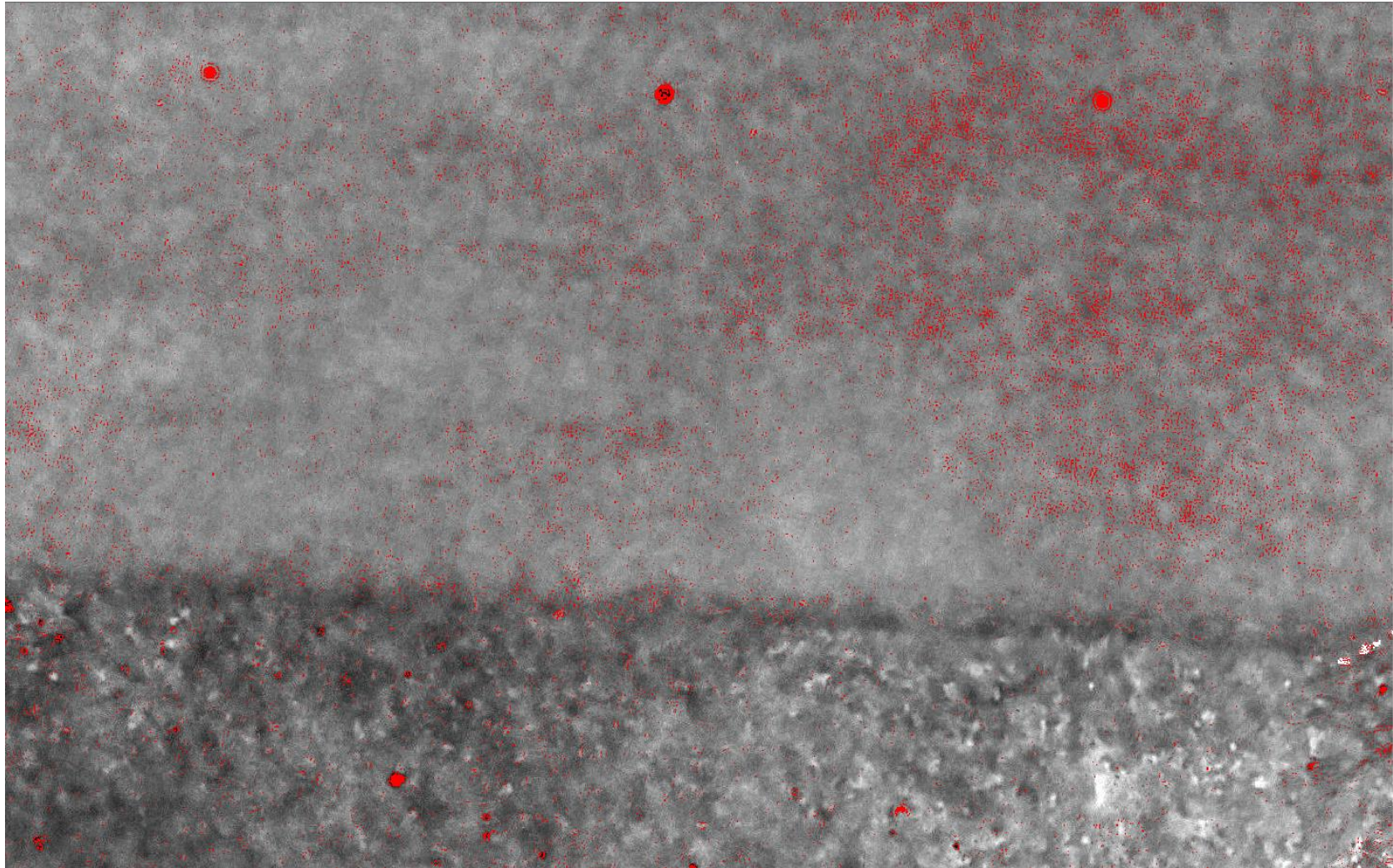
Appendix A- OVERVIEW OF METHODOLOGY ONE



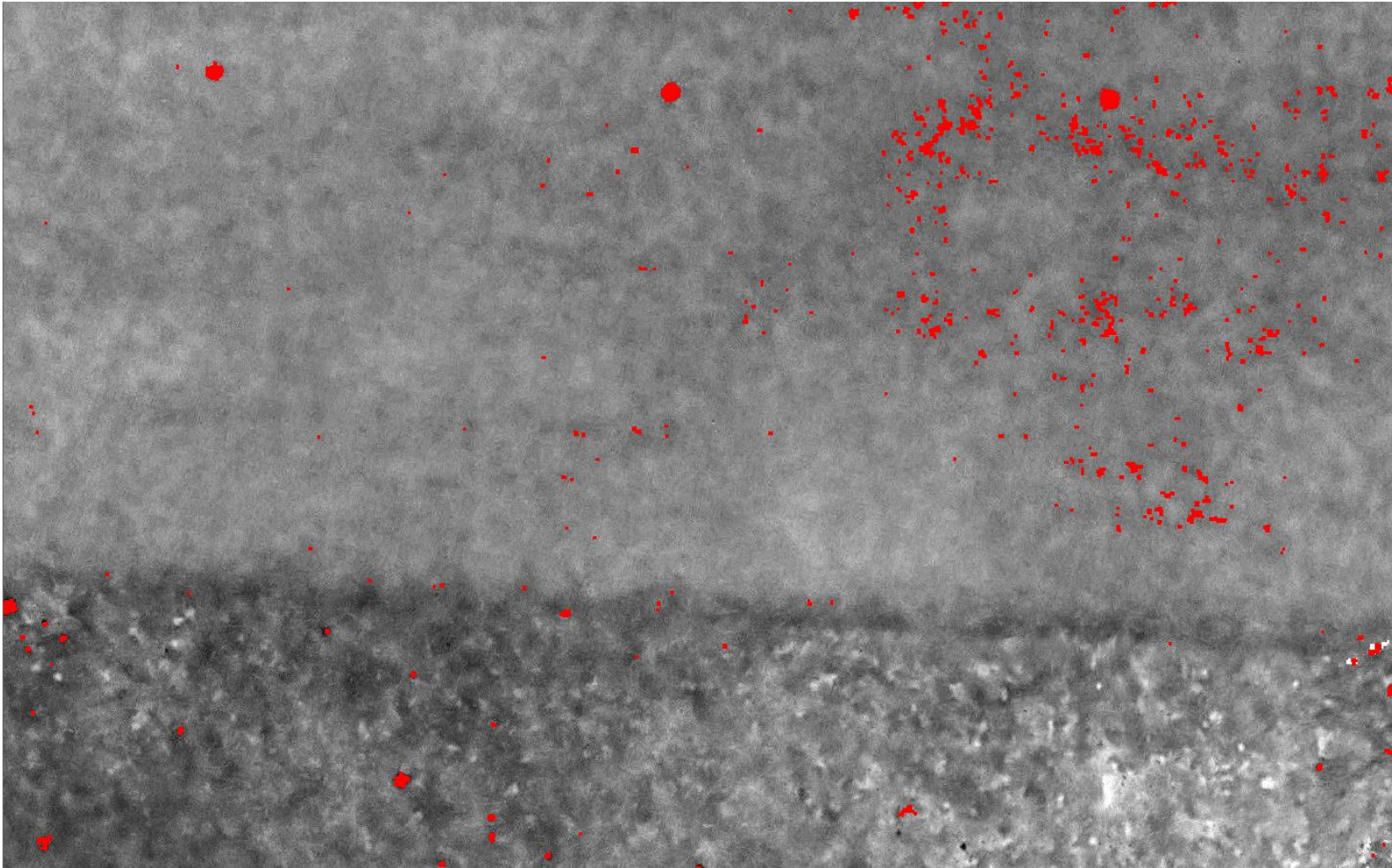
1: Subset of study area mines highlighted



