Using Very High Resolution Remotely Piloted Aircraft Imagery to Map Peatland Vegetation Composition and Configuration Patterns within an Elevation Gradient

by
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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

GIS has developed over the decades from theory to highly accurate scientific observation using satellites that provide high resolution imagery. Over the last decade drones have been introduced to the world of GIS and have been able to overcome some of the issues present in satellite and aerial imagery such as lower resolution for smaller objects and temporal constraints. My thesis aims to explore how accurately RPAS can identify vegetation communities classed by morphological structure when compared to ground based vegetation surveys in peatlands in Alberta. The wetland sites are situated across subregions that are currently not mapped by the Alberta Merged Wetland Inventory. Our research aims to answer the following questions: 1) Assess at how differing image resolution (2 cm and 3 cm) influence the ability to identify morphologically functional classes within the RPAS imagery. 2) Test the accuracy at which different morphological functional trait classes of vegetation could be digitized from remotely sensed imagery, highlight which classes had the highest and lowest accuracy and try to explain why. 3) Investigate if RPAS can be used to map out vegetation composition and configuration to replace ground based surveys. 4) Determine across an elevation gradient within the subregion groups (subalpine, montane and upper foothills) if there are any significant landscape metrics patterns that change across these subregions using elevation as a controlling variable. Flights were conducted with RPAS to collect imagery with a resolution of 2 cm and 3 cm then classified into digitized classes that represent the morphological structure of different vegetation across 18 peatland. 13 different features were classified in the 18 peatlands. All 18 peatland boundaries were delineated using slope, which removed classes such as roads, objects, culverts, and bridges. The delineated peatlands were then run through a landscape metric package in R to determine spatial patterns of vegetation at both landscape and class level. Landscape Metrics revealed composition and configuration characteristics that were significant when plotted against elevation for landscape level metrics. Replication of the results once accuracy has been increased using either higher resolution imagery or other sensors to determine validity of the results is needed.

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Thank you to my colleagues and friends at the University of Waterloo for being amazing people and I'm so excited to follow your journeys after graduation.

Thank you to my partner Philip, for without your love and unconditional support I would have never changed careers and taken this risk to follow my dreams. You and Owen have been the light that has kept me going.

Land Acknowledgement

We acknowledge that this study site sits on the traditional territory of the Stoney tribe, Piikani Nation, Tsuu T'ina Nation. We acknowledge that the University of Waterloo sits on the traditional territory of the Neutral, Anishinaabeg and Haudensaunee peoples.

Dedication

I’d like to dedicate this thesis to my two dear friends that were lost during the span of my masters. To Griff and Tyke.

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1.0 Introduction

A healthy wetland is one of the most valuable habitats on Earth owing to the fact that wetlands provide a multitude of ecosystem services such as water filtration of sediment and pollutants (Díaz et al., 2012), flood risk reduction (Acreman et al., 2013), support high levels of biodiversity (Flinn et al., 2008), biogeochemical cycling (Deng et al., 2021), control disease (Keesing et al., 2010) and numerous other interconnected kinships wetlands have with neighboring habitats on various scales (Keddy, 2016; Clarkson et al., 2013). Inland wetlands gain the majority of their monetary value (62%) for moderating extreme events, water flow regulation, waste treatment, water purification, erosion prevention and nutrient cycling (Davidson et al., 2019).

Wetlands are complex biomes, making restoration to pre-disturbance structure and function difficult and uncertain even after a decade of restoration efforts (Haapalehto et al., 2011). The combination of time and complexity and our interconnectedness with wetland services suggest that wetland protection is critical, and that a balance between conservation and development of the landscapes they reside in is needed. Canada recognizes the importance of wetlands as the federal government has valued its wetlands at just over 5 billion dollars annually (Anielski et al., 2014). This financial value is determined from a consumptive, non- consumptive and natural disaster protection standpoint (Ramsar Convention on Wetlands, 2018; Anielski et al., 2014).

Despite the critical role wetlands play in the provision of ecosystem services and their monetary value, Canada is one of the only developed nations that does not have a comprehensive wetland inventory (Ducks Unlimited, Canadian Wetland Inventory, 2021). It is estimated that Canada was home to 25% of the world's wetlands; however, 3.5% or 20 million hectors have been lost (Ramsar Convention on Wetlands, 2018). While gaps in the Canadian Wetland Inventory are being filled through private and commercial data collection, in the province of Alberta many areas remain unmapped (e.g., alpine, subalpine, montane, upper foothills subregions). Not only are these wetlands excluded from the Alberta merged wetland inventory (Figure 1), but there is also a lack of empirical data and understanding about different subregions in Alberta such as subalpine, montane and upper foothills wetland vegetation composition and configuration, their resilience to landscape disturbances, their role in the storage and conveyance of snowmelt, and what the impacts of their loss are on downstream water quality, quantity and ecosystem health (Somer et al., 2020; Bow River Basin Counsel, 2021).

Vegetation composition (what types of species are present) and configuration (where those species are patterned across a landscape) are determined by many factors such elevation, salinity and fertility along with secondary variables that are influenced by all of the above such as water quantity and flow path, competition and disturbance (Keddy, 2016). Using the morphological structure of vegetation to group species with similar shape and structures together, is a classification that allows for a simplified way that is effective in monitoring and evaluation tools (McPartland et al., 2019; Körner, 1994). Landscape metrics are a way to quantitatively delineate a landscape by patches (vegetation communities) to find the spatial patterns of patches, classes of patches and entire landscape mosaics to provide a composition and configuration that can be used as a surrogate for visualizing real life change (Turner et al., 2001; McGarigal, 2006). They provide a way to quantify landscape patterns that are fundamental to understanding different functional relationships within landscape ecology (Cardille et al., 2017).

While many human and natural processes may alter the composition and configuration of vegetation communities, there is need for an evaluation tool that is validated to monitor the health and condition of subalpine, montane, and upper foothills peatlands in Alberta. Bolding (2018) assessed the effectiveness of using landscape metrics to create maps of the wetland vegetation composition and configuration in the Prairie Pothole region of Alberta. This task was labor intensive and required the use of a handheld GPS to walk the perimeter of the wetland and determine dominant plant cover for every reference point. There is reason to believe that the composition and configuration of peatland vegetation will change with changes to hydrological and climatic responses, and projected changes in climate for Alberta estimate warmer temperatures and more extreme precipitation events (Gizaw et al., 2016; Schneider, 2013), which may alter hydroperiods of mapped and unmapped subalpine, montane and upper foothills peatlands. Little is known about how these peatlands influence extreme precipitation events in the Bow River Basin (Tebaldi, 2006; Bow River Basin Counsel, 2021).

Remotely Piloted Aircraft Systems (RPAS) offer a way to attain very high resolution imagery, in remote locations, on a flexible time scale, at lower cost and fast processing time which has the potential to replace the need for walk around ground based surveys to monitor composition and configuration within peatlands (McPartland et al., 2019; Palace et al., 2018; Horning, 2018). Furthermore, very-high-resolution (e.g., ~2.5 cm) optical imagery allows more details to be seen which can facilitate vegetation surveys in remote, hard to access locations (Sankey et al., 2018). Satellite imagery has been shown to not deliver the detail (in resolution) needed for species level classification (Sankey et al., 2010), can be limited due to cloud cover, not temporally flexible, and have a slower processing time (Ruwaimana et al., 2018). Mapping wetlands can pose a challenge due to their heterogeneity in size and location. Remote sensing allows the user to study the system from different scales, map, and quantify landscape composition and configuration with minimal physical impact. While wetland boundaries can roughly be mapped via satellite with lower resolution (10 m), determining the composition and configuration of vegetation communities seems to be unsuccessful for certain vegetation classes (Kaplan, 2017).

In my thesis, I use novel RPA remote sensing technology on a sample of subalpine, montane, and upper foothills peatlands in Alberta, Canada to meet my Objectives: 1) look at how differing image resolution (2 cm and 3 cm) influence the ability to identify morphologically defined classes within the RPAS imagery. Studies (e.g., Chen et al., 2004) have shown that texture is more effective at improving accuracy at finer resolutions but depending on the Minimum Mapping Unit (MMU) and the scale of what you are trying to measure accuracy might not increase (Ming et al., 2011). Using human vision to determine vegetation within RPAS generated imagery while mapping aquatic open water wetland vegetation and peatlands (2.5 cm - 5.6 cm resolution) generated mixed accuracy results (33% - 100%) for different vegetation classes and ways of grouping them (Husson et al., 2014; Díaz-Varela et al., 2018). Considering the classes that achieved lower than 50% were those that were vegetation that commonly grow interspersed with neighboring vegetation, and classes that achieved higher than 70% were those that had a distinct texture or had open water surrounding them, I predict a similar outcome for classes within this study, in that shrubs, will achieve a high accuracy and interspersed vegetation such as grasses, mosses will have the lowest accuracy. 2) Test the accuracy at which different morphologically defined classes of vegetation could be digitized from remotely sensed imagery and highlight which classes had the highest and lowest accuracy. Past studies (Chen et al., 2004; Nijland et al., 2009) determined that with a more heterogeneous texture of classes that accuracy went down, however this makes sense as with coarser resolution imagery more details are lost. Zweig et al. (2015) and Husson et al. (2014) both used 5 cm resolution imagery and similar classes (categories) of vegetation within open water wetlands and high accuracies were achieved. Ways of categorizing vegetation will have an impact on accuracy as well and for my thesis because I am looking to see if RPAS imagery could replace ground based surveys, my classes tried to reflect the classes used in the ground based survey as best as possible. Because the resolution is still not finer than my smallest object being measured (grasses and moss) I predict that grasses, broadleaf and moss will achieve mixed to low accuracy results due to the intermixing seen within these vegetation classes. 3) I would like to investigate if RPAS can be used to map out vegetation composition and configuration to replace ground based surveys. If vegetation in peatlands can be mapped to a level at which validated metrics can be detected this technology has high potential to hold value as another tool for evaluation and monitoring on not only open water wetlands but peatlands as well. 4) Determine across an elevation gradient within the subregion groups (subalpine, montane and upper foothills) if there are any significant landscape metrics patterns that change across these subregions using elevation as a controlling variable. Subregions are groups of natural regions that are defined by vegetation, climate, elevation, latitude and physical geography therefore one would expect to see changes among vegetation communities across an elevation gradient (Natural Regions Commitee, 2006). Mountainous regions in Europe (Bruun et al., 2006) have demonstrated that both competition: between species decreases, and the species pool declines across an elevation gradient. In the Pacific Northwest, forested wetland vegetation communities have also been documented to show pattern changes along an elevation gradient (Hough-Snee, 2020). In the Rocky Mountain and Foothills region of Alberta elevation is strongly linked to a climate gradient, which as temperatures rise it is predicted that plant communities found at lower elevations will migrate over time and replace those at higher elevations (Schneider, 2013). Using the landscape metrics generated from my digitized vegetation classes for each of the 18 peatlands I will plot them against elevation to determine if there are any significant patterns related to the elevation gradient and determine if RPAS imagery can indicate them.

2.0 Methods

2.1 Study Area

The study area covers 3278.165 km^2 in the Upper Bow River Basin of Alberta, Canada. For Albertans, the run off that comes from snow and ice melt in the Rocky Mountains accounts for 8-20% of the total average discharge into the Bow River (Bash and Marshall, 2014). The Bow River is expected to experience more rain vs. snow as climate change progresses and temperatures rise (Masud, M. B., 2018).

The Kananaskis region is heavily used for recreation and economic activities such as logging, and cattle grazing (Public Lands Act, 2000; Bow River Basin Counsel, 2021). Our study sites were purposely selected away from direct anthropogenic disturbance to limit the variables involved in composition and configuration of vegetation at varying elevations (Lei, 2020). However, that does not mean these sites are protected from these recreation or economic activities affecting them in the future.

The 18 sites flown via RPAS were located within the subalpine, montane, and upper foothills subregions within an elevation gradient (1415 - 2106m asl) (Lei, 2020). Wetlands make up approximately 14% of the area within the selected subregions (Natural Regions and Subregions of Alberta, 2006). However no wetlands in these subregions have been mapped in the Alberta Wetland Inventory documented by Ducks Unlimited or at least made available for public access (Figure 1). All 18 sites were classified into the broad group of peatlands, as reference to the Alberta Wetland Classification System (Branch and Floor, 2015).

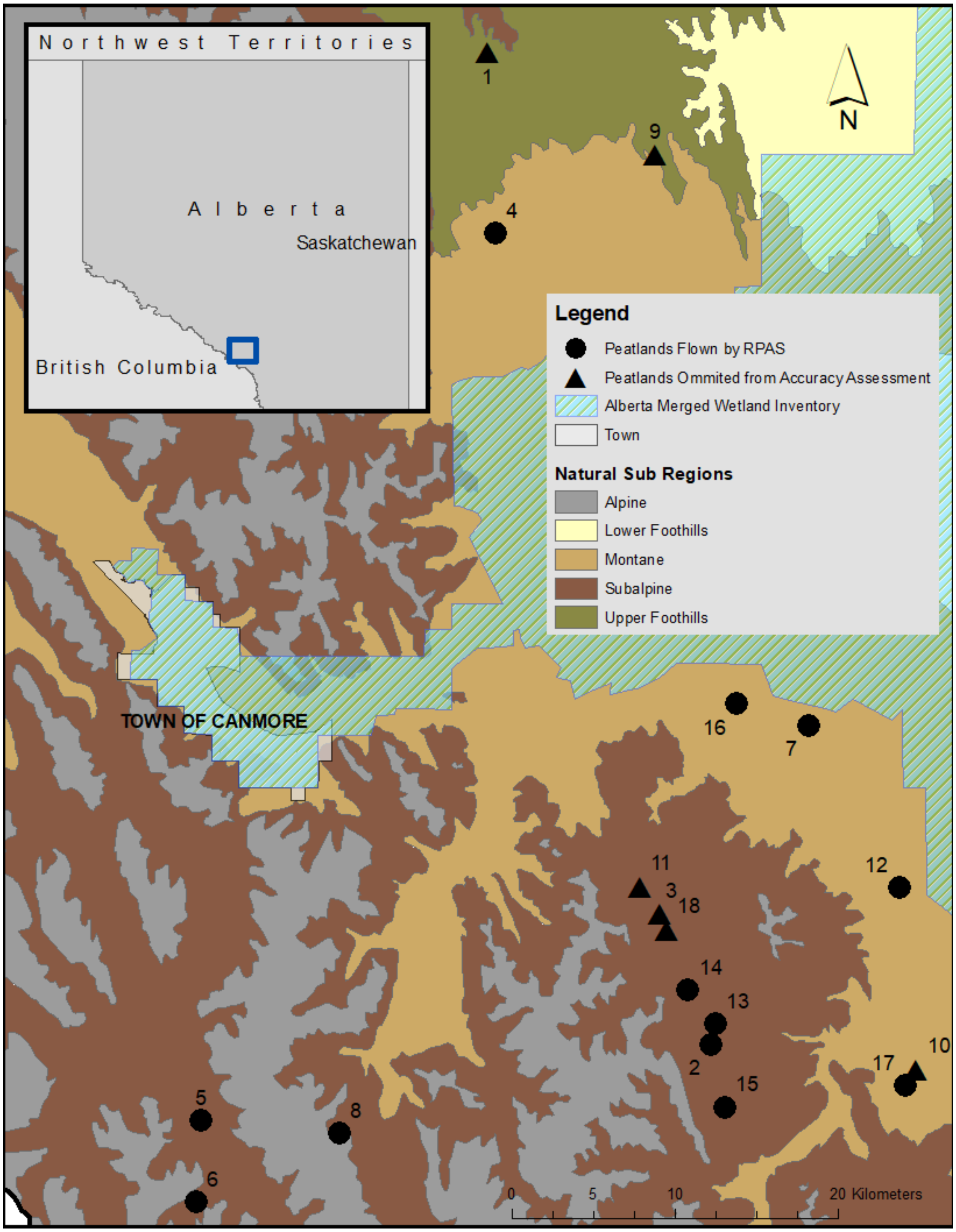


Figure 1: Map of study region showing locations of the 18 peatlands flown via RPAS and the Alberta Merged Wetland Inventory. Triangles represent the peatlands omitted from the accuracy assessment. Peatlands that were flown span across 3 subregions: subalpine, montane, and upper foothills encompassing an elevation gradient of 1400 m – 2150 m. Points numbered 1- 18 reference Appendices listing individual peatland maps.

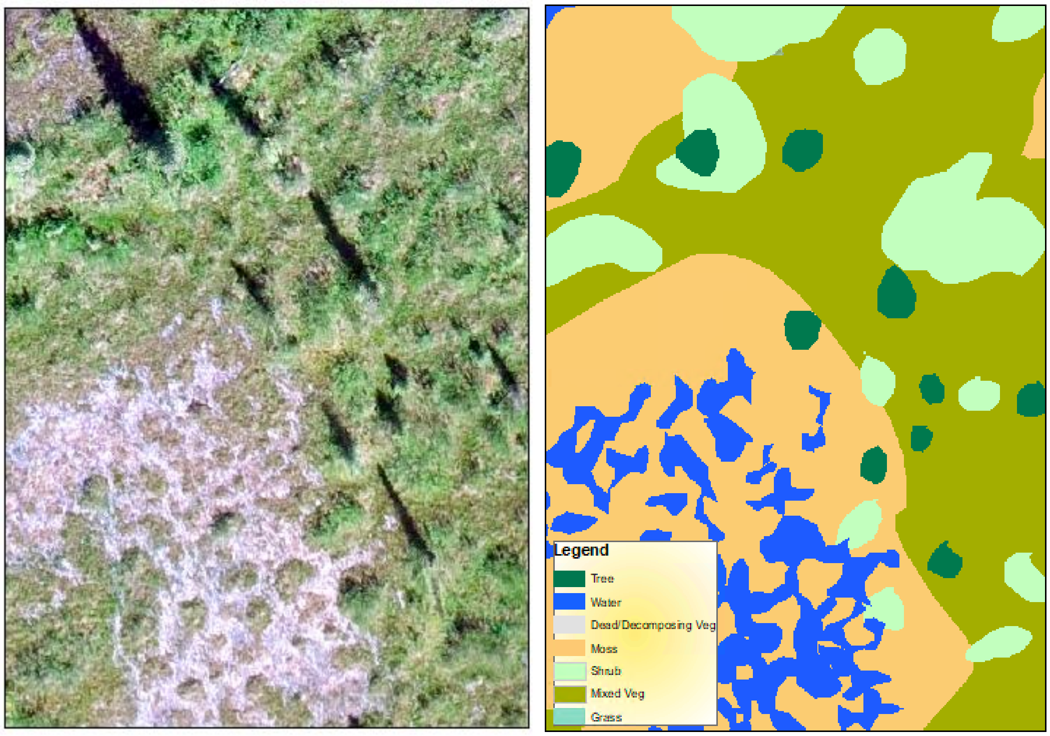
2.2 Remotely Piloted Aircraft Systems (RPAS) Survey

Imagery of the 18 peatlands surveyed were acquired using a RPA called the Inspire 1 made by DJI. The camera that was used to collect imagery was a Zenmuse Z3. Each flight from the DJI RPAS was flown at 60 m above ground level (AGL) at a speed of 3.5 m/s and 40 m AGL at a speed of 2.5 m/s, which resulted in a spatial resolution of 2 cm and 3 cm respectively. The 40 m flights were only flown over the area that encompassed the transects and the respective quadrats in avoidance of terrain, whereas 60 m flights encompassed the maximum extent with some overlap of forested area in order to capture as much of the basin that was used in the vegetation sample.