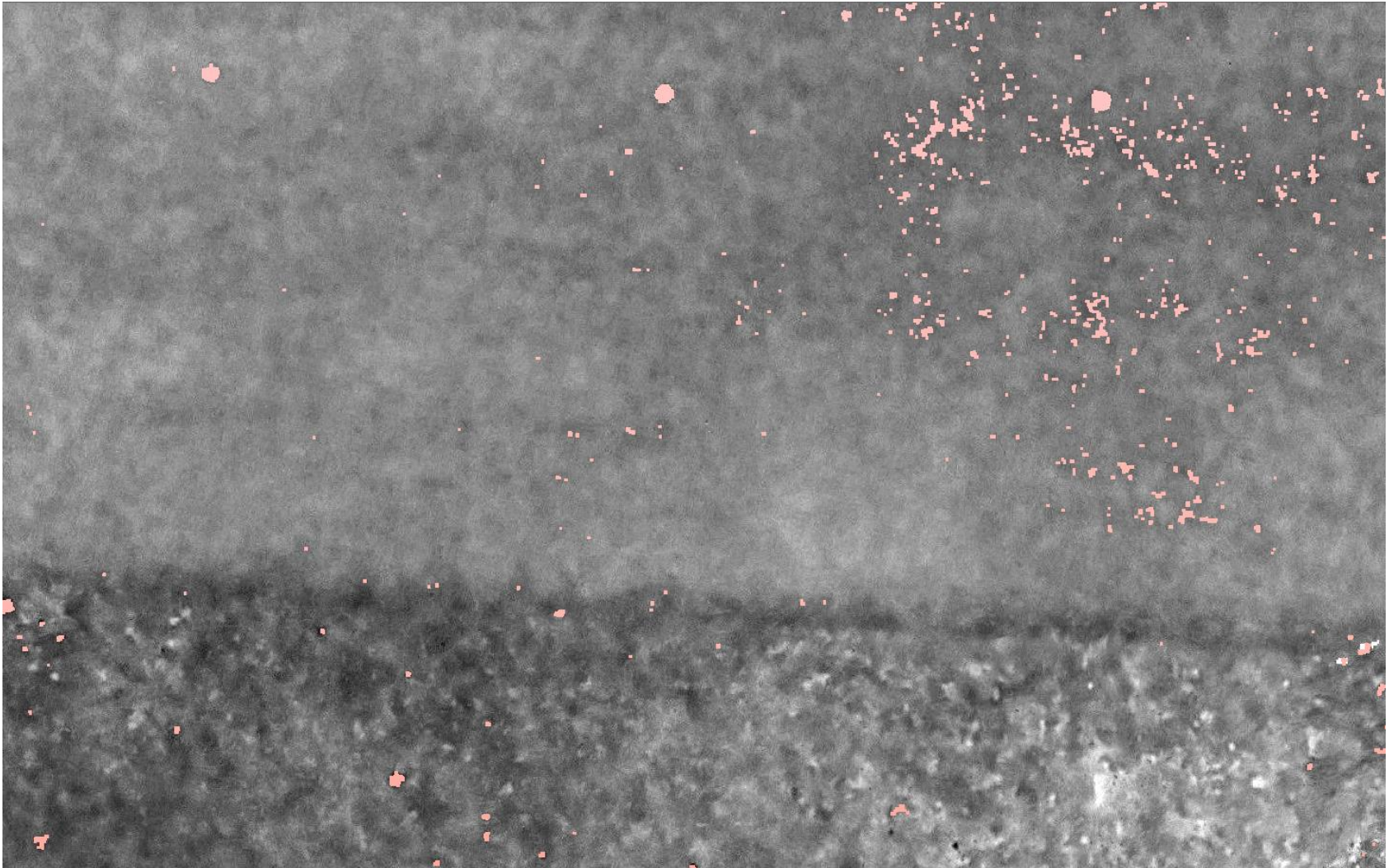
2: Principal Component 4 of 7 (PC4)



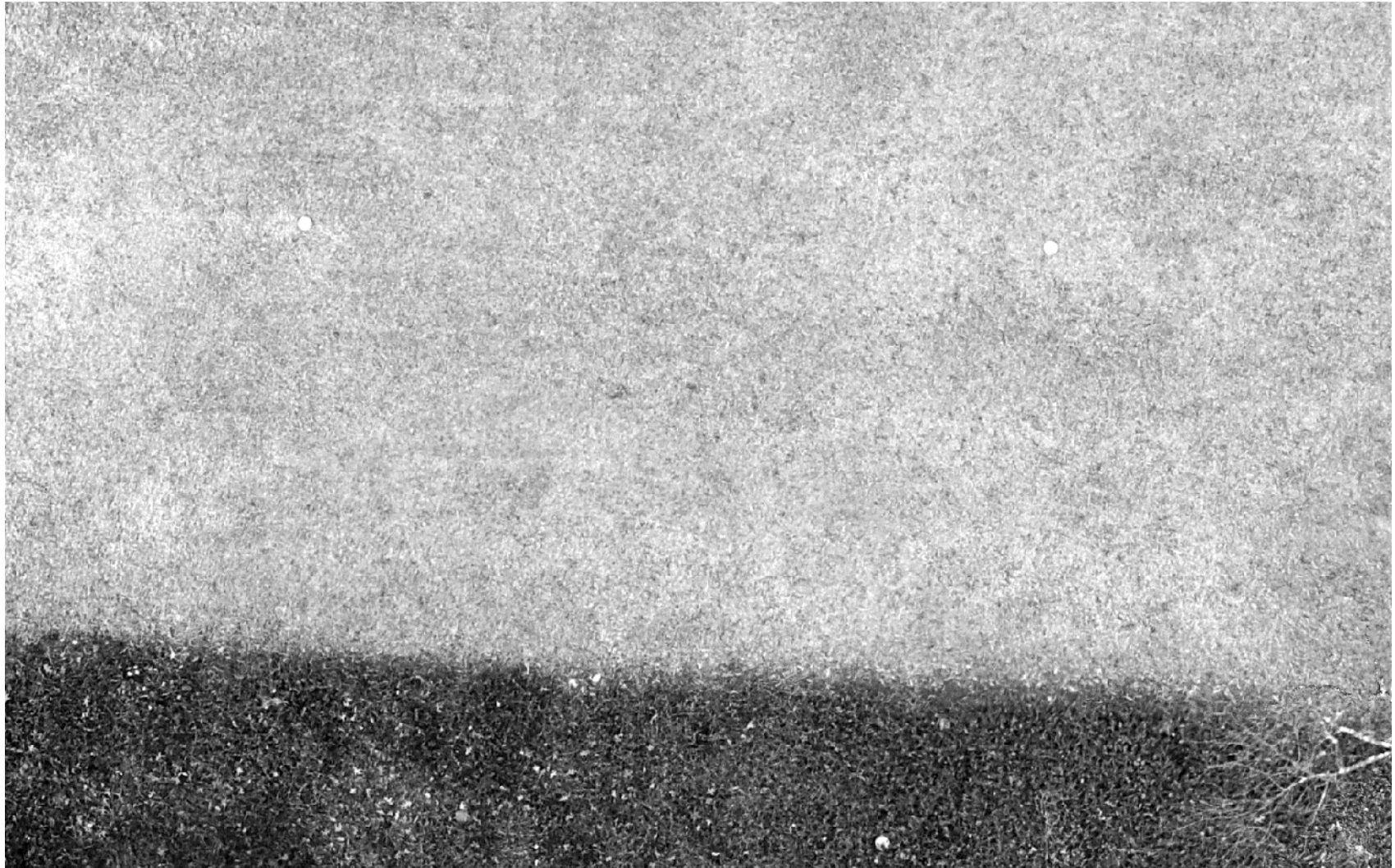
3: Potential mines highlighted by threshold based on digital number (DN) value of PC4



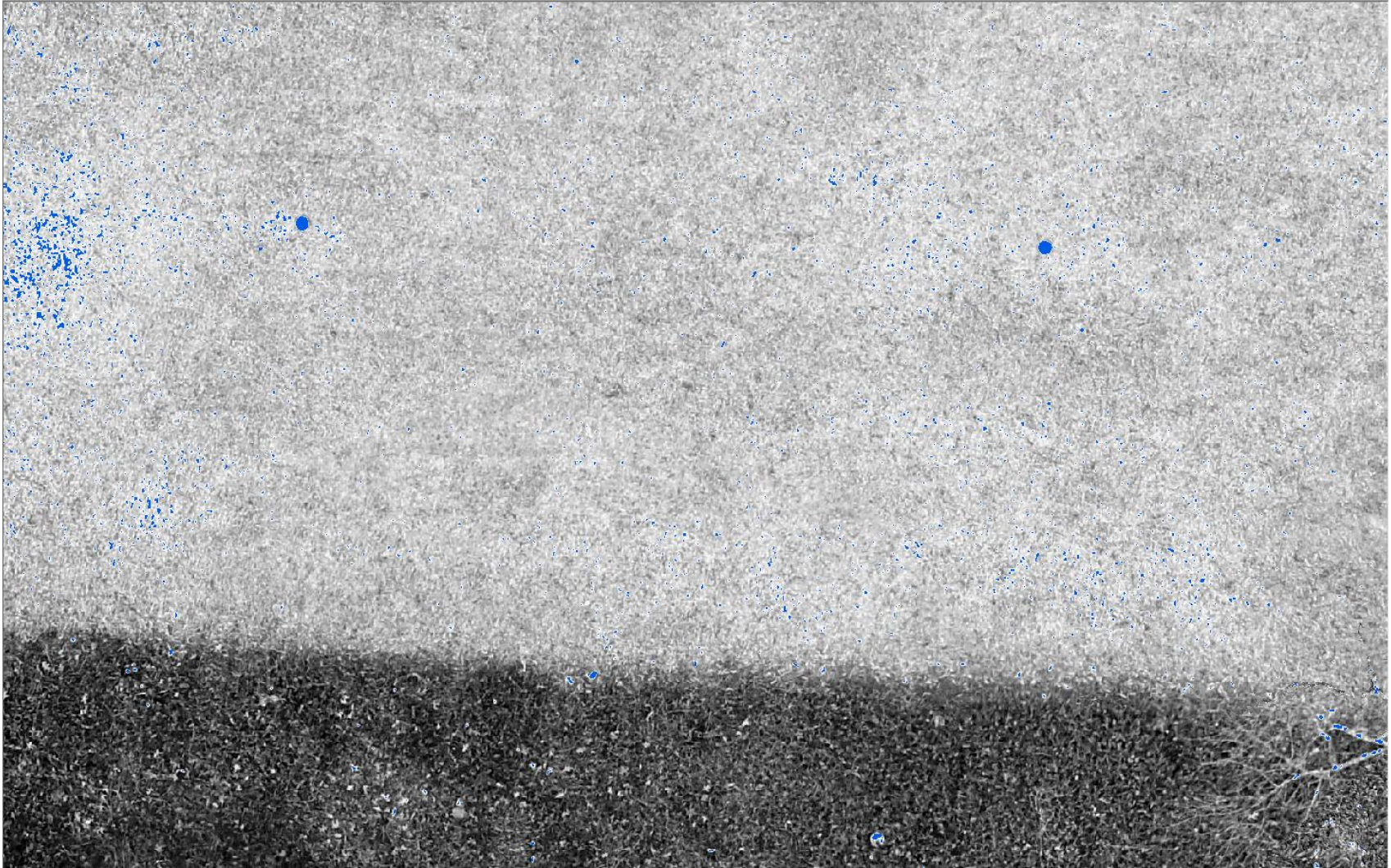
4: Boundary clean removes noise and cleans up edges of PC4