Before each flight was executed, ground control points (GCPs) were distributed around the peatland. GCPs were ideally placed around the border and within the interior area of the peatland but certain sites made this impossible topographically. A minimum of 10 and a maximum of 18 GCPs were placed accordingly depending on the size of the site. The GCPs were recorded with a base station and rover configuration using two Leica Viva GS14 receivers and a Leica Viva CS15 field controller, which achieved an average rover accuracy of 5 cm or less. Our GCPs were 12” x 12” floor tiles comprising two black and white ¼ section squares that provided high contrast and a distinctive center point. The GCPs were used in structure-from-motion generation of ortho-mosaic for each sample site using Pix4D (Pix4D SA, Switzerland).

2.3 Image Classification

The RPAS imagery was processed using Pix4D v.3.2.10 (Pix4D SA, Switzerland) to generate an ortho-mosaic of each of the 18 peatlands. Ortho-mosaics were imported into ArcMap for on-screen manual digitizing to differentiate between vegetation communities based on their morphological structure and texture. Before digitizing commenced, (Lei, 2020) co-interpreted the imagery to determine the vegetation communities that could be visually identified by morphological structure and texture and then digitized into respective classes that replicated classes used in the ground based survey (Table 1). Image classification was done through image interpretation of the 3 cm resolution imagery. Each peatland was digitized at a scale of 1:100 with a minimum mapping unit of 30 cm (3 cm pixels x 10 pixels) to identify the variation in vegetation types. The process commenced with the delineation of trees and tree cover, due to the ease of identifying their color, texture, and shape. After the delineation of trees, the following cover and vegetation community types were systematically digitized to ensure consistency across all study sites: water, rocks, dirt, shrubs, grass, moss, mixed vegetation (mix of grass and shrubs), and any other non-vegetative objects such as humans, and roads. A mixed vegetation class was required because at 1:100 it was not possible to 1) differentiate interspersed vegetation such as broadleaf or sedge from shrubs or grasses depending on the species or 2) accurately determine the boundary between two vegetation communities. After all vegetation and cover classes were delineated, boundaries between adjacent polygons of the same vegetation or cover type were dissolved.



A) B)

Figure 2: A) Ortho view of a peatland before classification flown at 60 m and 1:100 B) Same area of peatland after classification at 1:100

Identified morphological based vegetation classes were present in all 18 sample peatlands allowing for a visual for how the classes change within subregions and elevations. Once the digitization was complete, an accuracy assessment was conducted between digitized RPAS data and the ground based surveys done in geolocated quadrats by using a confusion matrix for each compared resolution of optical imagery.

Table 1: Land cover type and land cover descriptions for both RPAS and ground based surveys.

Land Cover Type	**RPAS-derived Morphological Description**	**Ground-based Description**
Tree	Conical shaped with dark green coloring, elevated texture, shading around	Woody vegetation > 2 m in height
Shrub	Round clusters of light green blue coloring, elevated texture similar to trees	Woody Vegetation > 2 m in Height
Grasses	Thin strand texture with little to no elevated texture	Graminoid vegetation, generally less than 1 m in height (e.g., sedges, rushes, grasses)
Broadleaf	N/A	Forbs and other herbaceous ground cover that is less than 1 m in height
Mixed Shrub/ Vegetation	Evenly mixed vegetation with borders of shrubs and grasses difficult to determine, usually clumps of shrubs with patches of thin strands 50:50 mixed	Shrubby vegetation interspersed as fine-scale clumps or evenly mixed at about 50:50 with either herbaceous vascular or non-vascular plants
Open Water	Blue or dark brown smooth texture, usually with light reflecting on image	Water
Bare Ground/ Dirt	Brown smooth texture	Exposed soil
Litter/ Decomposing Vegetation	White trees either standing or laying down	Standing dead trees and decomposing vegetation
Rock	Grey circles with little to no seen texture	Exposed rock

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2.4 Vegetation Assessment

Vegetation surveys can be subject to error in two ways: error of omission and misclassification. Imperfect detections, meaning misclassified or omitted species data, occur within almost every kind of ground based survey whether animal or plant type surveys, and although there is no known technique to eliminate error there are ways in which to reduce error (Morrison, 2016; Chen et al. 2013). The techniques used in the vegetation assessment, reduced errors of omission to 10% or less, and reduced misclassification by eliciting two observers during the vegetation surveys. By doing this, what one user missed the other identified (Lei, 2020). The combined approach that was used in this ground based survey yielded a high accuracy for identifying vegetation within peatlands, reduced errors of omission and afforded misidentification to be negligible for the classification results used in this study (Lei, 2020).

Within each of the 18 peatlands, three 50 m transects were established, approximately 50 m apart, to perform a vegetation assessment. Along each transect, (n = 5), 1 m x 1 m quadrat were equally spaced. At each peatland in concert with the ground based assessment, we acquired GPS coordinates of the middle of each quadrat using our Leica equipment.

Figure 3: The center of every quadrat, including end points, were recorded by GPS receiver and are represented by blue dots. The yellow line illustrates one of three transects through the peatland. Black squares establish the transect beginning and end points.

Within each quadrat, vegetation was identified as respective species and their relative abundance estimated as percent composition. If understory vegetation was present then both canopy and understory vegetation was identified and added to the total percentage composition. The ground based assessment conducted in the field identified the composition of a quadrat and dominant vegetation cover using the protocol in Table 2.

Table 2: Ground based protocol used for determining dominant cover for each quadrat.

Shrubs	If >40% shrubs, then shrub
Mixed Shrub	If >15% shrubs and no more than ~20% anything else, then mixed shrub
Moss	If <15% shrubs and >40% moss, then moss
Grass	If <15% shrubs and >40% grass, then grass If >50% grass + litter, and grass is at least 20%, then grass
Water	If >50% open water and <~20% shrubs, then water
Litter	If >60% litter and not >30% grass or >15% shrub, then litter

The dominant cover type for each quadrat was used to determine the accuracy of the RPAS data. Using the ground based protocol (Table 2) the RPAS imagery was interpreted for each geolocated quadrat to determine what the dominant vegetation cover was for: 3 cm – 1:100, 3 cm – 1:50, 2 cm – 1:50, and 2 cm – 1:50 with a reduction of two vegetation classes.

2.5 Accuracy Assessment Analysis

To address objectives 1 and 2, I conducted an accuracy assessment using confusion matrices which provided a way to look at resolution and individual class error. Of the 18 sites flown, 12 were used to assess the accuracy associated with using remotely piloted aircraft imagery (Figure 1). Sites that were not completed in parallel with the ground based survey were removed from the accuracy assessment because the GPS equipment (SX Blue II+ GNSS Technical Schematics) used by the ground based vegetation survey team derived an average horizontal accuracy of < 2.5 m, which is insufficient to ensure alignment with RPA data to the 1 m x 1 m quadrats. One additional site was removed because the RPAS data was not collected correctly resulting in misalignment between imagery and ground control points that could not be corrected.

The degree of correspondence between ground-based vegetation assessment and RPAS derived data was based on comparisons of dominant vegetation within each quadrat (n=15) in each peatland (n = 12). Two peatlands incurred errors or missing GPS data for one quadrat, which yielded a total of 178 quadrat comparisons. Furthermore, ground-based data was compared against imagery acquired at 40 m and 60 m above ground altitude with 2 cm and 3 cm resolution imagery respectively. Accuracy was assessed based on the dominant morphological vegetation class interpreted in each quadrat since the ground-based fieldwork did not identify the spatial configuration of vegetation communities within the quadrat.

To understand the accuracy among different vegetation communities classified using RPAS optical imagery, a confusion matrix approach was used to quantify and assign error. The dominant vegetation in RPAS imagery was identified by using the same means as the ground based protocol (Table 2). However, the ground based assessment did not include trees or woody vegetation greater than 2 m of height. Therefore, we were unable to assess the correspondence between the ground based assessment and aerial data for those vegetation types. A confusion matrix was completed for: 3 cm - 1:100, 3 cm - 1:50, 2 cm - 1:50, and 2 cm - 1:50 with a reduction of two vegetation classes. For the fourth confusion matrix, the 'Broadleaf' (n = 11), all 11 were merged into the 'Grass' class. For the 'Litter' class (n = 14), 6 were merged to 'Grass', 4 were merged to 'Shrubs', 2 were merged to 'Moss', and 2 were merged to 'Mixed Vegetation' as dictated by the subsequent highest percent composition in replace of 'Litter'.

2.6 Analysis of Spatial Composition and Configuration

To address objectives 3 and 4, the digitized maps were refined to ensure consistency in peatland boundary delineation and to remove human constructed features (e.g., removing upslope roads and non-peatland area). To conduct these refinements, a coarse boundary was delineated using a 25 m resolution DEM (Digital Elevation Model). The lack of secondary evidence of peatland boundary resulted in using a coarser resolution to account for potential error in boundary delineation, although this will potentially overestimate peatland area compared to a higher resolution DEM. The boundary was refined by eliminating area around the peatland that contained an increase in slope greater than 4.5 degrees. Studies have delineated wetland boundaries with high accuracy using a slope of 4.5 degrees in the absence of soil samples, additional hydrological data, and complete boundary vegetation surveys (e.g., Zheng et al., 2017; Islam et al., 2008).

The final delineated peatlands were provided as input to assess the composition and configuration of vegetation communities within each peatland using class and landscape level metrics. A total of 198 landscape metrics were calculated (64 landscape level metrics and 134 class level metrics). Landscape metrics (patch, class and landscape level) have been found to be highly correlated and therefore we conducted a correlation analysis and with an initial cutoff of 0.75 (McGarigal, 2006). Using a cutoff value of 0.75 demonstrated a strong correlation, and removed 83% of correlated metrics leaving a viable set of both class and landscape level metrics. Correlated metrics were removed in R using the caret Package (Kuhn, 2016), which reduced the number of potential metrics for selection to 34. The remaining 17% (34 metrics) were plotted against elevation using a linear regression to determine if the patterns of vegetation differed along the elevation gradient (1400 m – 2150 m). 7 landscape level metrics showed significance.

3.0 Results

3.1 Comparison of Ground Survey and RPAS Vegetation Dominance

The overall accuracy of 2 cm imagery digitized at a scale of 1:50 was 60%, while 3 cm imagery digitized at 1:50 and 1:100 was 51% and 31%, respectively (Tables 3-5). This outcome is expected and aligns with classification improvements with increasing resolution of satellite-based data (e.g., Chen et al., 2004). The outcome of our accuracy assessment demonstrated that both finer resolution 2 cm data collection and finer scale (1:50) image interpretation compared to 3 cm and a scale of 1:100 resulted in higher accuracy of delineated peatland vegetation communities using RPAS.

While the overall accuracy of RPA data is substantially lower than the de facto remote-sensing standard of 85% (e.g., Wulder, 2006; Foody, 2008), specific classes performed well (75%-85%). For example, shrubs were identified at an accuracy of 85% at 2 cm resolution and 1:50 scale digitization (Table 5). Grass was more distinctly identified at a finer scale of digitizing (1:50) and was identified with 78% and 68% accuracy (Tables 5, 4) at 2 cm and 3 cm, respectively. Since tree cover was purposefully excluded from the quadrat selection in the biological survey and this vegetation type is most easily identified in RPA imagery, it is anticipated that the accuracy associated with tree cover would be at least as high as that of shrubs. With the inclusion of tree cover the overall accuracy would have been higher.

Upon interrogating confusion matrices quantifying quadrats in alignment and differing between the ground-based assessment and RPAS digitized data (Tables 3-6), two classes were unable to be identified from the RPAS data: litter and broadleaf vegetation. Both of these types of vegetation have been a source of failure in previous studies (e.g., Homolova et al., 2013; Palace et al., 2018). Misclassification associated with these two classes is partly due to colour and texture that is similar to moss or grass as well as that some quadrats contained an overstory shrub canopy (e.g., Labrador Tea, *Rhododendron groenlandicum* (Oeder) Kron & Judd).

The outcome of the error associated with litter and broadleaf is that RPAS data are not sufficiently refined to delineate those classes of interest for ground based assessment. To further understand the RPAS accuracy, the broadleaf class was aggregated into the grass class and litter was aggregated into the runner up to the dominant class. This aggregation step yielded more successful results (an increase of 12%), achieving an overall accuracy of 72% (Table 6).

At all altitudes and scales of digitizing, confusion also occurred between the mixed class of shrub and vegetation with other classes. Most differences were due to RPA classification, of the ground based assessment of mixed vegetation, as a non-mixture and dominated by either shrub or moss. Most mixed vegetation could be termed as the matrix in which a transition zone exists between patches (Gökyer, 2013). In hindsight, the thresholds used to identify this class are qualitatively defined, are not based on community function, and could have been classified in a different manner that yields a higher accuracy of RPA image interpretation.

Table 3: Confusion matrix showing the results of the classification at 3 cm and 1:100 scale.

		RPAS Classification									
		Shrubs	***Grass***	***Broadleaf***	***Mixed Veg***	***Moss***	***Water***	***Litter***	***Rock***	***Total***	***True Positive Rate %***
Ground Survey Classification	***Shrubs***	27	0	0	19	0	0	0	0	46	58.70%
	Grass	2	3	0	30	2	0	0	0	37	8.11%
	Broadleaf	0	0	0	11	0	0	0	0	11	0.00%
	Mixed Veg	15	0	0	14	1	0	0	0	30	46.67%
	Moss	6	0	0	22	9	0	0	0	37	24.32%
	Water	0	0	0	0	1	1	0	0	2	50.00%
	Litter	2	1	0	6	5	0	0	0	14	0.00%
	Rock	0	0	0	0	0	0	0	1	1	100.00%
	Total	52	4	0	102	18	1	0	1	n = 178	35.97%
	Precision %	51.92%	75.00%	0.00%	13.73%	50.00%	100.00%	0.00%	100.0%	48.8%	Overall%: 31.00

Table 4: Confusion matrix showing the results of the classification at 3 cm and 1:50 scale.

	RPAS Classification										
Ground Survey Classification		***Shrubs***	***Grass***	***Broadleaf***	***Mixed Veg***	***Moss***	***Water***	***Litter***	***Rock***	***Total***	***True Positive Rate %***
	Shrubs	36	2	0	8	0	0	0	0	46	78.26%
	Grass	1	25	0	7	4	0	0	0	37	67.57%
	Broadleaf	2	8	0	1	0	0	0	0	11	0.00%
	Mixed Veg	8	3	0	17	2	0	0	0	30	56.67%
	Moss	7	7	0	12	11	0	0	0	37	29.73%
	Water	0	0	0	0	1	1	0	0	2	50.00%
	Litter	2	1	0	6	4	1	0	0	14	0.00%
	Rock	0	0	0	0	0	0	0	1	1	100.00%
	Total	56	46	0	51	22	2	0	1	n =178	47.78%
	Precision %	64.29	54.35	0.00	15.69	50.00	50.00	0.00	100.00	41.79	Overall%: 51.00

Table 5: Confusion matrix showing the results of the classification of 2 cm and 1:50 scale.

	RPAS Classification										
Ground Survey Classification		***Shrubs***	***Grass***	***Broadleaf***	***Mixed Veg***	***Moss***	***Water***	***Litter***	***Rock***	***Total***	***True Positive Rate %***
	Shrubs	39	1	0	4	2	0	0	0	46	84.78%
	Grass	1	29	0	3	4	0	0	0	37	78.38%
	Broadleaf	2	8	0	0	1	0	0	0	11	0.00%
	Mixed Veg	6	2	0	15	7	0	0	0	30	50.00%
	Moss	3	6	0	5	23	0	0	0	37	62.16%
	Water	0	0	0	0	1	1	0	0	2	50.00%
	Litter	4	5	0	1	3	1	0	0	14	0.00%
	Rock	0	0	0	0	0	0	0	1	1	100.00%
	Total	55	51	0	28	41	2	0	1	n = 178	53.17%
	Precision %	70.91	56.86	0.00	53.57	56.10	50.00	0.00	100.00	48.43	Overall%: 60.00

Table 6: Confusion matrix showing results of the classification of 2 cm and 1:50 scale with a reduction of two vegetation classes.