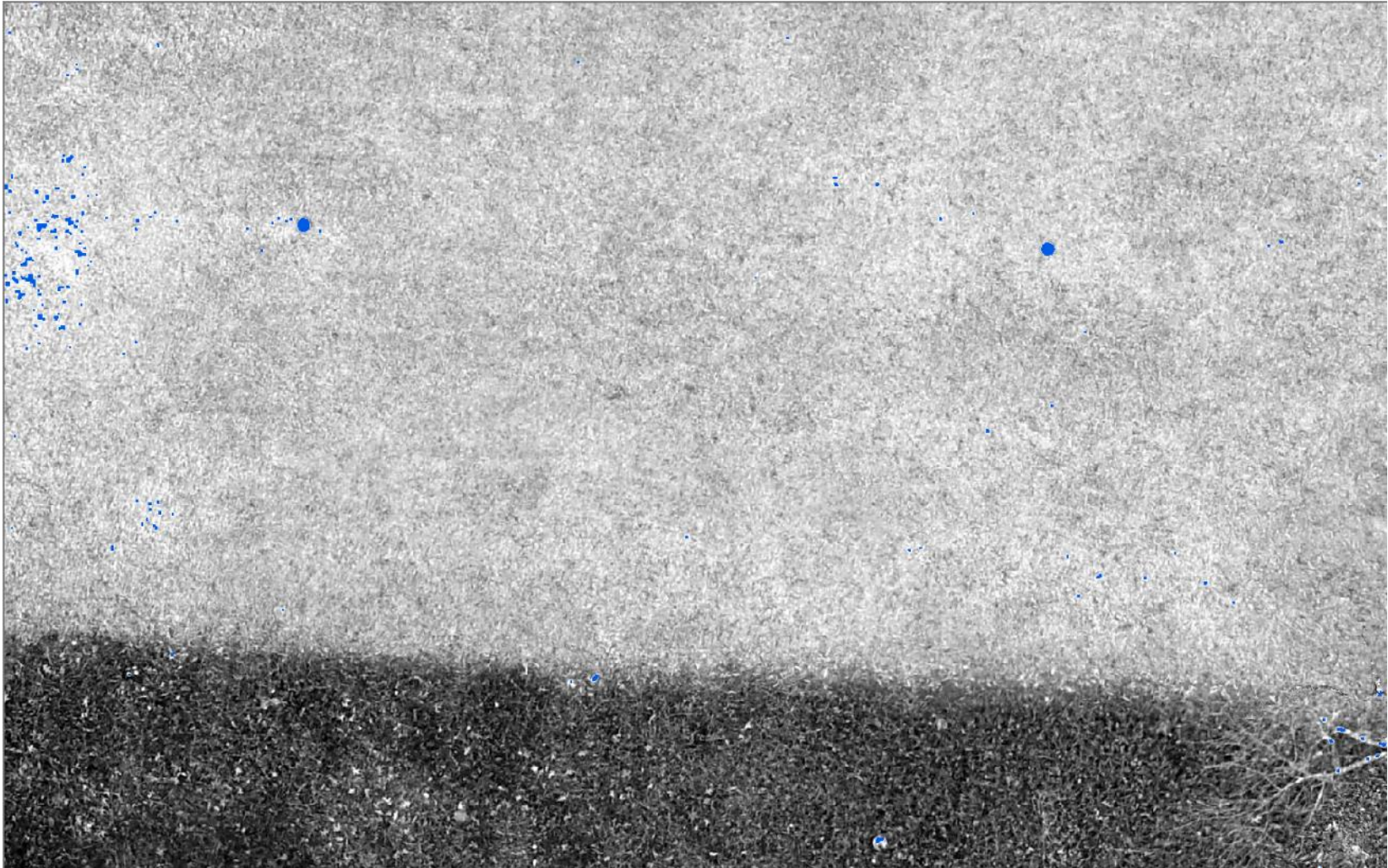
5: PC4 Pixels are grouped based on the number of adjacent pixels low values are removed to remove noise



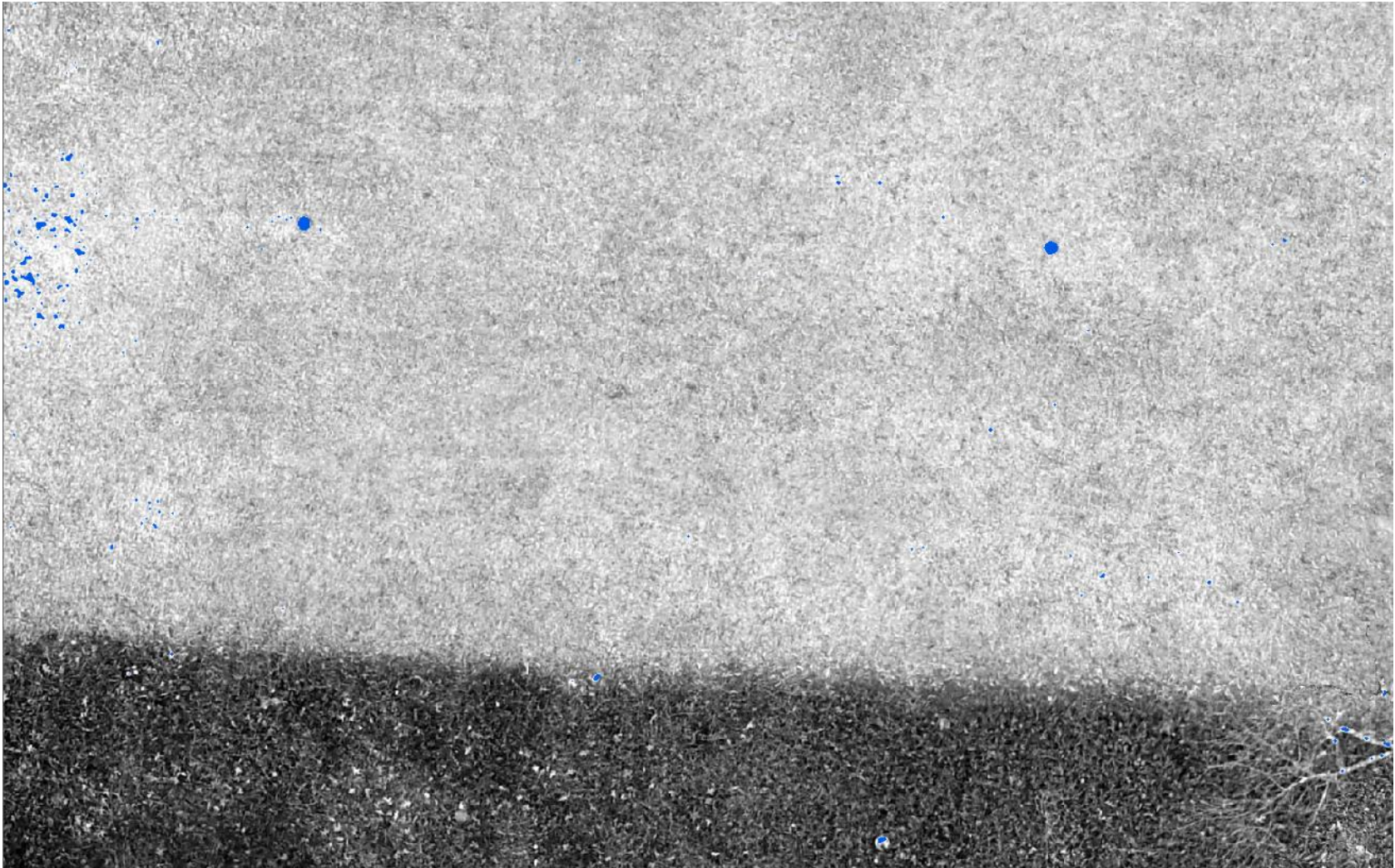
6: Principal Component 1 of 7 (PC1)



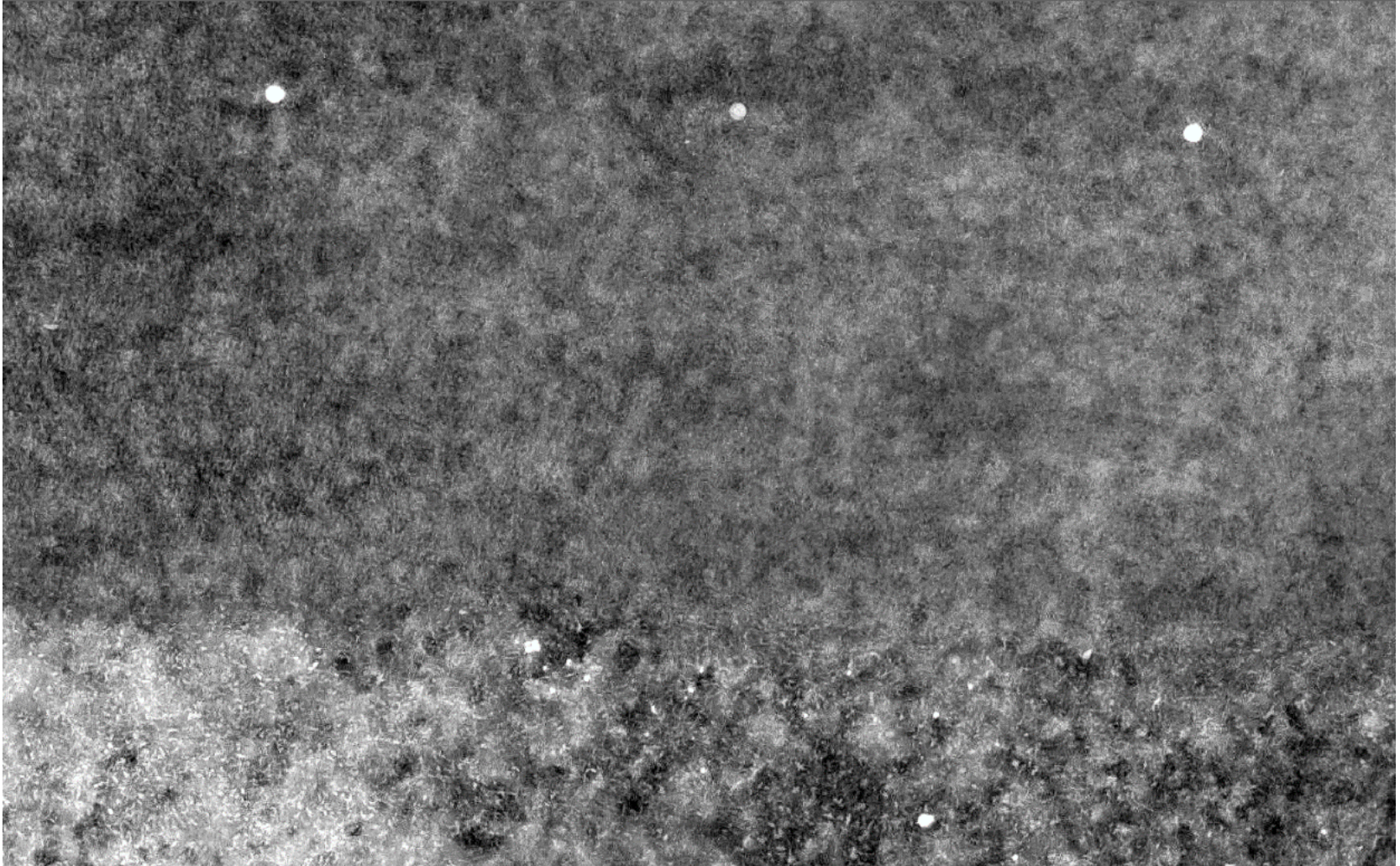
7: Potential mines highlighted by threshold based on digital number (DN) value of PC1



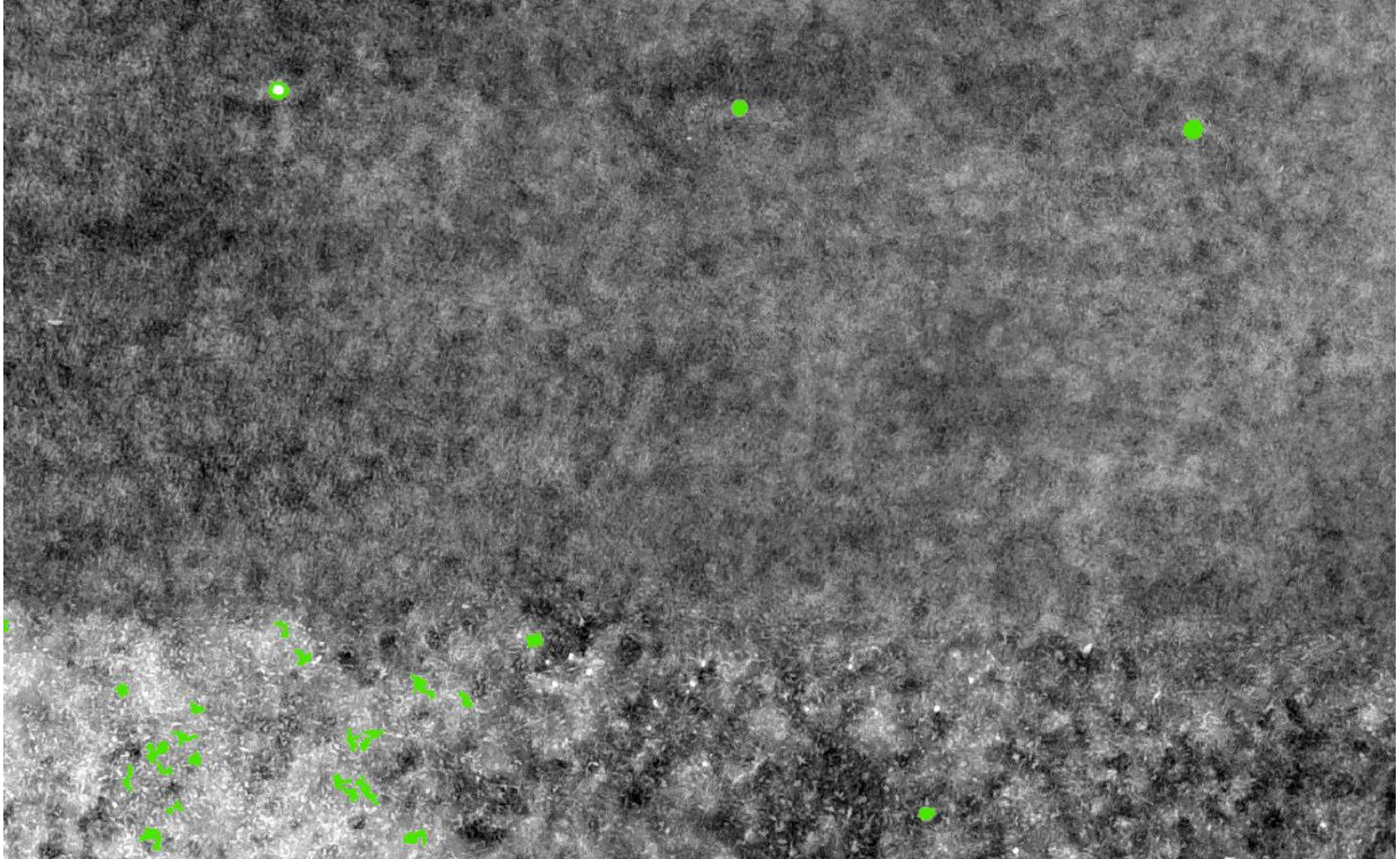
8: Boundary clean removes noise and cleans up edges of PC1