		RPAS Classification							
Ground Survey Classification		***Shrubs***	***Grass***	***Mixed Veg***	***Moss***	***Water***	***Rock***	***Total***	***True Positive Rate %***
	Shrubs	42	2	4	2	0	0	50	84.00%
	Grass	3	42	2	6	1	0	54	77.78%
	Mixed Veg	7	2	16	7	0	0	32	50.00%
	Moss	3	6	5	25	0	0	39	64.10%
	Water	0	0	0	1	1	0	2	50.00%
	Rock	0	0	0	0	0	1	1	100.00%
	Total	55	52	27	41	2	1	n = 178	70.98%
	Precision %	76.36	80.77	59.26	60.98	50.00	100.00	71.23	Overall%: 72.00

The 2 cm imagery at 1:50 was the clearest and most accurately identified dominant vegetation. However, accuracy for determining different vegetation varied. When shrubs or grasses in were in large communities, identification accuracy was very high. In contrast, when a quadrat contained multiple clusters of different types of vegetation identification accuracy was lower. Accuracy was further reduced if there were multiple layers of vegetation present within the quadrat such as an overstory of shrubs and understory of grasses, broadleaf with moss or litter. This weakness of optical imagery cannot be overcome without the assistance of additional sensor information (e.g., LiDAR, Structure from motion (Sfm); Alonzo et al., 2020). While the overall accuracy metric provides an assessment of the general performance of the RPA data collection and manual interpretation against the biological assessment, variation in accuracy among sites spanned from 37%-100% (Figure 4). Peatland sites that averaged under 50% had more moss, broadleaf and litter within them as dominant morphological classes in the sampled quadrats, and based on the resolution of the imagery did not provide the pixels with enough texture or homogeny to be able to identify the correct dominant class. Whereas sites that achieved and accuracy of 75-100% were dominated by shrubs, grass, or mixed vegetation morphological classes which did have the texture and homogeny in their larger size to identify those classes to a higher percentage. An important note to take into account is that the lowest accuracy was achieved for the peatland that exhibited more subalpine meadow conditions than the others (Figure 4, rightmost and highest elevation peatland). Subalpine meadows tend to be dominated by broad-leafed plants (forbs, graminoids) which are challenging to classify with optical imagery given similarity in their structure and degree of intermixing. Although this site contained peatland the area of it was smaller compared to other sites flown in this study. Increased specificity of vegetation classes may require multiple sensors (Ivashchenko et al., 2021; Hernandez-Santin et al., 2019) or hyper-spectral data (Räsänen et al., 2019).

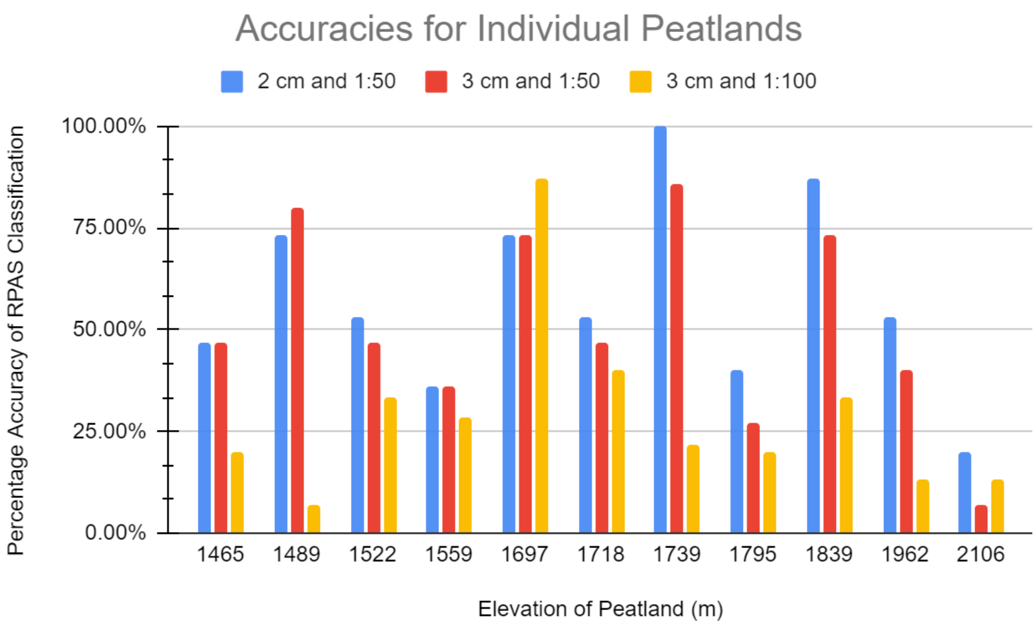

Figure 4: Individual peatland accuracy achieved with different resolutions of RPA imagery and scale of manual digitizing.

3.2 Relationship Between Composition and Configuration with Elevation

The outcome of our accuracy assessment identified that a resolution of 2 cm at a scale of 1:50 yielded improvements to accuracy (20 – 30% increases). At the time of data collection the 40 m (2 cm resolution) RPAS imagery was only flown over the transects and quadrats and not the entire peatland area as was the 60 m RPAS imagery. Because of this issue in the data collection, the 60 m (3 cm resolution) RPA imagery for all 18 peatland locations after boundary delineation (as described in *2.6 Analysis of Spatial Composition and Configuration)*, were chosen to be manually digitized using the 3 cm resolution data. Each peatland after delineation had a different number of morphological classes (6 min- 9 max), present at each location. Furthermore, our peatland boundary delineation approach (refer to *2.6 Analysis of Spatial*

Composition and Configuration) resulted in variable peatland sizes (ranging from 7400 m^2 - 101,100 m^2) and the exclusion of upland tree cover. Tree cover was still present in lower elevations in these sample sites indicating that using tree line alone would not be accurate at boundary delineation for these peatlands in this area. The vegetation and land cover classes analyzed in the landscape metrics package in R for community composition and configuration included: trees, shrub, grass, moss, mixed veg, water, rock, bare ground, and litter.

The landscape metrics (both class and landscape level) generated were narrowed down after removing very strongly correlated (Pearson) metrics (>0.75, Schober, 2018). The remaining metrics were regressed against elevation to see how vegetation composition and configuration of morphological structure based classes changed across the elevation gradient seen within subregions of Alberta. Only those metrics once plotted against elevation with a p-value less than α=0.05 were considered statistically significant and were retained. This process identified the following seven metrics: Standard deviation of related circumscribing circle (shape metric), Mean shape index (shape metric), Standard deviation shape index (shape metric), Mean fractal dimension index (shape metric), Mean radius of gyration (area and edge metric), Normalized Landscape Shape Index (aggregation metric), and Patch Richness Density (diversity metric) (McGarigal, 2015; Table 7). (See Appendices A1-A7)

Table 7: Landscape Metrics and the Significance when Plotted Against Elevation.

Landscape Metric	**P- Value**	**R^2**
Standard Deviation of Related Circumscribing Circle (Shape Metric) Landscape Level	0.027	0.12
Mean Shape Index (Shape Metric) Landscape Level	0.0032	0.43
Standard Deviation Shape Index (Shape Metric) Landscape Level	0.009	0.11
Mean Fractal Dimension Index (Shape Metric) Landscape Level	0.032	0.23
Mean Radius of Gyration (Area and Edge Metric) Class Level (Mixed Vegetation)	0.003	0.39
Normalized Landscape Shape Index (Aggregation Metric) Landscape Level	0.029	0.21
Patch Richness Density (Diversity Metric) Landscape Level	0.026	0.28

The patch shape metrics can be used to describe the compactness of vegetation communities, which when related to their size and adjacent communities provide insight into edge effects between vegetation communities as well as the level of complexity of peatland vegetation (McGarigal, 2015). The mean shape index describes the compactness of vegetation patches relative to a geometric square. The closer a patch is to resembling a square, the mean shape index approaches a value of zero. Assessment of vegetation community patch shape, using the mean shape index, found that vegetation patches became more irregular with increasing altitude (Figure 5) within each peatland. Changes in mean shape index were statistically significant (p-value 0.0032, and R^2 0.43).

Corroborating the mean shape index are the standard deviation of related circumscribing circle, standard deviation shape index, and mean fractal dimension index. Respectively, these metrics demonstrate that vegetation patches become less compact and more elongated ($p=0.027$ and $R^2=0.12$), less similar to each other (for the same vegetation community; p-value 0.009 and R^2 0.11), and the patches becoming more complex in their shape (p-value 0.032 and R^2 0.23) with increasing elevation within each peatland (Table 7).

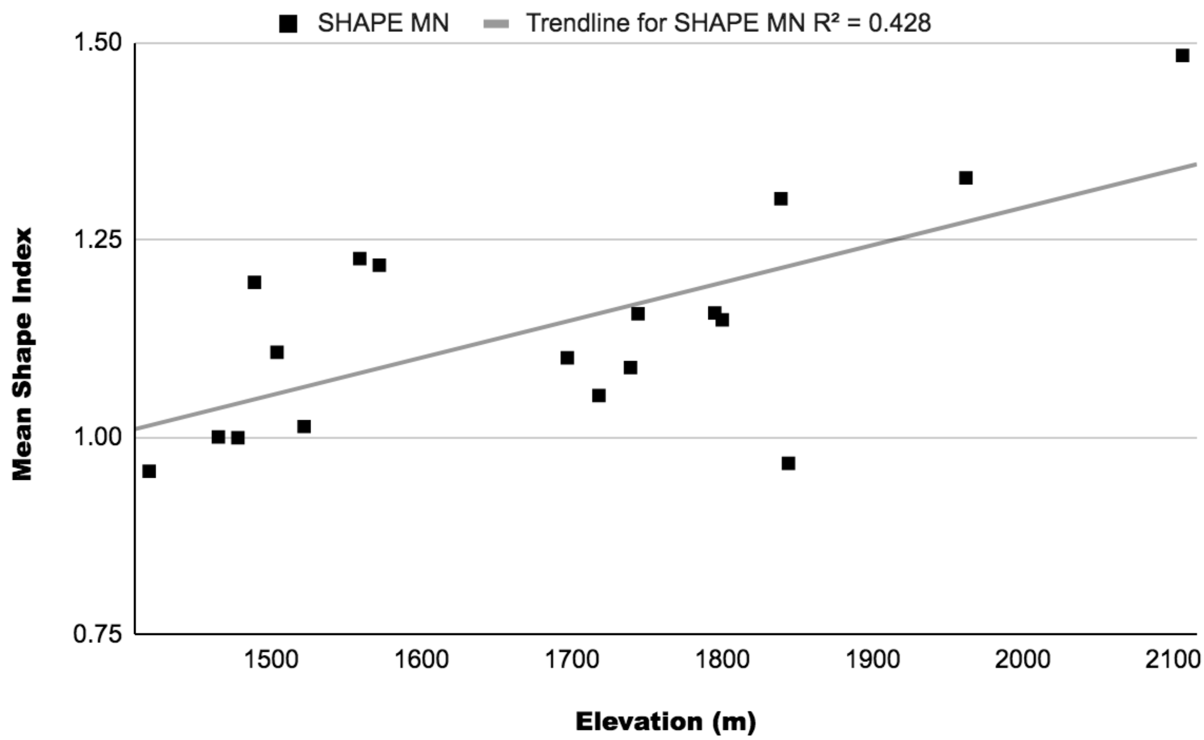

Figure 5: Mean shape index metric plotted against elevation, trendline showing significance as elevation increases.

In addition to the shape of vegetation communities within the landscape level, the area and edge of vegetation patches can be described using class level metrics. The mean radius of gyration gives an indication of the area and compactness of patches of a specific vegetation type (Mixed Vegetation) by measuring the distance of each cell within a patch to the centroid of that patch and reports the mean distance among those cells. Values of mean radius of gyration are bounded on the lower end at zero, when a patch comprises only a single cell, but can increase without limit as patch size and elongation increase. All 18 peatlands had patches with more than one cell. 'Mixed Vegetation' returned significant patterns and was the only class of 9 to show significance with elevation. With increasing elevation, the mean radius of gyration increases, indicating that the 'Mixed Vegetation' class expanded to larger and more irregular patch shapes with elevation. This area-edge metric was statistically significant in its relationship to elevation (p-value = 0.003, R^2 0.39).

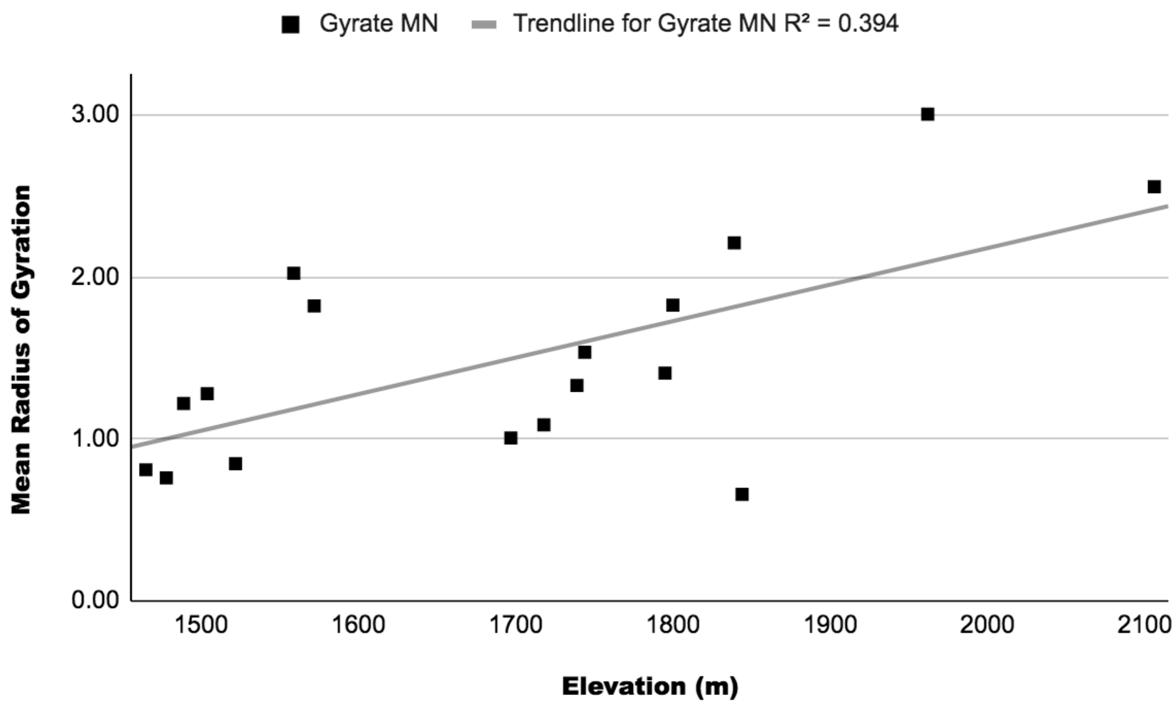

Figure 6: Mean radius of gyration metric plotted against elevation, trendline showing significance as elevation increases.

Measurements of aggregation are used to assess the dispersion and isolation of patches of a specific vegetation community. These types of metrics can provide insight into patterns where patches may become more irregular but more connected and therefore less fragmentation exists in the landscape. The Normalized Landscape Shape Index (aggregation metric, NLSI) measures the aggregation of classes within the landscape. As the value of the metric approaches 0 the shapes of classes consist of a single square or are dominated by one patch with little spatial variation and as the metric reaches 1 the classes become more fragmented with varying shape class sizes. The NLSI decreased with increasing elevation among our sample of peatlands, demonstrating that vegetation communities are less fragmented with less variation in class sizes with increasing elevation. The NLSI was statistically significant when regressed against elevation (p-value 0.029, R^2 0.21).

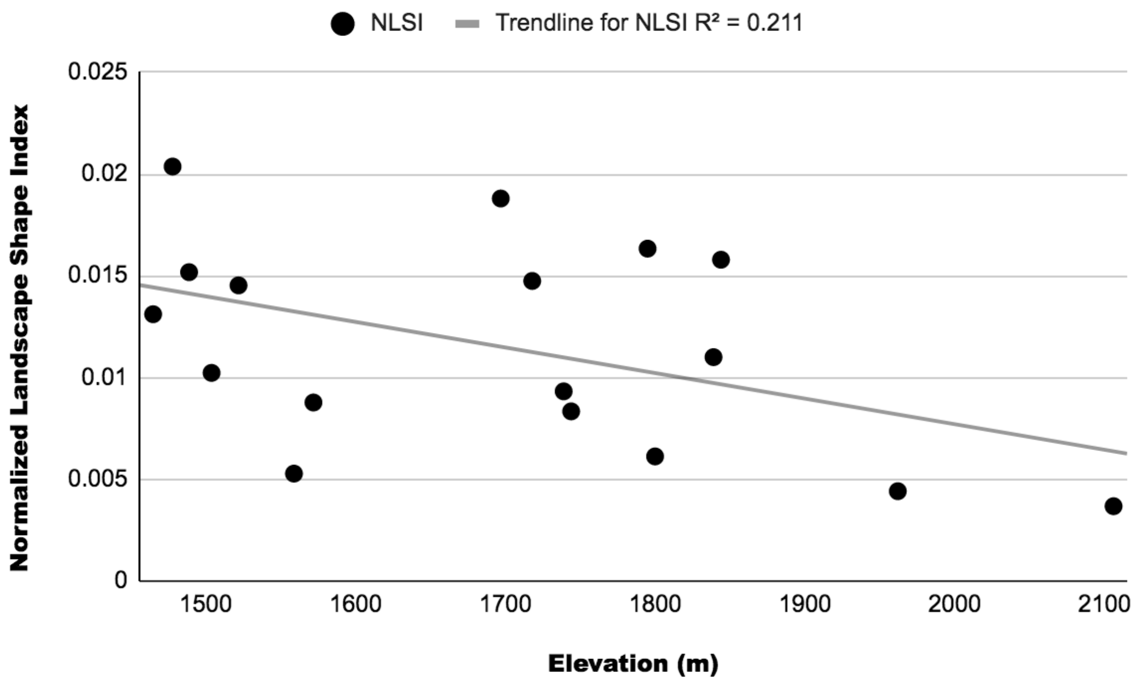

Figure 7: Normalized landscape shape index metric plotted against elevation, trendline showing significance as elevation increases.

Patch Richness Density shows the relative density (patch types (classes)) present in the peatland divided by the area (in hectares). The output gives a density per 100 hectares and as values increase from zero so does the density. Considering our metrics were looking at community composition and configuration it's most likely that patch richness density increases because as elevation increased the topography turned more mountainous and contained more rocks and bare ground in our RPAS imagery. Patch richness density was similar across most sites because unless there was rocks, dirt or decomposing trees other classes were present in every peatland. The p-value = 0.026 and R^2= 0.28. (McGarigal, 2015) The diversity metric indicates that the density of patches increases as the elevation does. While patch shape and aggregation explains only a small portion of the variance among vegetation community patches, the low p-values among the seven landscape metrics demonstrate that variation in the configuration of vegetation communities occurs across a subalpine elevation gradient of 1400-2100 m.

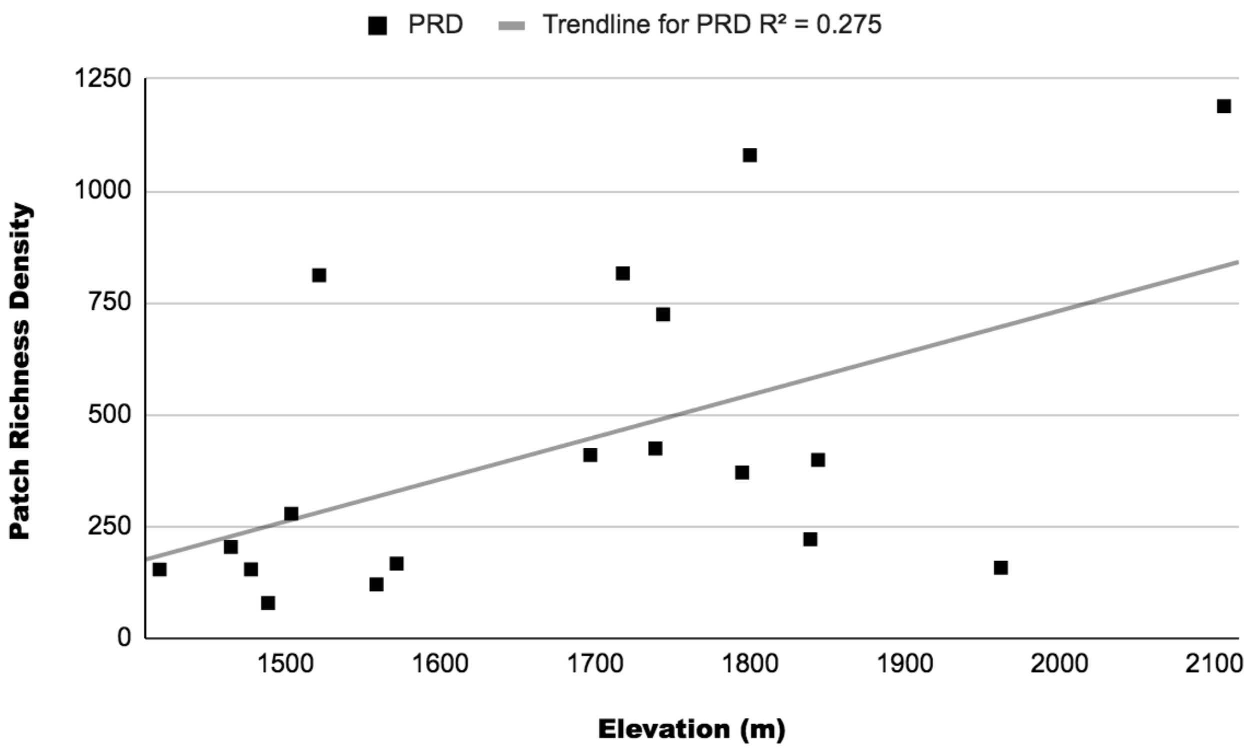

Figure 8: Patch richness density metric plotted against elevation, trendline showing significance as elevation increases.

4.0 Discussion

The presented research sought to use novel RPAS technology and complete 4 research objectives. To address Objectives 1 and 2, I looked at how differing image resolution (2 cm and 3 cm) influenced the ability to identify morphologically grouped classes within the RPAS imagery. To do this I evaluated the accuracy using confusion matrices at different resolutions and scales. My work demonstrates that optical imagery resolution of 2 cm and 3 cm produces different accuracy results. Based on the results different resolutions can distinguish different class accuracies, the highest achieved using 2 cm resolution and classifying at an image scale of 1:50. However as seen in various studies (Zweig et al., 2015; Palace et al., 2018; McPartland et al., 2019) all of which used coarser resolution than I did nonetheless achieved higher overall accuracies for their classes of vegetation. Their results signify that resolution is only critical based on the species or group, of vegetation being identified. Differences between these studies ranged from the grouping of classes into more broad encompassing classes that represented vegetation of interest, to various types of wetlands that support completely different species. Zweig et al. (2015) used 9 classes to describe open water wetland vegetation using 5 cm resolution and they achieved an overall accuracy of 69%. Whereas McPartland et al. (2019) used 5 classes to describe vegetation of interest using hyperspectral imagery using 1 m^2 and achieved an overall accuracy of 90%. For coarse vegetation communities, particularly those with vertical structure and difference from adjoining classes provide the most accurate classifiable potential when using only human vision. For example, delineation of shrubs achieved an accuracy of 85% and grass obtained an accuracy 78% both of which in the RPAS imagery had a distinct difference from the majority of the other classes. Using lower resolution hyperspectral imagery could allow to see the boundaries between vegetation classes such as grasses and mosses, much better than with human vision alone (McPartland et al., 2019). Burai et al. (2015) looked at 1 m resolution hyperspectral imagery and determined the accuracy of various dominant species within grasslands and marshes. Accuracy ranged from 30% - 100%, and the lowest accuracies were seen in the various dominant grassland species and all marsh species. The higher accuracies were seen among dominant species found in the sedge meadow (Burai et al., 2015). Although using sensors increases the accuracy in distinguishing between certain interspersed vegetation types perhaps there is a threshold of 1 m or less to produce high accuracy results for finer interspersed vegetation types.

In other research done on mapping peatland vegetation Palace et al. (2018) used functional morphological classes to map an area in the subarctic using 3 cm image resolution. The classes used were landcover types that translated over to dominant vegetation such as graminoid, shrub, and hummock found within those particular land covers in the study site. A texture analysis was used to determine the entropy, evenness and angular second momentum (measure of homogeny) and found that all vegetation classes had high evenness, entropy and angular second momentum, meaning that they had a lot of texture and it was evenly distributed amongst cells in peatlands. Studies done on open water wetlands (Husson et al., 2014; Husson et al., 2016; Zweig et al., 2015; Gilmore et al., 2008) at pixel resolutions of 6 cm – 2.4 m, where the majority of vegetation was able to stand out from open water, achieved accuracies ranging from 63% - 100%. Whereas studies that mapped peatlands (Räsänen et al., 2019; Palace et al., 2018; McPartland et al., 2019; Diaz- Varela et al., 2018) at pixel resolutions of 2.5 cm - 1 m achieved accuracies ranging from 35%- 100%. This indicates that resolution is not the sole factor responsible for higher accuracy when mapping various vegetation types, and instead more emphasis on what type of species are being mapped should instead influence decisions when selecting between resolutions and sensors. My results are similar to those of Zweig et al.

(2015) and Husson et al. (2016) in that vegetation with distinct coarser texture or vertical structure can be identified accurately using human vision direct - to RPAS attained imagery however higher resolutions achieved higher accuracy results. This suggests that while identifying wetland vegetation in open water wetlands using RPAS has been successful to a higher acceptable accuracy (over 85%) using RPAS to identify peatland vegetation will need possibly more sensors to distinguish between vegetation types in order to identify the correct dominant species. Tree cover was not assessed, but was the most easily identifiable vegetation community and therefore accuracy is likely to be at or above 85% as seen in other RPAS studies that mapped trees (Zweig et al., 2015; McPartland et al., 2019). While accuracy improved with reduced altitude and finer scale digitizing, yielding a maximum overall accuracy of 60%, other flight parameters, different classes of vegetation and sensors should be evaluated.

To assess Objective 2 and determine the accuracy at which different morphological structure based classes of vegetation could be digitized from RPAS imagery, I used an error matrix in order to understand which classes did better or worse in comparison. I found that shrubs achieved the highest accuracy at every resolution and scale, and litter and broadleaf did the worst while moss achieved moderate accuracy (30 – 60%). It is important to acknowledge that the community structure within a specific time will fluctuate year to year, season to season depending on different variables (Liu et al, 2020). However, drones offer flexibility to collect data anytime of the year as long as weather conditions are favorable for safe flights. Using RPAS only during peak vegetation growth, which this study has looked at, has been found to limit understory vegetation accuracy in other studies and increasing the RPAS collection frequency would yield improved accuracy (Hernandez-Santin et al, 2019). It may be the case that mosses are more easily identified during suboptimal growth periods when canopy vegetation is yet to dominate (e.g., in non-growing season). In other remote sensing studies (Chen et al., 2004; Nijland et al., 2009) show that another reason for this lack of accuracy could be the heterogeneous texture among pixels that make it difficult to determine the dominant species, similar to what was seen at varying resolutions. In studies that mapped wetland communities (Zweig et al., 2015) they too struggled at 5 cm resolution to identify vegetation that lacked a distinct way of identifying them by texture or vegetation that separates the distinct class. One particular class that did poorly in Palace et al. (2018) was graminoids, which have a morphological structure to grass and achieved an accuracy of 50%. However in McPartland et al. (2019) showed very low error for 4 classes (Forest, Shrub, Graminoid and Tussock Grass) using hyperspectral imagery for peatlands in Alaska. Using a combination of sensors to see understory vegetation (Wing, 2012) and inclusion of vegetation indices (e.g., NDVI) and hyperspectral sensors may yield improved results for identification and delineation of mosses and broadleaf vegetation.

Predicting understory vegetation in different ecosystems presents very different problems e.g., shrubs or tall grass verses forest canopy. Mid-altitude aerial LiDAR (Gilmore et al., 2008) and hyperspectral imagery (McPartland et al., 2019) has also had a small number of high accuracy studies published with regards to classifying vegetation communities in wetlands and more research done with contemporary RPA data should be done using sensors with point densities >400 per square meter to investigate a resolve for this problem. Using multispectral imaging with a small amount of classes (trees, shrubs, herbaceous vegetation, crops, water, and bare ground) as seen in Ahmed et al (2017) demonstrated that multispectral imaging is 95% effective at identifying and deciphering these broad groups of vegetation. Investigating whether accuracy can be maintained with multispectral imaging for more specific classes of vegetation such as mosses, broadleaf and grasses within peatlands merits verification.

Although the accuracy did not meet the 85% *de facto* remote sensing classification standard in every class, accuracy was very high in certain vegetation classes and those classes can provide insight on peatland vegetation community patterns especially since *Salix* spp.(shrub) has been verified to signify disturbance in other wetlands in monitoring evaluation tools in other subregions of Alberta (Bolding, 2018) and contingent on if it is proven to be an indicator in subalpine, montane and upper foothills peatlands could then be monitored with greater than 80% accuracy with RGB imagery. My results demonstrate potential for the use of manual classification of dominant vegetation that is coarser, contains vertical vegetation communities, however, accuracy for delineating finer or understory vegetation communities (e.g., mosses, broadleaf) and cover (e.g., litter) require further investigation and likely the use of alternative sensors (e.g., hyper-spectral, LiDAR) will be needed in order to accurately classify them.

To complete Objective 3, I wanted to investigate if RPAS can be used to map out vegetation composition and configuration to replace ground based surveys. A need for an effective evaluation tool for wetland health in the prairie pothole region was filled by Bolding (2018) where he used ground based surveys to create dominant species composition across various wetlands and ran landscape metrics against various groups of healthy and unhealthy wetlands to determine metrics that indicated disturbance. Using RPAS to replace the ground based surveys would reduce field data collection time and allow faster results to be generated up until the landscape metrics part of the evaluation.

When using landscape metrics as part of an evaluation tool, scale is critically important to what you are trying to measure as patterns will change with various scales of resolution and classes being measured (Lausch et al., 2002; Castilla et al., 2009). In my thesis I chose to look at morphological structure-based classes across 18 different peatlands at 3 cm resolution imagery at both landscape and class level metrics. Although the results comparing RPAS imagery surveys to ground based surveys were unable to be verified to a high degree of accuracy (less than 85%), I believe that this still proves that it is possible to map the composition of a peatland to a high degree of accuracy, contingent on either a change to sensors or classes. Hedwall et al. (2017) looked at how vegetation communities changed in peatlands in Sweden over a 20 year time frame and they found classes of vegetation such as *Sphagnum* spp., shrubs, grasses that change in area and size due to temperature. If the same is true for Alberta's peatlands in the subalpine, montane and upper foothills using alternative sensors to increase accuracy of remotely sensed imagery could provide an efficient way to monitor these classes. Another study done in Sweden by Palace et al. (2018) found that shrubs and hummocks were the best vegetation to monitor permafrost in which using RGB for shrubs would suffice.

Although results of the landscape metrics in this study will be limited to how accurately the data was identified there is still merit in using the imagery as accuracy was only based on a 1 x 1 m squared parameter for identifying dominant vegetation and errors were frequently misclassified for their secondary dominant morphological class. Majority of the other research out in the field of RPAS remote sensing of vegetation uses a minimum area of 2 m^2 for the ground based vegetation sample, allowing more texture to be classified in the comparing imagery (Husson et al., 2016). Reclassifying the landcover could help for certain classes by grouping them into broader vegetation covers, however for this study I tried to replicate the vegetation collected from the ground based survey as best as possible and is the reason such classes were chosen. More work would need to be done to replace RPAS surveys with ground based surveys (Bolding, 2018). The knowledge about indicators and their ability to be mapped in the peatlands in Alberta's subalpine, montane and upper foothills subregions is not known. Those indicators would need to be linked and validated against metrics in order to become an effective way to evaluate peatlands. However certain classes were related to metrics that were validated to indicate disturbance in other subregions of Alberta such as *Salix* spp. and *Carex* spp. which with using RGB imagery and human vision we demonstrated can be done.

To complete Objective 4 and determine if across an elevation gradient within the subregion groups (subalpine, montane and upper foothills) there are any significant landscape metrics patterns that change across these subregions using elevation as a controlling variable. We found that some metrics changed with increasing elevation however the function, and operation of a these metrics found is still unknown. The ‘Mixed Vegetation’ class changed across the elevation gradient signifying that area of transition between clusters of vegetation does seem to change. Castilla et al., (2009) proved over repeated sampling that metrics change with resolution, therefore there could be a bias depending on the resolution. Seven landscape metrics showed statistically significant changes in pattern with elevation and these metrics covered the shape, the area and edge, and aggregation of vegetation patches as well as the diversity of vegetation communities giving information about the appearance of the vegetation classes within each peatland. Whether or not these provide useful information about the subregions or not would have to be connected to a function of how the ecosystem preforms at different elevations with these vegetation patterns. What is driving the vegetation to grow in less fragmented and larger patches is yet to be known or validated, and will need to be further investigated.

As seen in other studies that looked at mapping wetland vegetation communities along an elevation gradient (Hough-Snee, 2020; Bruun et al., 2006) saw that elevation was connected to hydrological paths of flow, and or soil properties which have a known relationship to vegetation community composition. To further link and validate these metrics and discover what drives these landscape patterns an overlay to each wetland with the hydrological flow path would need to be connected to elevation. Once that is done however using environmental gradients is a simple way to examine natural variation in vegetation community responses to environmental changes (McGill et al., 2006).

The Natural Subregions of the subalpine, montane and upper foothills have different climate predictions based on modeling done by Schneider (2013). One prediction is that as the temperatures warm that there will be more diversity within the montane and upper foothills subregions as lower elevation vegetation migrates into higher elevation vegetation creating an increase in diversity during the transition (Schneider, 2013). The results of the patch richness density metric demonstrate this pattern, however this metric is subject to area bias. Patch Richness Density is a metric weighted against area and therefore because of our vast range in sizes it is subjective to bias (McGarigal, 2015). It is important to remember that the number of species increases with area (Keddy, 2016) and therefore because our sites had varying sizes increased patch area density will increase as area increases. On a species level done with a ground based survey, showed that there was no significance found comparing species composition to elevation although some optima was seen with indicator species (Lei, 2020).

Outcomes from the pattern analysis of our 3 cm optical imagery corroborated findings from quadrat and transect analysis in that with increasing elevation the pattern of vegetation communities became more complex and more evenly distributed. The ground based assessment found smaller more dispersed patches with elevation and increasing complexity (Lei, 2020). More complexity within increasing elevation may be due to the species dominating quadrats at higher elevations (1800 m+) (*Sphagnum* spp. and *brown mosses* spp., *Salix* spp., *Carex* spp., and *Betula glandulosa*) and their morphological characteristics. The ground based survey demonstrated that among *Sphagnum* spp. and *brown mosses* spp. *Salix* spp., *Carex* spp., and *Betula glandulosa* no species covered more than 25-30% of quadrats at higher elevations, which increases the difficulty with their spatial identification and delineation with remotely sensed data based on the heterogeneity of the texture within the imagery, hence larger patches of 'Mixed Vegetation' as elevation increased. As elevation increased along the gradient the patches of vegetation grew less fragmented and the patches extent increased, as seen similar with the ground based survey results. This shows some validity to our landscape metrics as they follow the same narrative as the ground based survey on species level composition (Lei, 2020), as did with class level ('Mixed Vegetation' class) and landscape level metrics.

5.0 Opportunities for RPAS in Wetland Research

Identification and delineation of fine scale peatland vegetation communities using remote sensing platforms presents a challenge because small leaves on mosses and strictly vertical vegetation with a small radius such as cattail (Typha spp.), require very high-resolution imagery and in many cases the vegetation is mixed rather than discretely identifiable as a specific vegetation type. While RPA are capable of acquiring imagery at very high spatial resolutions, temporal frequency can also play a critical role since leaf and flower phenology present themselves with different visible characteristics at different times of the year (e.g., Hernandez-Santin et al., 2019) or during years when certain conditions are met (e.g., the dark diversity pool, Pärtel et al., 2011).

The presented RPA data collection was conducted only once during the months of July and August. Improved classification accuracy and vegetation identification and mapping should be systematically evaluated throughout the growing season. While spatial-temporal data resolution and frequency of acquisition are somewhat obvious opportunities for improvement, ground-based perspectives and measurements are likely to contain some differences. For example, the ground based assessments inclusion of litter and identification of multiple layers of vegetation (e.g., shrub and below shrub) are not achievable with optical imagery. Future research could mitigate this issue through the inclusion of light detection and ranging (LiDAR) data acquisition, which have the ability to identify vegetation layers (e.g., Hernandez-Santin et al., 2019; Campbell et al., 2018) as well as vegetation height (e.g., Antonarakis et al., 2008), leaf angles (e.g., Zheng et al., 2009), and topography that can also aid in vegetation classification (e.g., Branton et al., 2018). While other sensors cannot get at the structure of the vegetation and topography similar to LiDAR data, multi- or hyper-spectral data can be used to calculate vegetation indices and specific spectral signatures using chlorophyll signatures that can improve vegetation identification (e.g., NDVI, Chen et al., 2021; Ahmed et al., 2017).