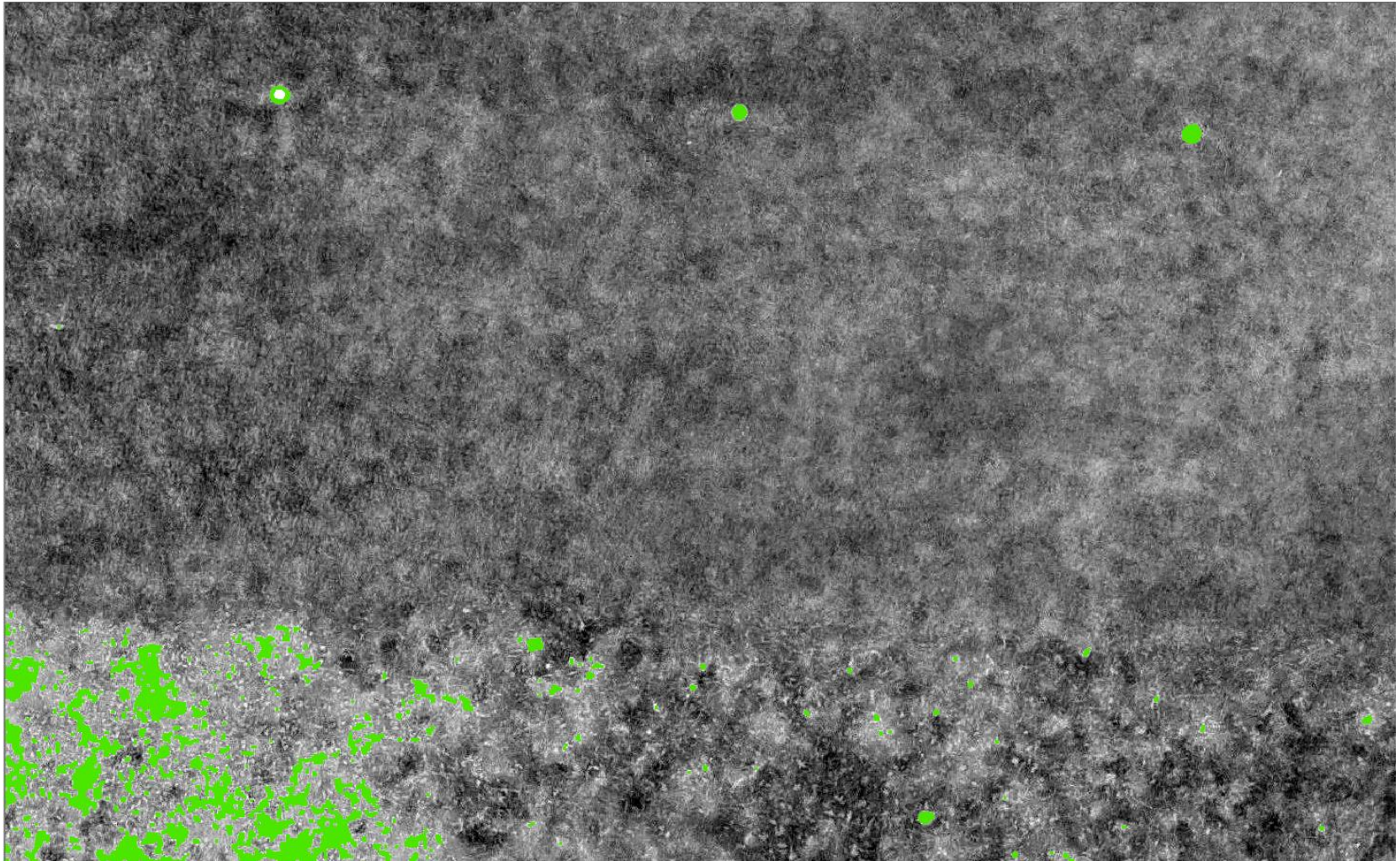
9: PC1 Pixels are grouped based on the number of adjacent pixels low values are removed to remove noise



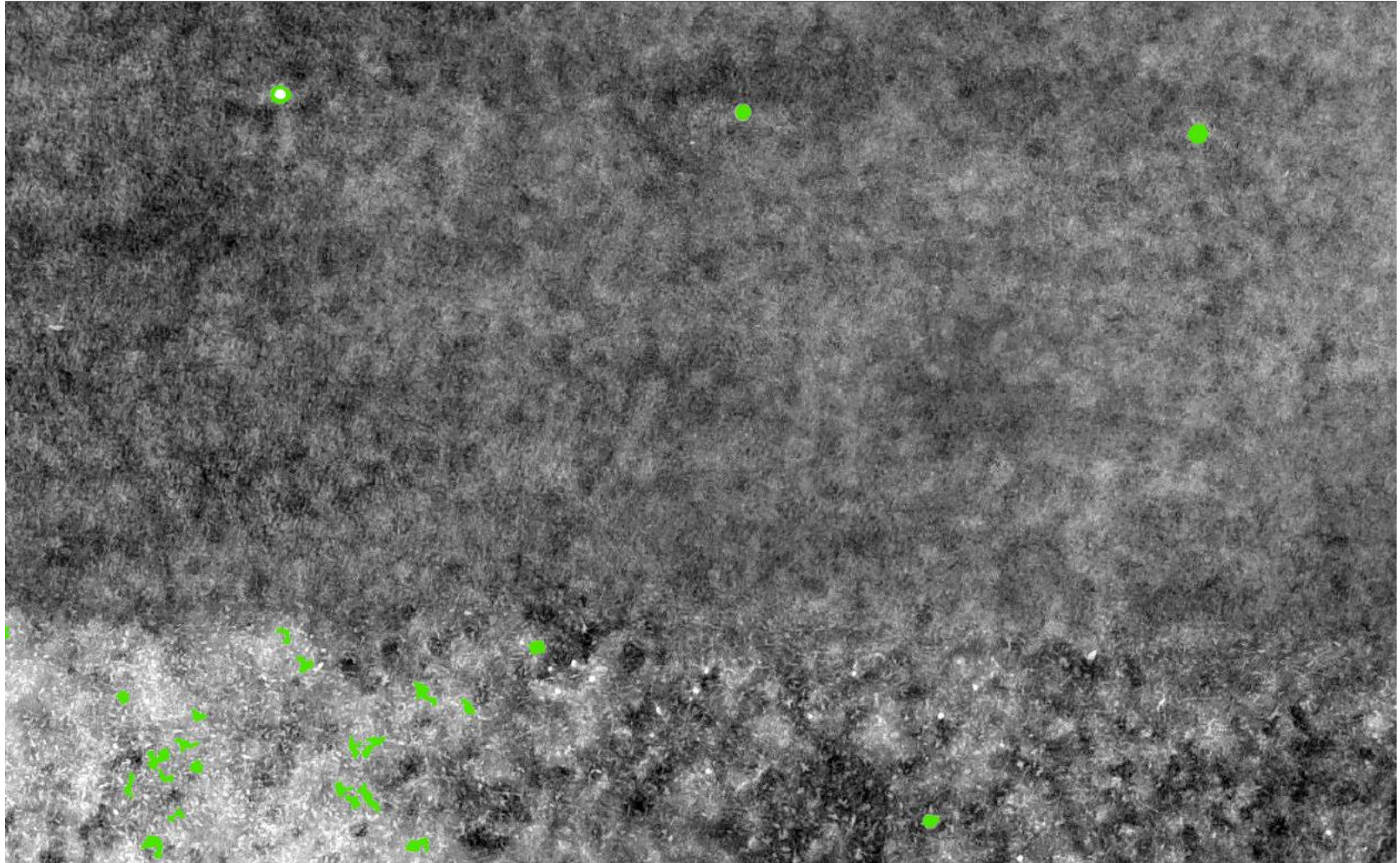
10: Principal Component 2 of 7 (PC2)