The presented research used image interpretation and manual digitization of vegetation communities to gain an understanding of what can be interpreted visually and to create a benchmark for comparison as manual interpretations are often found to result in higher classification accuracy than automated approaches (e.g., Huang et al., 2018). Among, automated classification methods, object based image classification is typically favored to avoid mixed pixel and speckling issues and pixel-based classification can miss distinguishing vegetation features (Hernandez-Santin et al., 2019; Baena et al. 2017). However, object-based classification uses a footprint method to establish a baseline for what the classified object could look like (Zarco-Tejada et al., 2014), which can be affected by a change in environmental conditions (e.g., sunlight, cloud cover, wind) that alter the vegetation colour, leaf direction, and vegetation movement. Mitigation of these effects can occur through strong flight planning, consistent environmental conditions, slow RPA flights, fast aperture image or data collection, and targeting key identifying features during the period they show up (Zarco-Tejada et al., 2014). Distinguishing between different tree species using object based classification has been verified by Baena et al. (2017) however object based classification used to distinguish finer scale vegetation such as grasses, mosses remains untested.

An opportunity exists for designing a hybrid approach to peatland vegetation characterization through the combined use of in situ and RPAS data collection. If the flight characteristics (i.e., altitude, sensor, daily and seasonal timing of flights) could be calibrated to field data collection, then peatland vegetation monitoring and long-term mapping could be achieved over seasons and years to quantify structural and spatial changes. For example, a systematic analysis of field and RPA data collection could identify that one or two on-the-ground field visits (spring and late summer) could be paired with multiple annual RPA campaigns, which would grossly reduce labor and field costs. In addition, the establishment of semi-permanent ground control points would further speed up the collection of RPA data.

While lower and slower flights come at the cost of flight time and computational overhead (e.g., more data and processing time), they are also constrained by the height of features (e.g., tree cover) in the study area. The presented research opted to use a safe altitude of 60m above ground level for the entire study area and 40m above ground level along biological assessment transects where vegetation heights were below this threshold. The 60m flights ensured that upslope tree cover did not come into contact with the RPA. Contemporary flight planning software has the potential to integrate digital elevation models and impose terrain following flights (Cui et al. 2014). However, flight-planning software accessible elevation models are coarse and deriving high altitude elevation models at finer resolution would require LiDAR, which has been excluded from these areas (e.g., Alberta lidar data collection; Altalis, 2021). Therefore, the inclusion of terrain following for high altitude wetland mapping is only advantageous as a proof of concept or when repeated sampling (i.e., flight campaigns) is planned.

In addition to resolution, acquisition of finer resolution elevation data (as opposed to the 25m DEM is available and used in the presented study) would for improved refinement of both the wetted area as well as peatland catchment for each study site. Finer resolution topographic data can accurately articulate surface runoff and hydrological channels and flow, which can be used to improve identification and delineation of vegetation communities as well as contribute to other insights about wetland function.

6.0 Conclusions

In conclusion, this thesis aimed to map subalpine, montane and upper foothills peatlands in areas that were not currently mapped, in order to answer different objectives. Considering the importance of peatlands and the configuration of their vegetation composition as accentuated in peatland studies around the world (Hedwall et al., 2017; Palace et al., 2018) being able to accurately map peatlands in Alberta remains of interest. I found that using optical RPAS imagery alone was not accurate enough to recommend replacing ground based surveys however with changes to the classification groups and using additional sensors, mapping peatlands with RPA yields high potential. Although increasing the resolution improved results of some vegetation classes, other classes will need a combination of other sensors and mixtures of functional morphological vegetation classes to provide a way to accurately account for all vegetation of interest.

Although elevation did not seem to play a role in species level configuration (Lei, 2020) there seems to be some level of connectedness to community level composition and configuration and are results were supported by (Lei, 2020) research. Larger studies with higher accuracy scores for vegetation identification should seek to replicate the results for class and landscape metrics seen for subalpine, montane and upper foothills peatlands. Patterns were seen in shape and aggregation metrics as elevation increased indicating that elevation is a variable to vegetation composition and configuration which shows congruence with other ground based surveys of these subregions (Schneider, 2013).

With climate change imposing low altitude conditions on high elevation subregions in the coming decades, understanding the species composition and configuration on multiple levels (species, community, and landscape) of peatlands will allow for educated decisions about evaluation and monitoring to be made. Using RPAS to gather the data needed to continue to map and monitor subalpine, montane, and upper foothills peatlands demonstrates a lot of potential to overcome previous limitations seen with mapping vegetation communities in the past. Although more work is needed to validate these results they present a way towards more effective vegetation survey evaluation and monitoring techniques.

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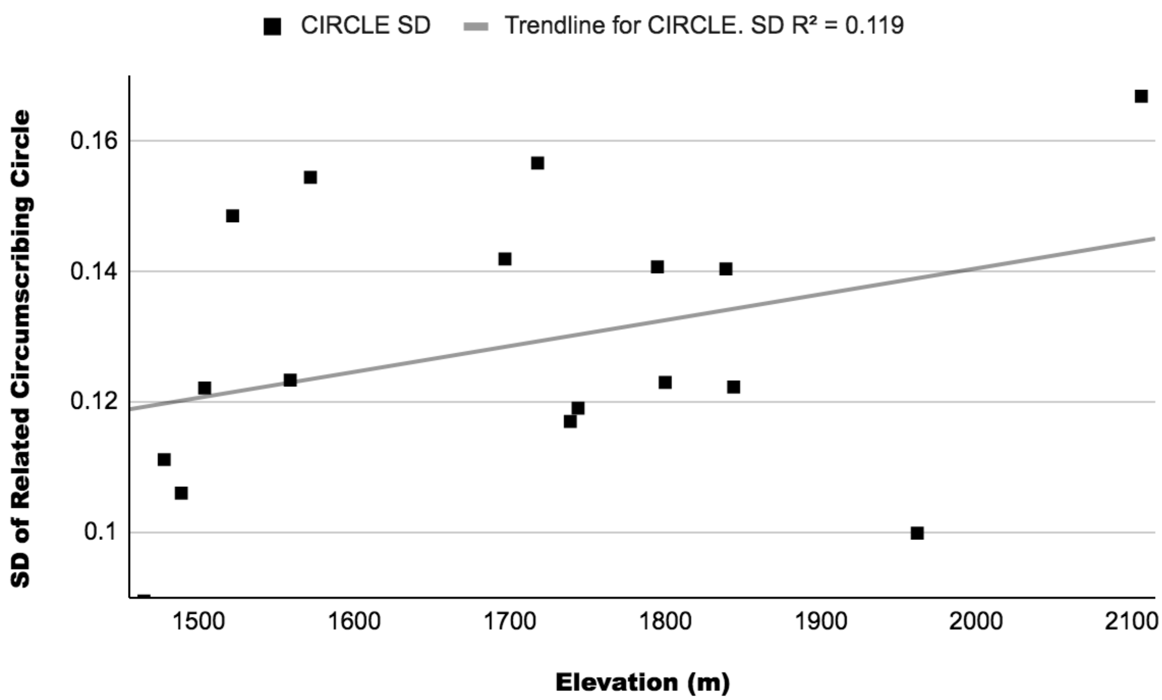
Appendices A:



A1: The standard deviation of related circumscribing circle (shape metric) assesses the size of circumscribing circles for each patch within a specific land cover class. This metric looks at the elongation and linear pattern of patches within their respective classes (McGarigal, K., 2015). The Standard deviation of the mean of the shape of the patches in each class reaches zero as the patches circumscribing circles are closer to the mean and the standard deviation of the circumscribing circle increases away from zero as the patches of each class become farther from the mean for each class. In our wetland sites we can see that patches within each class tend to become more deviated from the mean around 1500m and again around 1800m with a weak, but statistically significant, relationship to elevation ($p=0.0273$ and $R^2=0.119$).

Calculation Summary:
Sum of X = 30252

Sum of Y = 2.36

Mean X = 1680.6667

Mean Y = 0.1311

Sum of squares (SS_X) = 623980

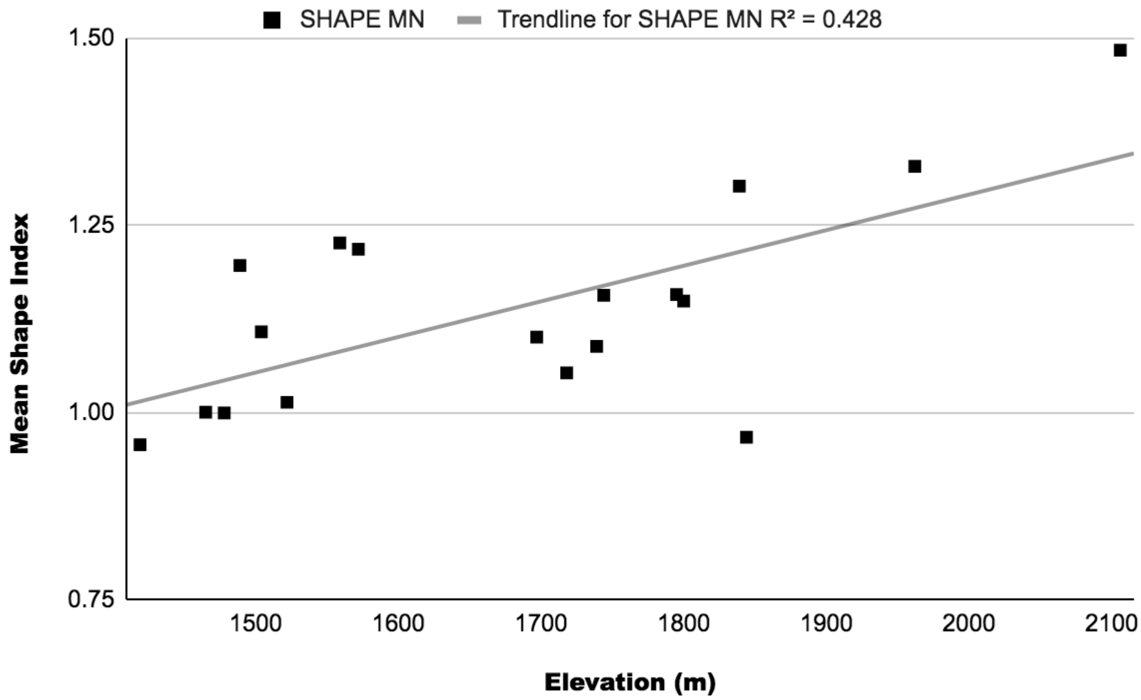
Sum of products (SP) = 41.5367

Regression Equation = $\hat{y} = bX + a$

$b = SP/SS_X = 41.54/623980 = 0.00007$

$a = M_Y - bM_X = 0.13 - (0*1680.67) = 0.01923$

$\hat{y} = 0.00007X + 0.01923$



A2: Mean shape index (Shape metric) describes the shape of the patches. The closer the value is to 0 the more square the patches are. As expected for vegetation we'd expect the patches to be round and not even, however our metrics are describing the shapes of the communities of vegetation in relation to the mean of the patch sizes. Our results show a trend towards more square shaped patches in elevations under 1800m. The p-value: 0.0032 and R2 = 0.428 indicating a significance. The mean of patches within the classes of the wetlands show a trend towards being less square shaped as elevation increases. (McGarigal, K., 2015)

Calculation Summary:
Sum of X = 30252

Sum of Y = 20.52

Mean X = 1680.6667

Mean Y = 1.14

Sum of squares (SS_X) = 623980

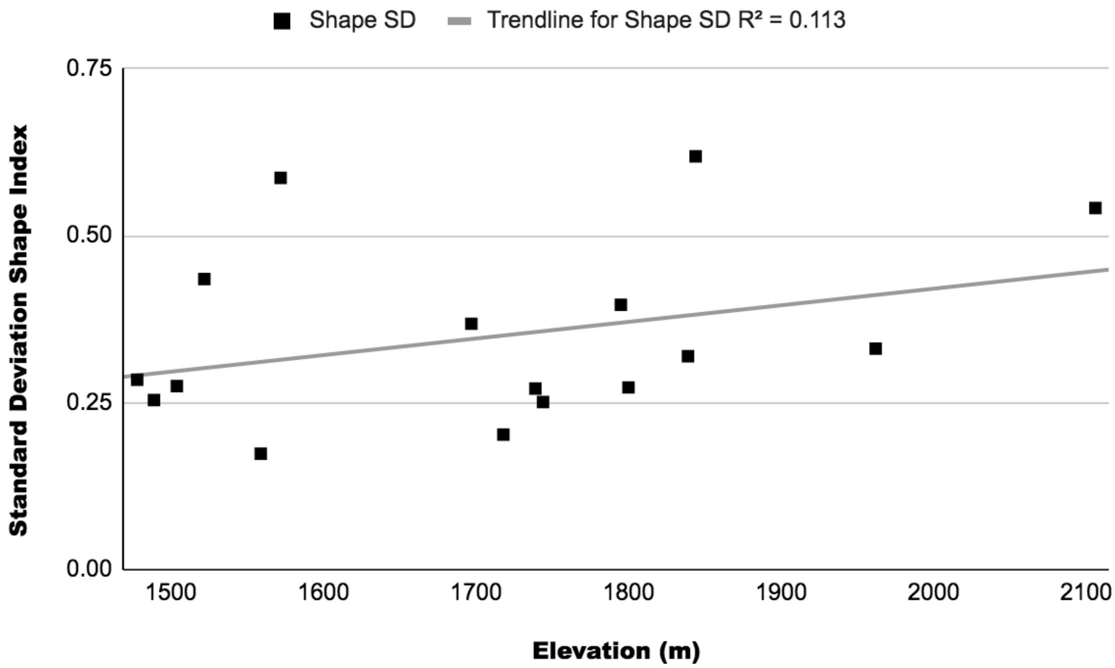
Sum of products (SP) = 293.9

Regression Equation = ŷ = $bX + a$

$b = SP/SS_X$ = 293.9/623980 = 0.00047

a = $M_Y - bM_X$ = 1.14 - (0*1680.67) = 0.34839

ŷ = 0.00047X + 0.34839



A3: Standard deviation shape index (Shape metric) describes the variation from the mean of all the shapes within a class. Closer to 0 indicates that the patches all have an identical shape and increases from 0 without limit as the complexity of shape increases from the mean. In our wetlands we see a slight significance in elevation to an increase of complexity of shapes from the mean. However most wetlands sit with a small variation of complexity as elevation increases. Considering these are vegetation communities we'd expect there to be some variation but nothing too complex. The p-value= 0.0093 and R2= 0.113 show some significance. (McGarigal, K., 2015)

Calculation Summary:
Sum of X = 30252

Sum of Y = 6.7

Mean X = 1680.6667

Mean Y = 0.3722

Sum of squares (SS_X) = 623980

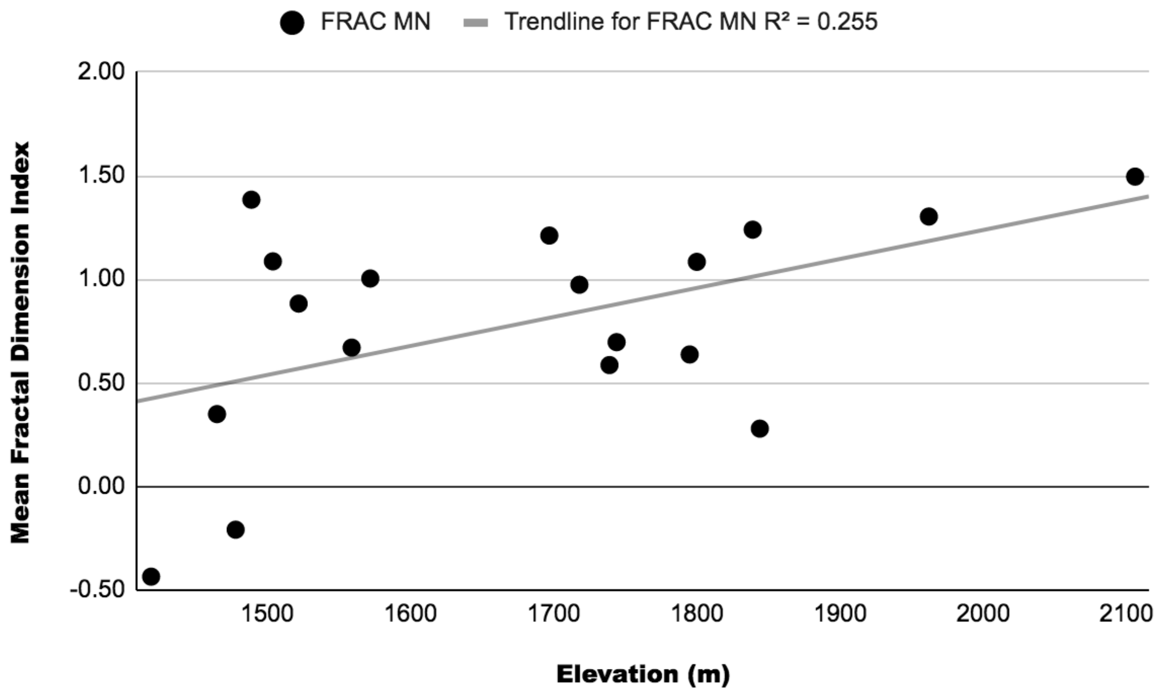
Sum of products (SP) = 341.9433

Regression Equation = ŷ = $bX + a$

$b = SP/SS_X$ = 341.94/623980 = 0.00055

a = M_Y - bM_X = 0.37 - (0*1680.67) = -0.54879

ŷ = 0.00055X - 0.54879



A4: Mean fractal dimension index (Shape metric) describes patch perimeter and patch area and gives insight into each wetlands patch complexity. A value of 1 = square patches and a value approaching 2 = irregular patches. This is complementary to the results for Mean shape index, as complexity of shapes trends towards increasing as elevation increases. However the trend is weak and it's more important to notice the complexity is somewhere between all the communities being square shaped and being more complex shapes. The wetlands in our study sample have a variation of community composition throughout them. The p-value = 0.0324 and R2= 0.225 show some significance. (McGarigal, K., 2015)

Calculation Summary:
Sum of X = 30252

Sum of Y = 14.23

Mean X = 1680.6667

Mean Y = 0.7906

Sum of squares (SS_X) = 623980

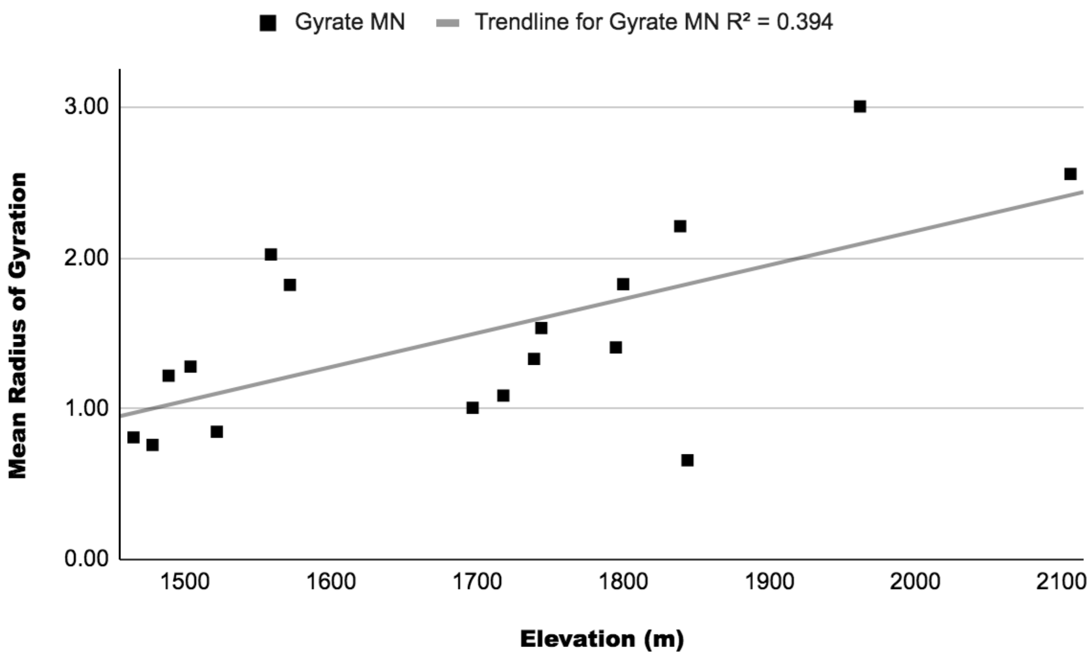
Sum of products (SP) = 877.9133

Regression Equation = $\hat{y} = bX + a$

$b = SP/SS_X$ = 877.91/623980 = 0.00141

a = $M_Y - bM_X$ = 0.79 - (0*1680.67) = -1.57407

$\hat{y} = 0.00141X - 1.57407$



A5: Mean radius of gyration (area and edge metric) determines for every patch what the mean gyrate to the edge of each patch, within each class. It tells us what cover each patch has across each wetland and helps to characterize both patch area and compactness. The smaller the cover of the patches (minimum 1 cell) the closer the gyration index will be to 0. All of the wetlands had patches with more than 1 cell which was expected for vegetation communities however there is a slight trend as elevation increases we start to see the mean radius of gyration increasing, indicating that potentially as elevation increases the patches start to get more compact across the wetland. This relationship had a p value = 0.0025 and R2 = 0.394 indicating significance. (McGarigal, K., 2015)

Calculation Summary:
Sum of X = 30252

Sum of Y = 26.01

Mean X = 1680.6667

Mean Y = 1.445

Sum of squares (SS_X) = 623980

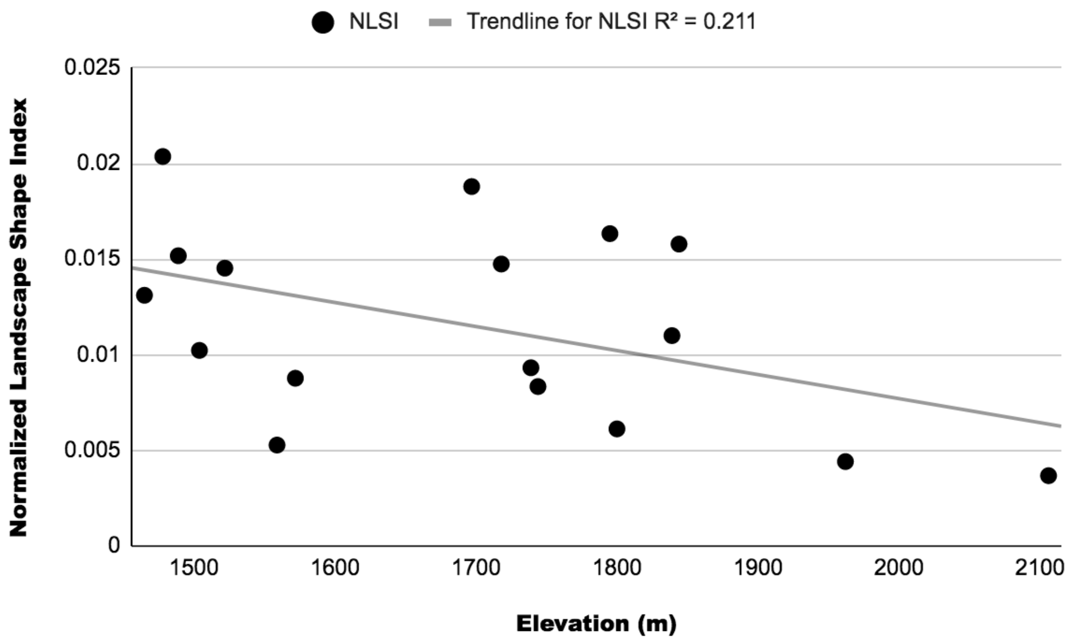
Sum of products (SP) = 1481.19

Regression Equation = $\hat{y} = bX + a$

$b = SP/SS_X$ = 1481.19/623980 = 0.00237

a = $M_Y - bM_X$ = 1.45 - (0*1680.67) = -2.54453

$\hat{y} = 0.00237X - 2.54453$



A6: Normalized Landscape Shape Index (Aggregation metric) measures the aggregation of classes within the landscape. As the output moves closer to 0 the shapes of classes consist of a single square or are dominated by one patch with little spatial variation and as the metric reaches 1 the classes become more fragmented with varying shape class sizes. In our set of wetlands it shows a negative trend towards becoming less fragmented with less variation in class sizes as elevation increased. This metric is in agreement with the mean shape index results. The p-value= 0.0289 and the R2= 0.211 show some significance. (McGarigal, K., 2015)

Calculation Summary:
Sum of X = 30252

Sum of Y = 0.22

Mean X = 1680.6667

Mean Y = 0.0122

Sum of squares (SS_X) = 623980

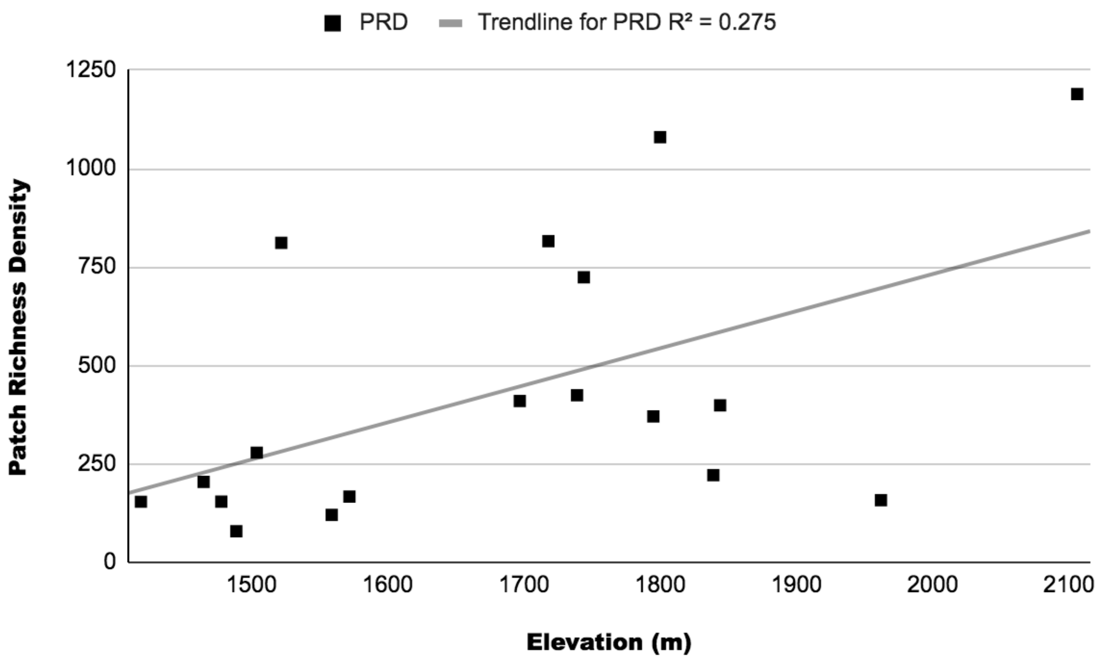
Sum of products (SP) = -10.6867

Regression Equation = $\hat{y} = bX + a$

$b = SP/SS_X$ = -10.69/623980 = -0.00002

a = M_Y - bM_X = 0.01 - (0*1680.67) = 0.04101

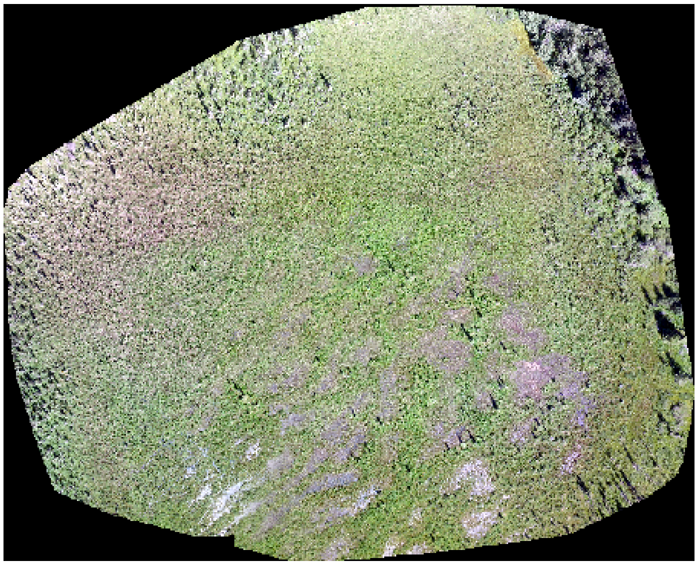
$\hat{y} = -0.00002X + 0.04101$



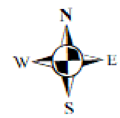
A7: Patch Richness Density shows the relative density (patch types (classes) present in the wetland divided by the area (in hectares). The output gives a density per 100 hectares and as values increase from zero so does the density. Considering our metrics were looking at community composition and configuration it's most likely that patch richness density increases because as elevation increased the topography turned more mountainous and contained more rocks and bare ground in our RPAS imagery. Patch richness density was similar across most sites because unless there was rocks, dirt or decomposing trees other classes were present in every wetland. The p-value = 0.0255 and R2= 0.275. (McGarigal, K., 2015)

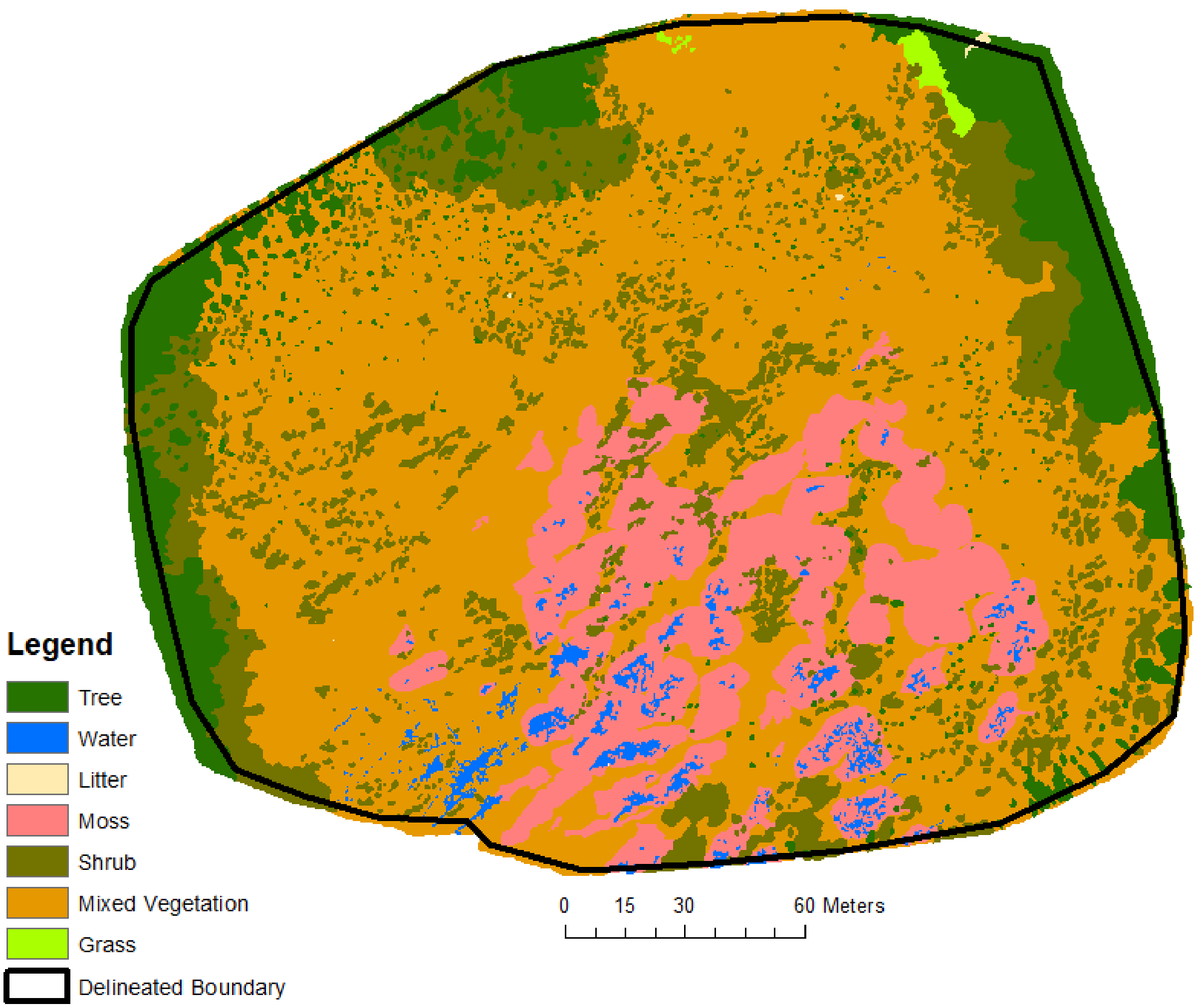
A8: Digitized maps of peatlands with the RBG composite from lowest elevation (1419 m) to highest elevation (2106 m). ‘Delineated Boundary’ refers to boundary cropped based on 4.5% slope.