11: Potential mines highlighted by threshold based on digital number (DN) value of PC2



12: Boundary clean removes noise and cleans up edges of PC2



13: PC2 Pixels are grouped based on the number of adjacent pixels low values are removed to remove noise

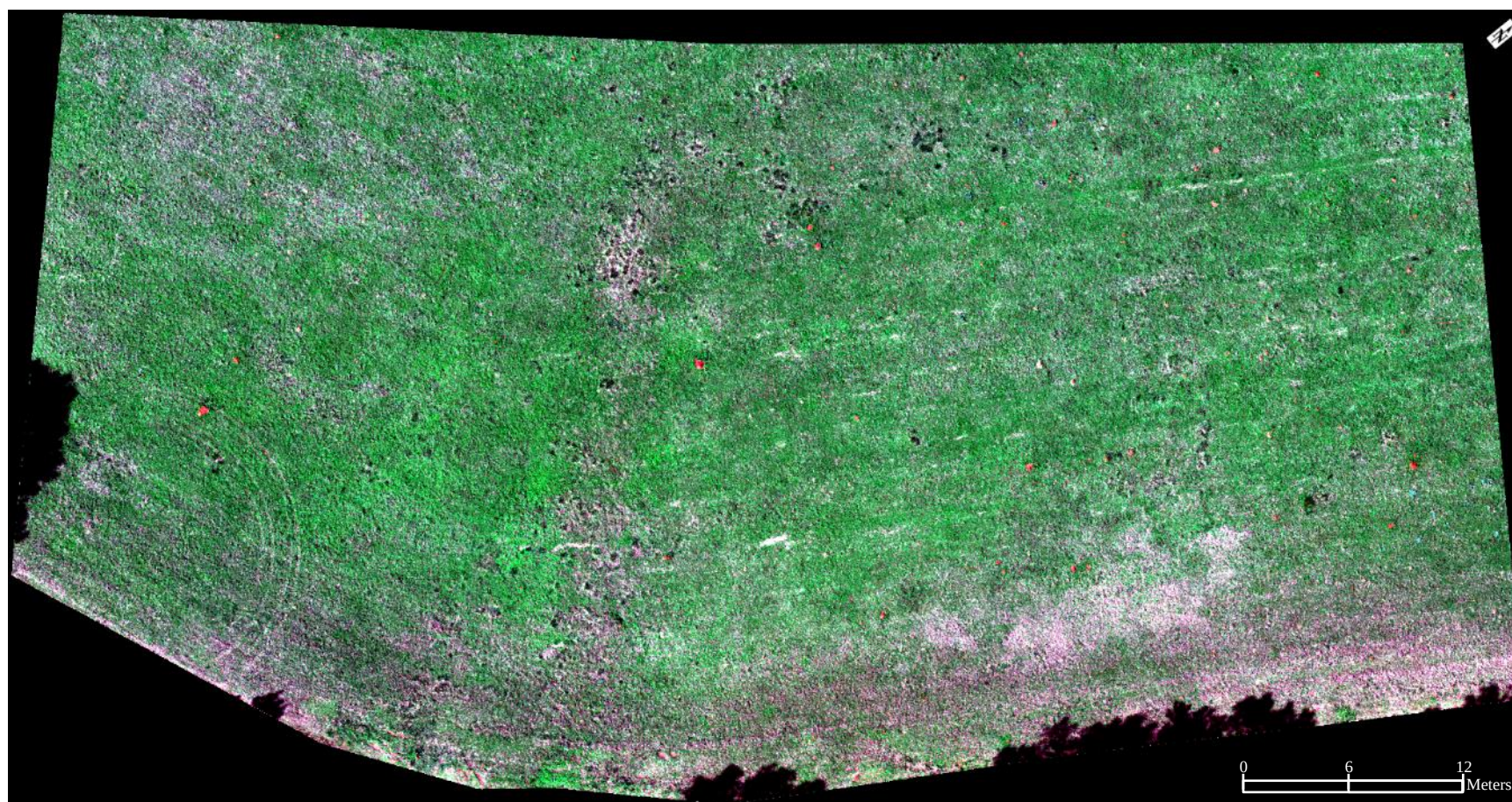


14: Composite Results anything that isn't a primary color (Red, Green, Blue) indicates that the process has indicated a potential mine in two or more principal components

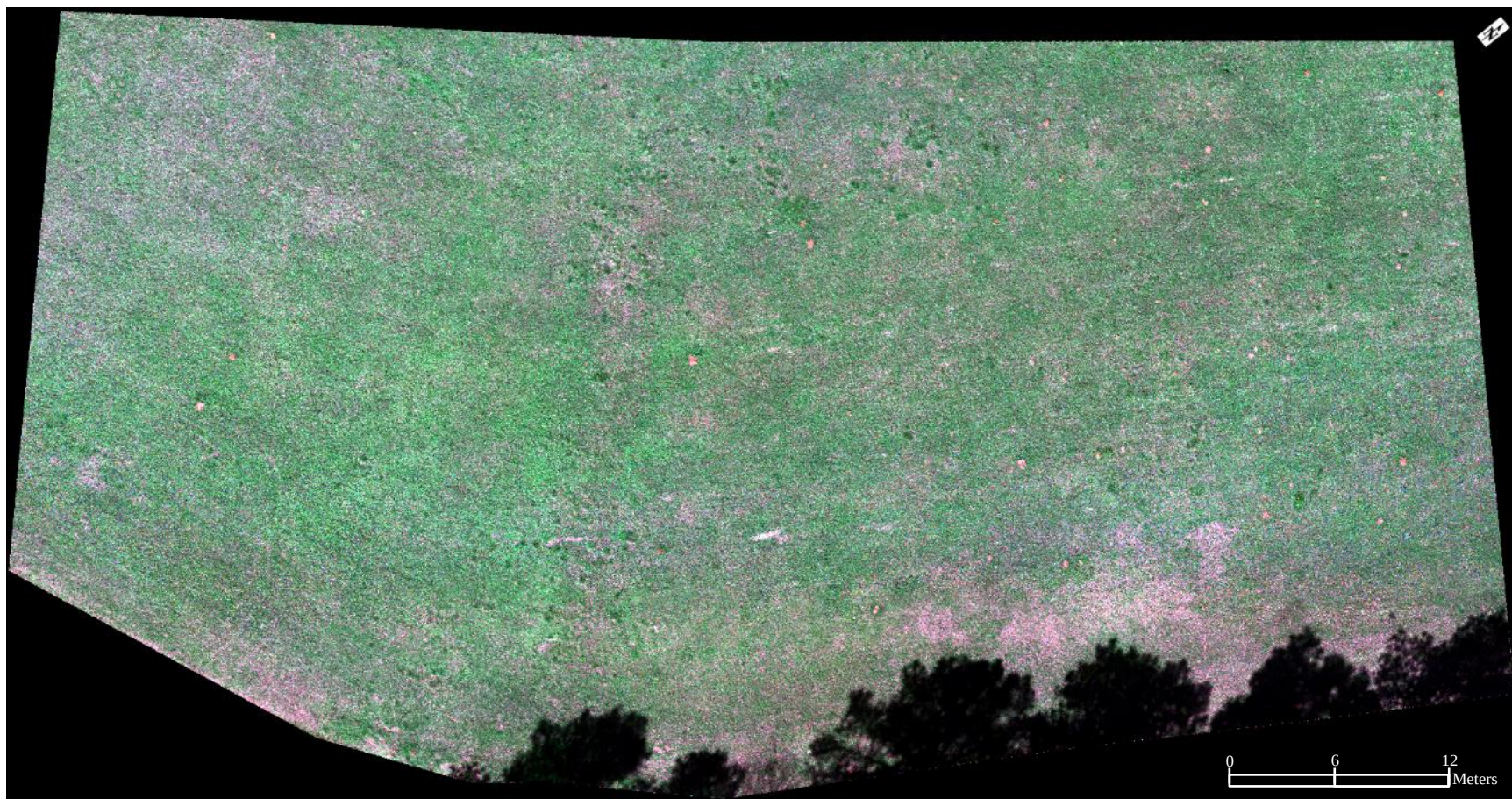


15: Remaining pixels after perimeter to area threshold is performed.

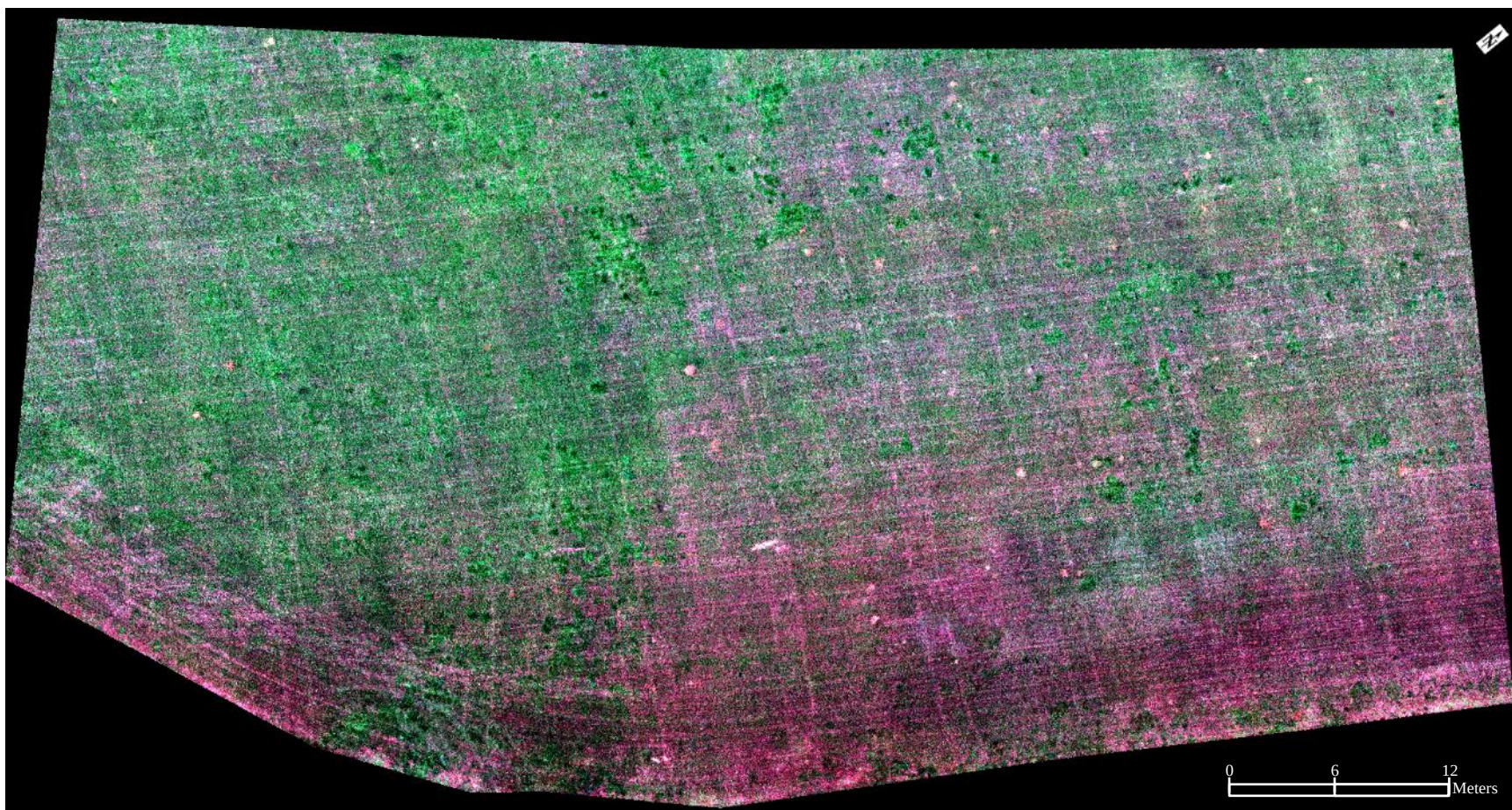
Appendix B – ORTHOMOSAICS SITE B



1: Orthorectified MicaSense RedEdge Mosaic – February 27th



2: Orthorectified MicaSense RedEdge Mosaic – March 23rd



3: Orthorectified MicaSense RedEdge Mosaic - April 20th

Appendix C – CLOSEUPS OF SIMULATION MINES

Because of the random 3rd party placement mine numbers in the images are different from the number used in the study. During the study each mine was assigned a sequential number.



Mine 1



Mine 2



Mine 3



Mine 4



Mine 5



Mine 6



Mine 7



Mine 8