A8.1:

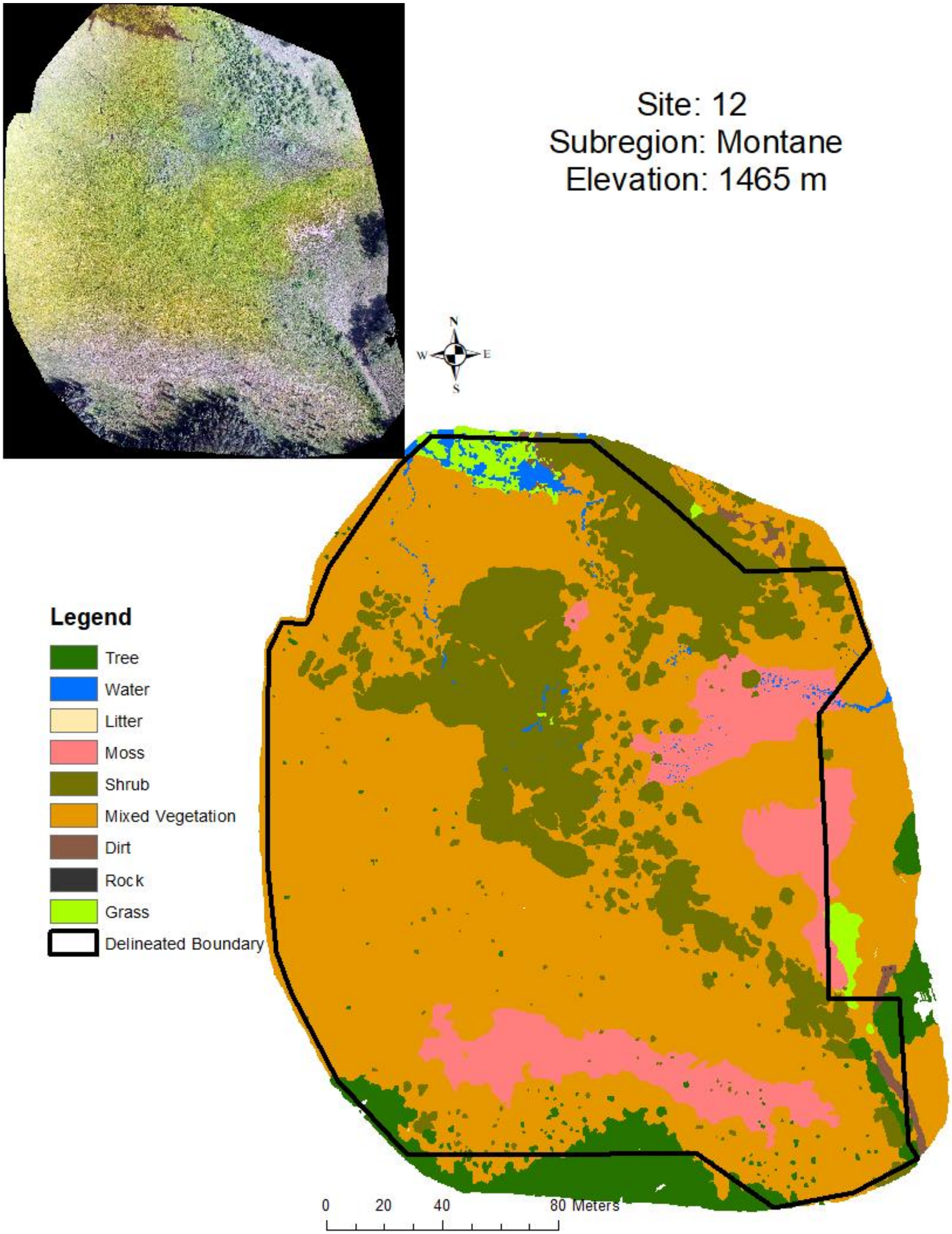


Site: 7
Subregion: Montane
Elevation: 1419 m

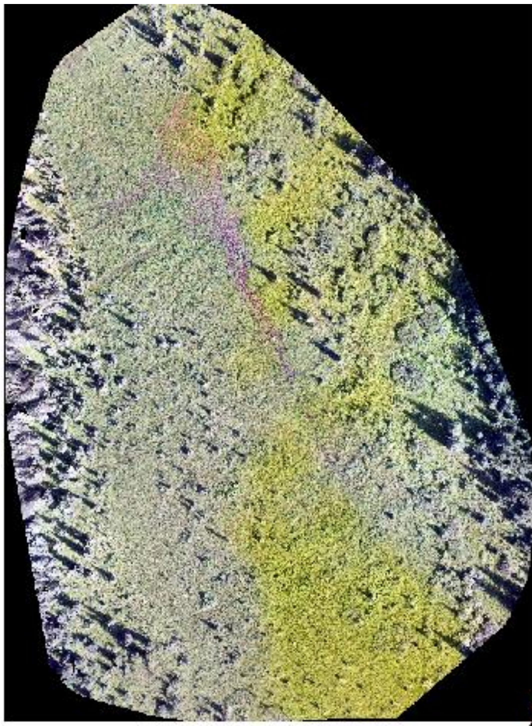


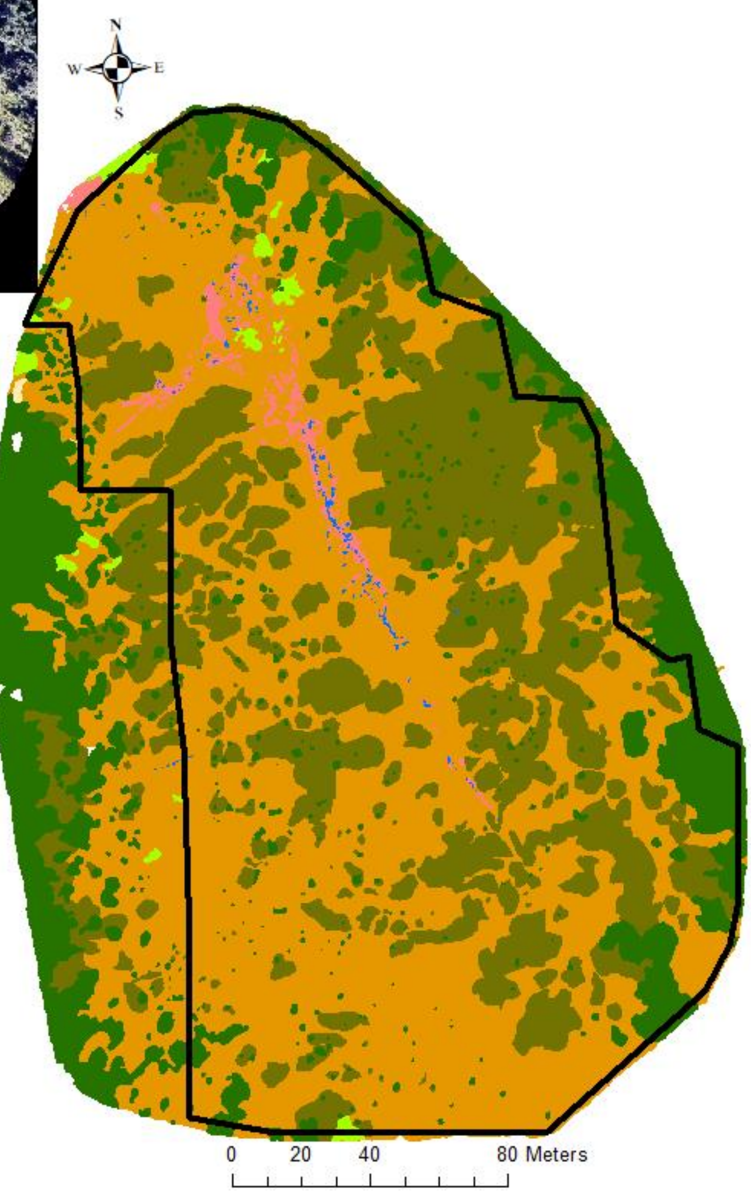


A8.2:


Site: 12
Subregion: Montane
Elevation: 1465 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Grass
Delineated Boundary
0
20
40
80 Meters

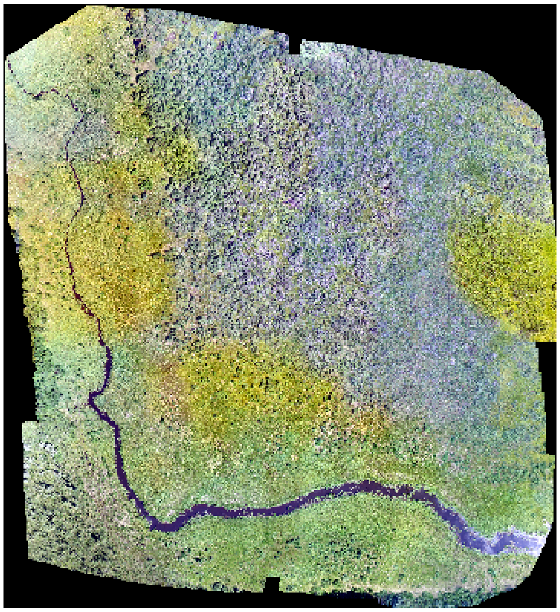
A8.3:



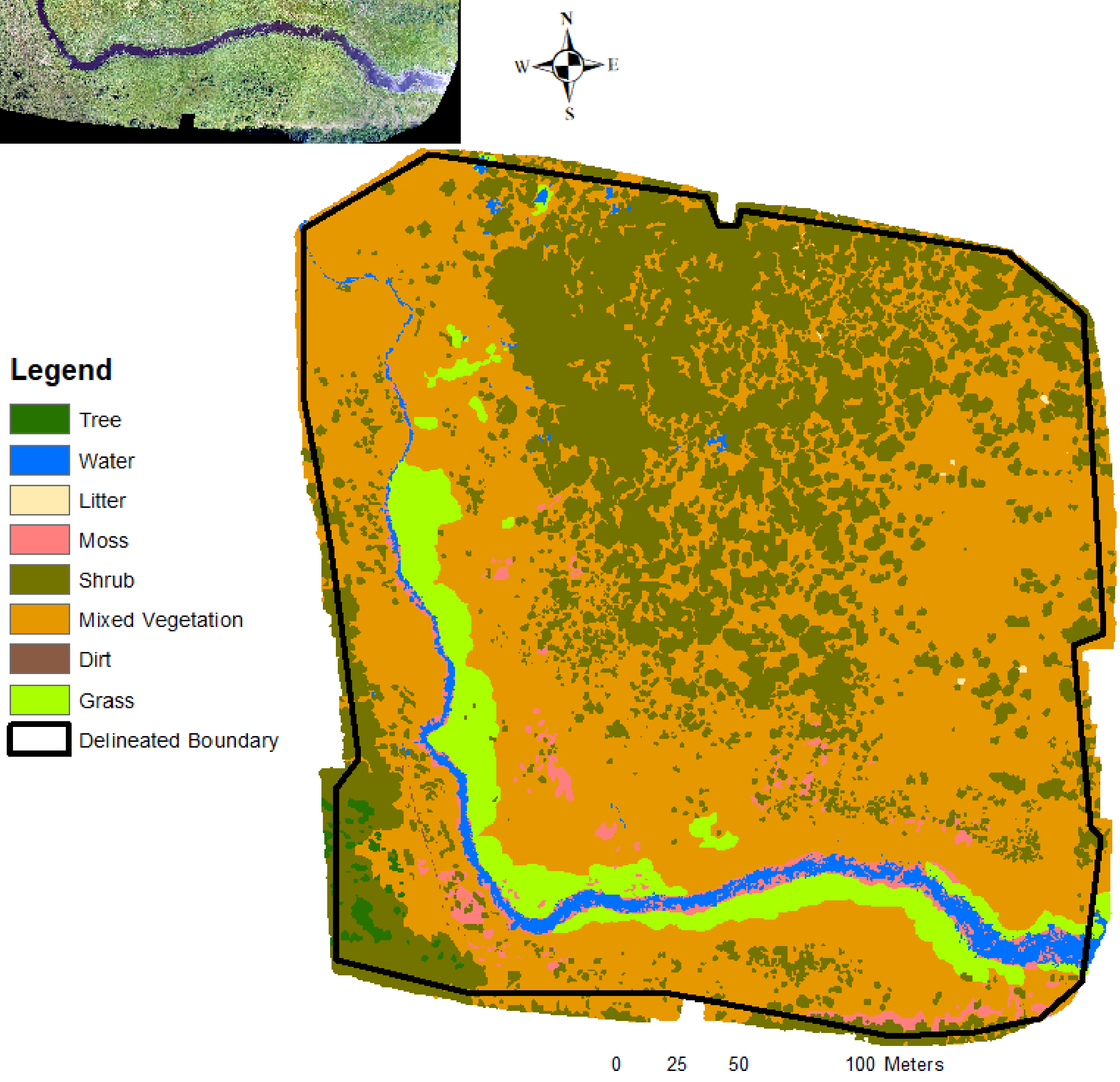


Site: 9
Subregion: Montane
Elevation: 1478 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Grass
Delineated Boundary
0
20
40
80 Meters

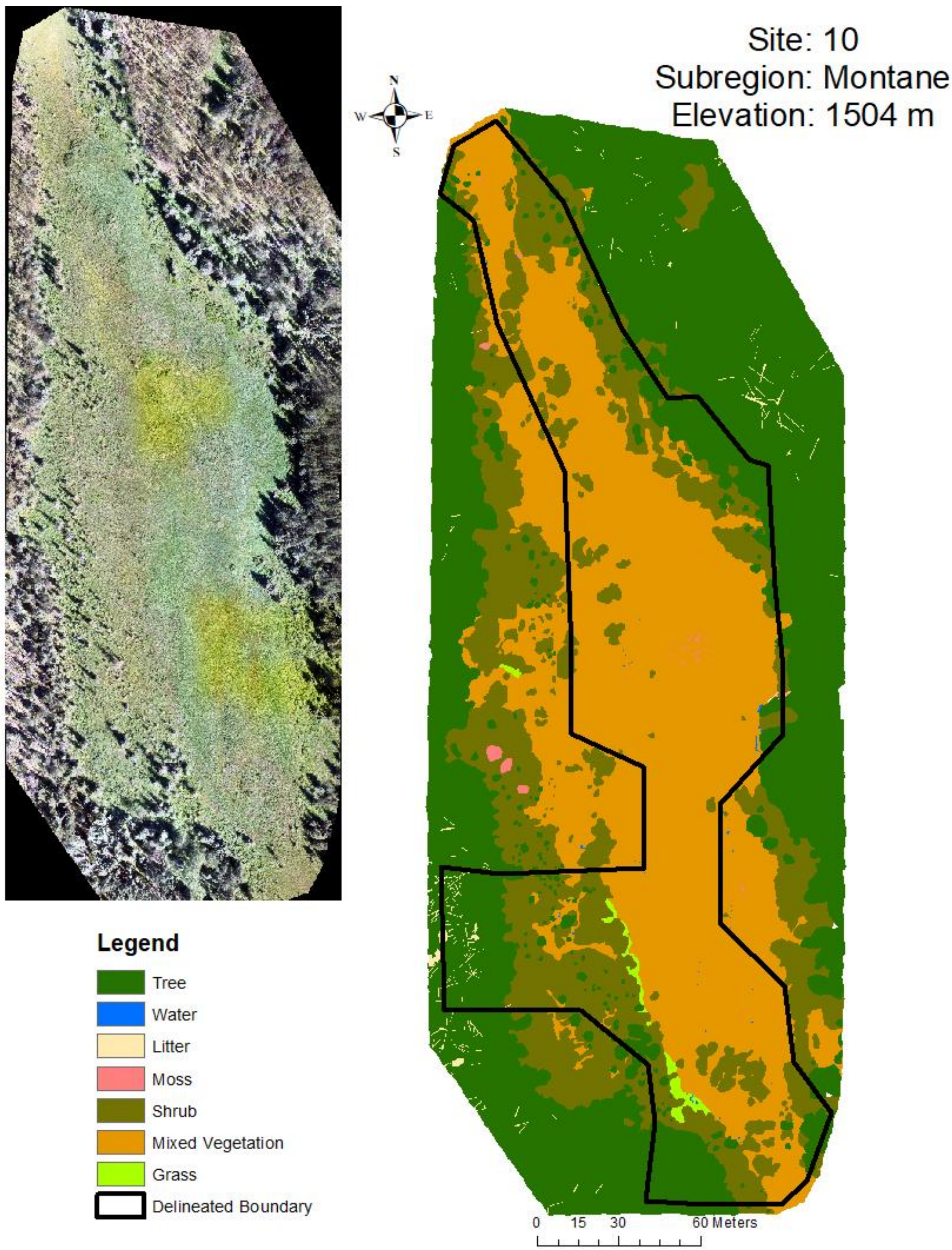
A8.4:



Site: 16
Subregion: Montane
Elevation: 1489 m

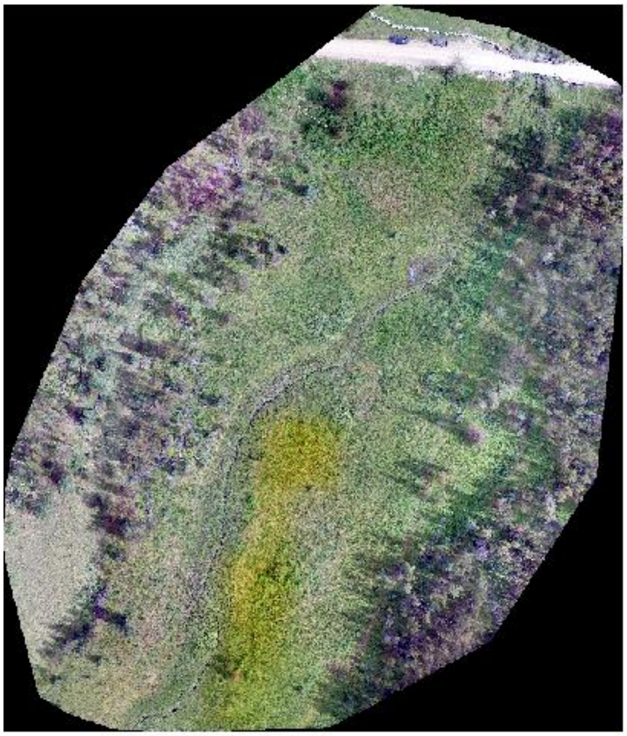


A8.5:

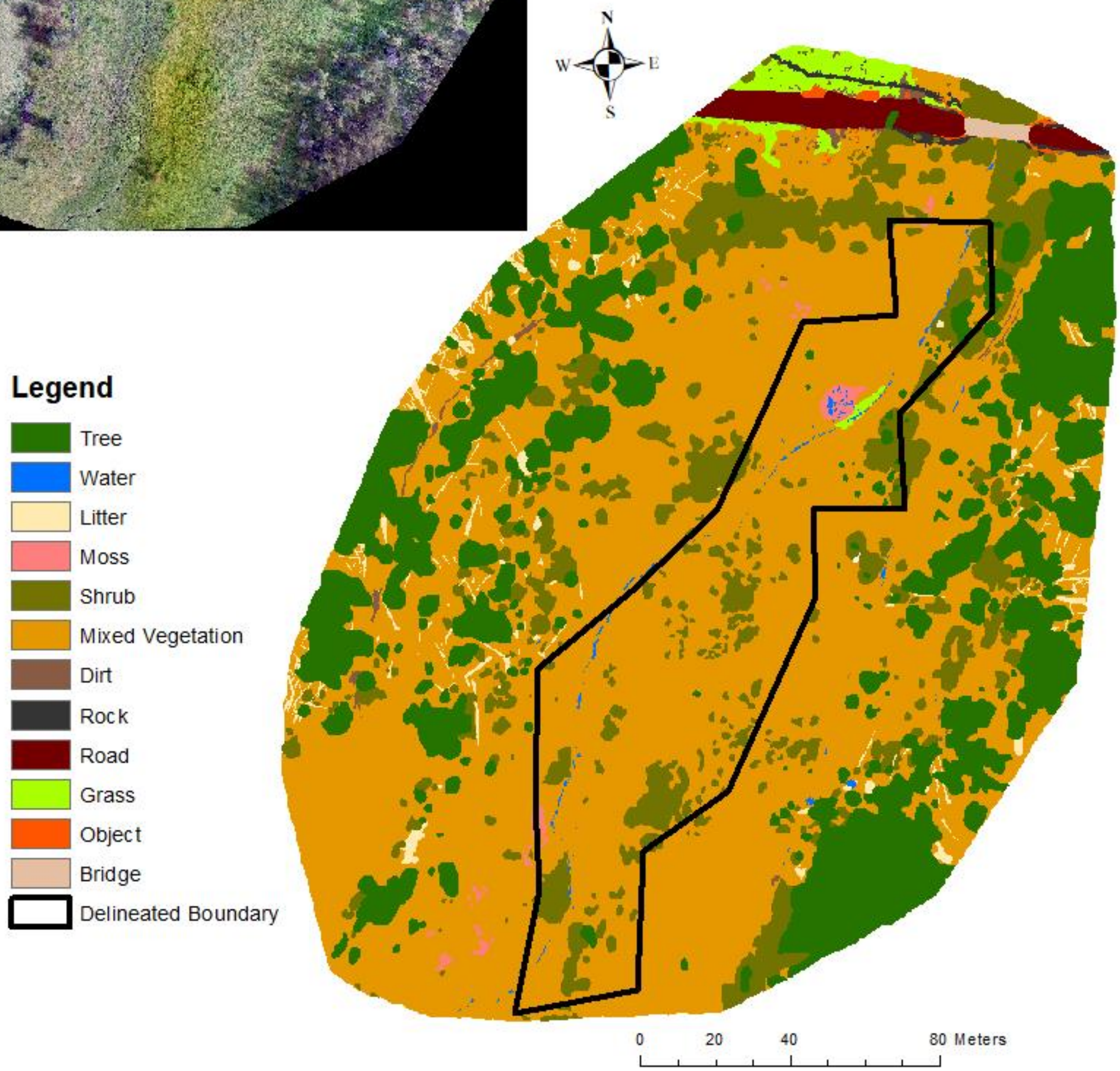


Site: 10
Subregion: Montane
Elevation: 1504 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Grass
Delineated Boundary
0
15
30
60 Meters

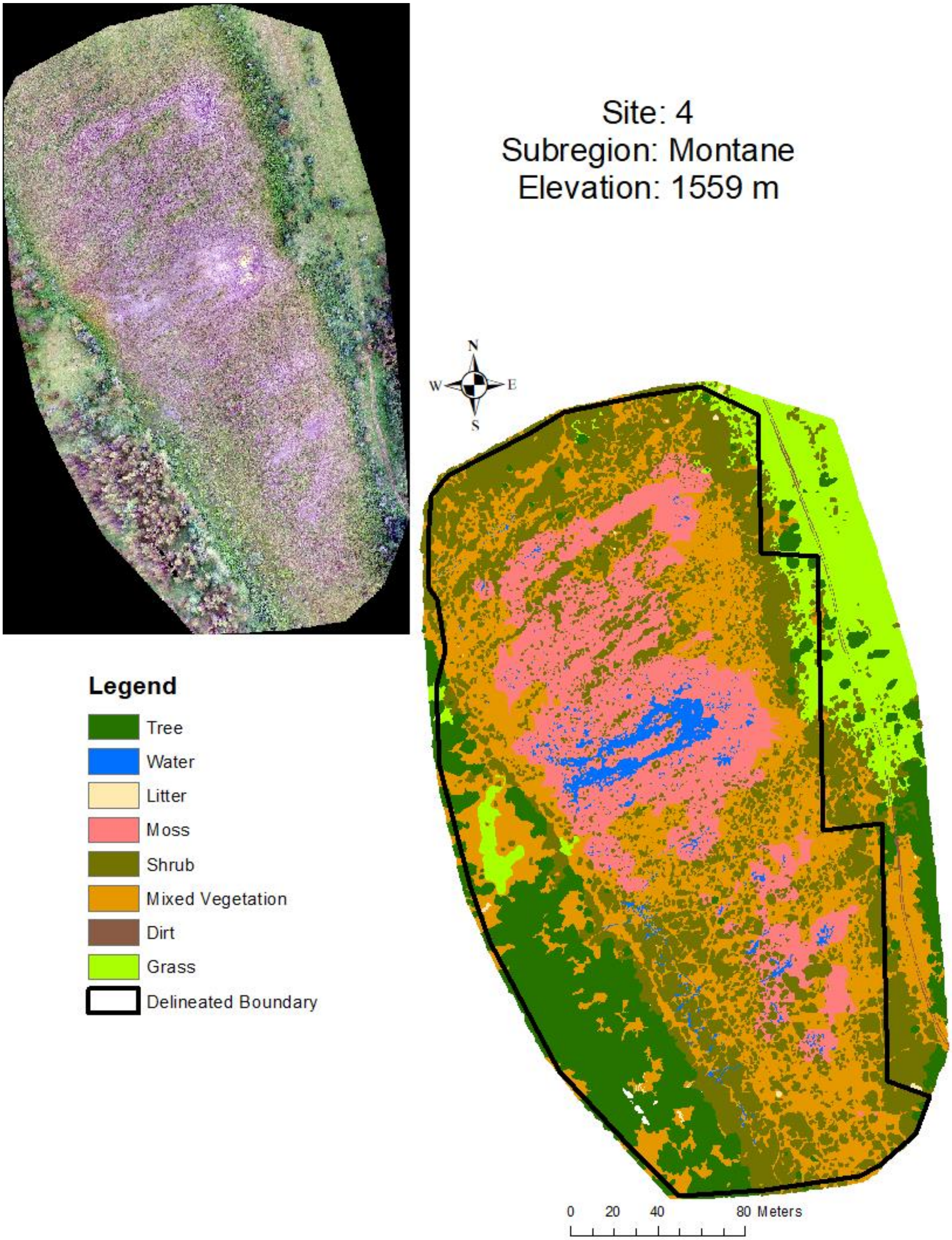
A8.6:



Site: 17
Subregion: Montane
Elevation: 1522 m

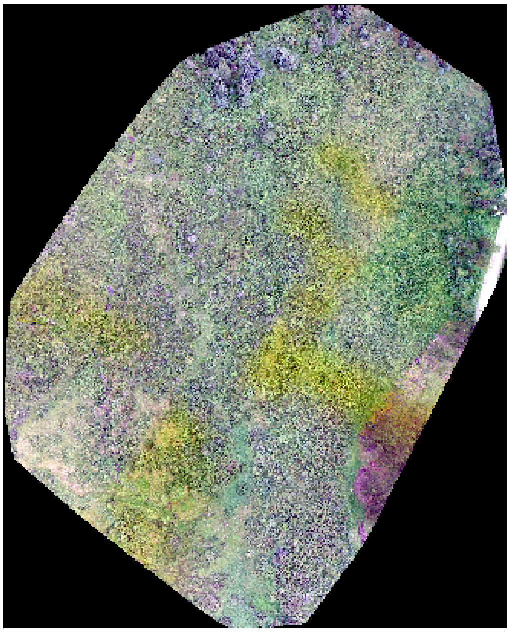


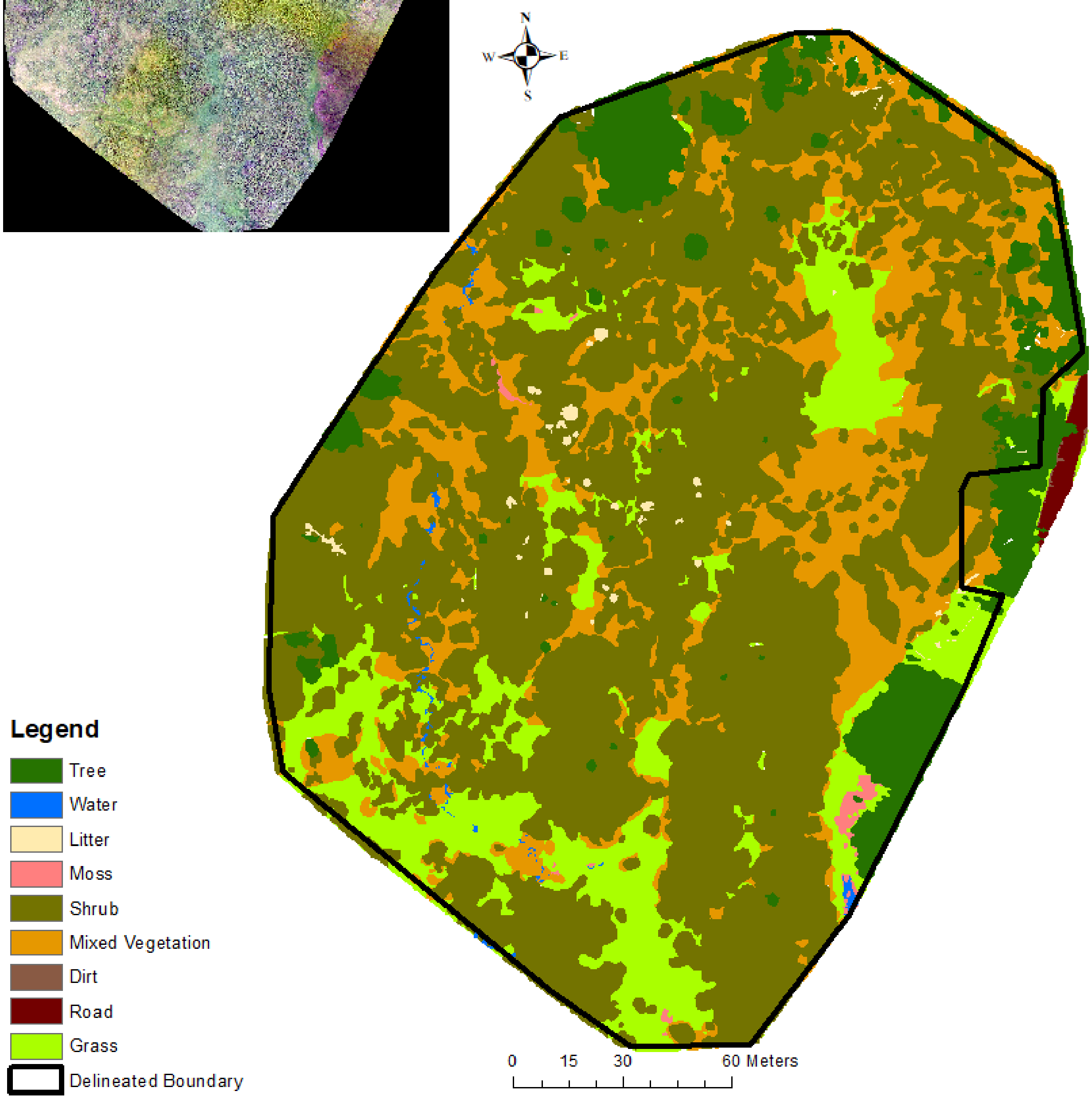
A8.7:



Site: 4
Subregion: Montane
Elevation: 1559 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Grass
Delineated Boundary
0 20 40 80 Meters

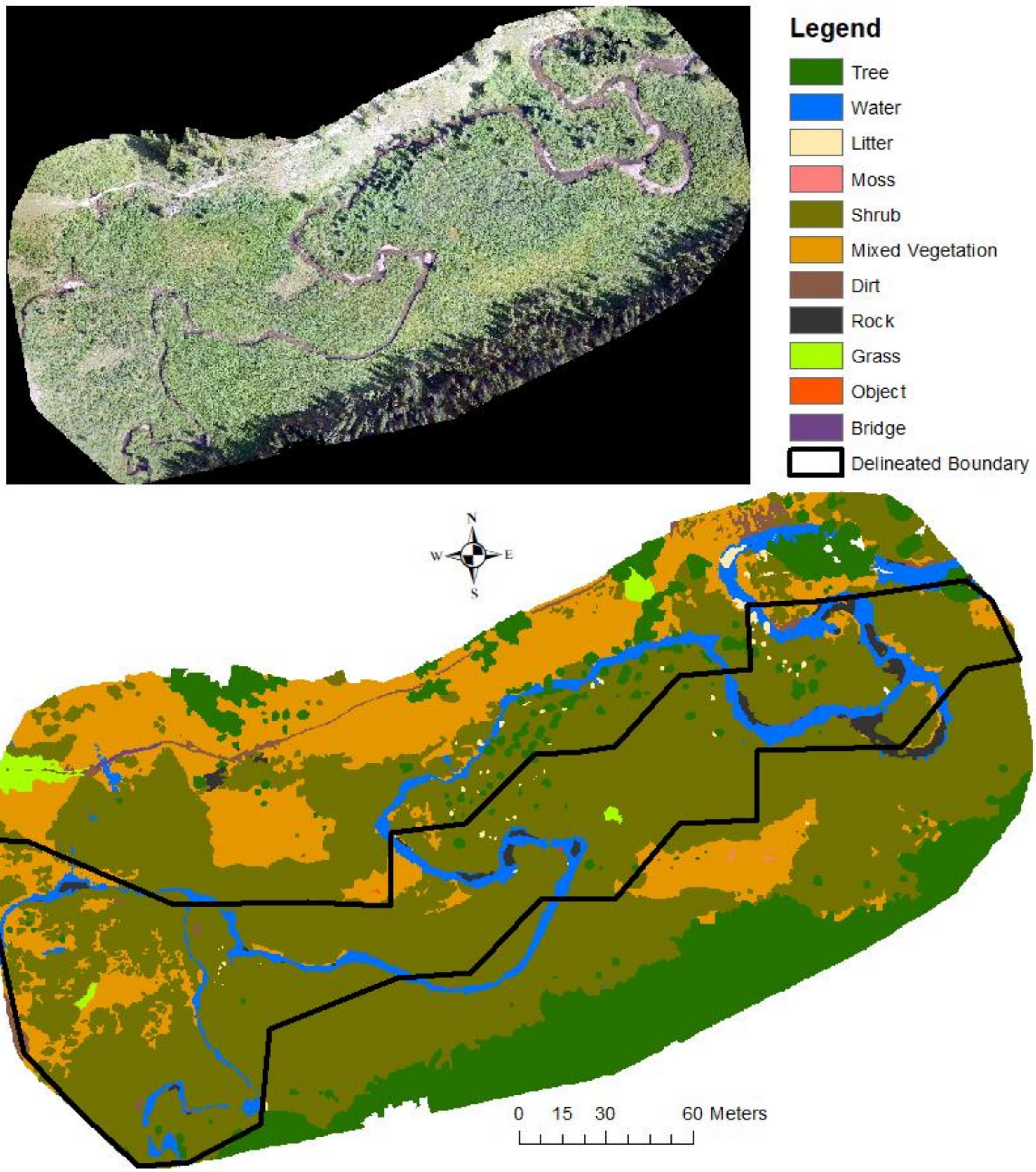
A8.8:



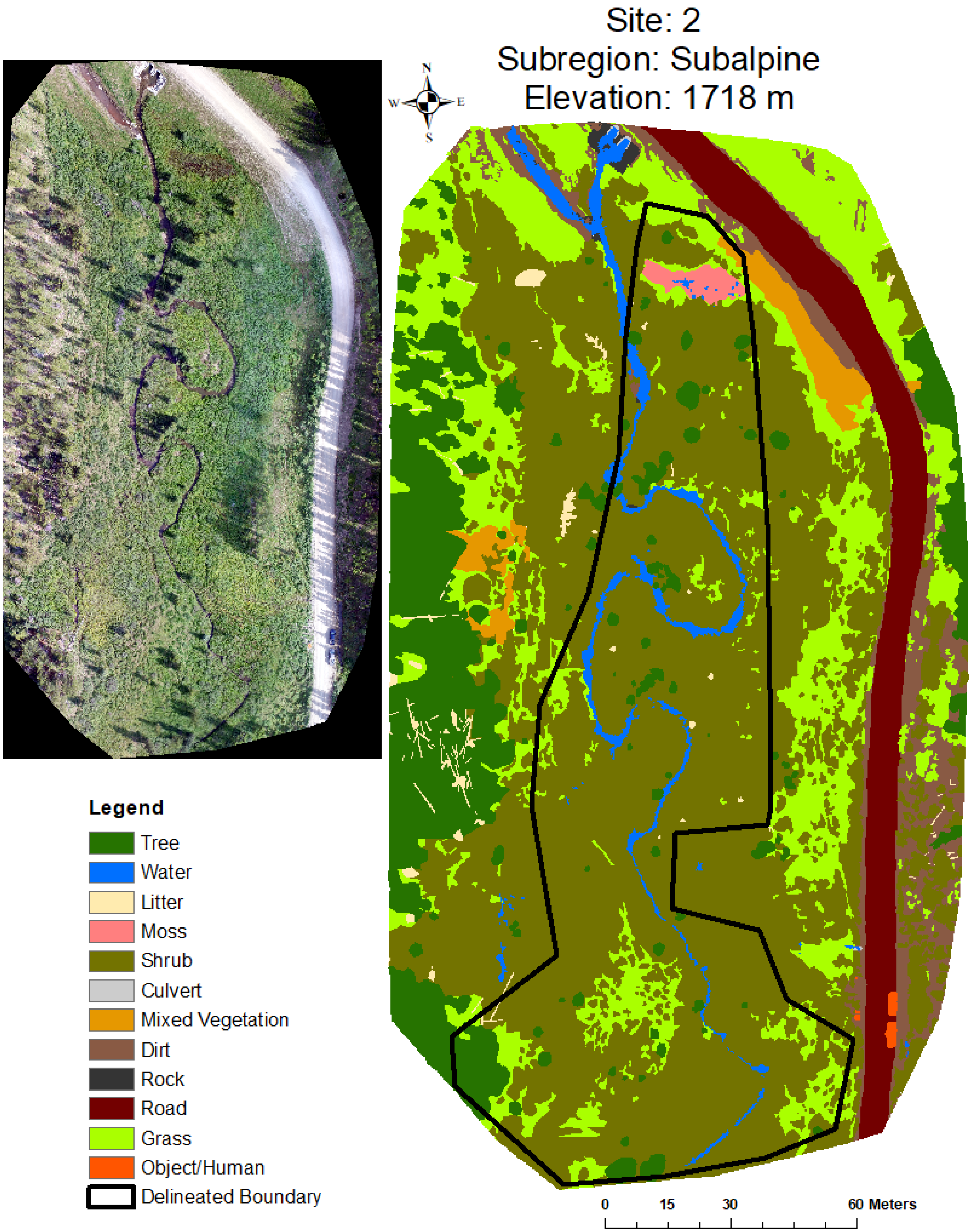

Site: 1
Subregion: Upper Foothills
Elevation: 1572 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Road
Grass
Delineated Boundary
0
15
30
60 Meters

A8.9:

Site: 13
Subregion: Subalpine
Elevation: 1697 m

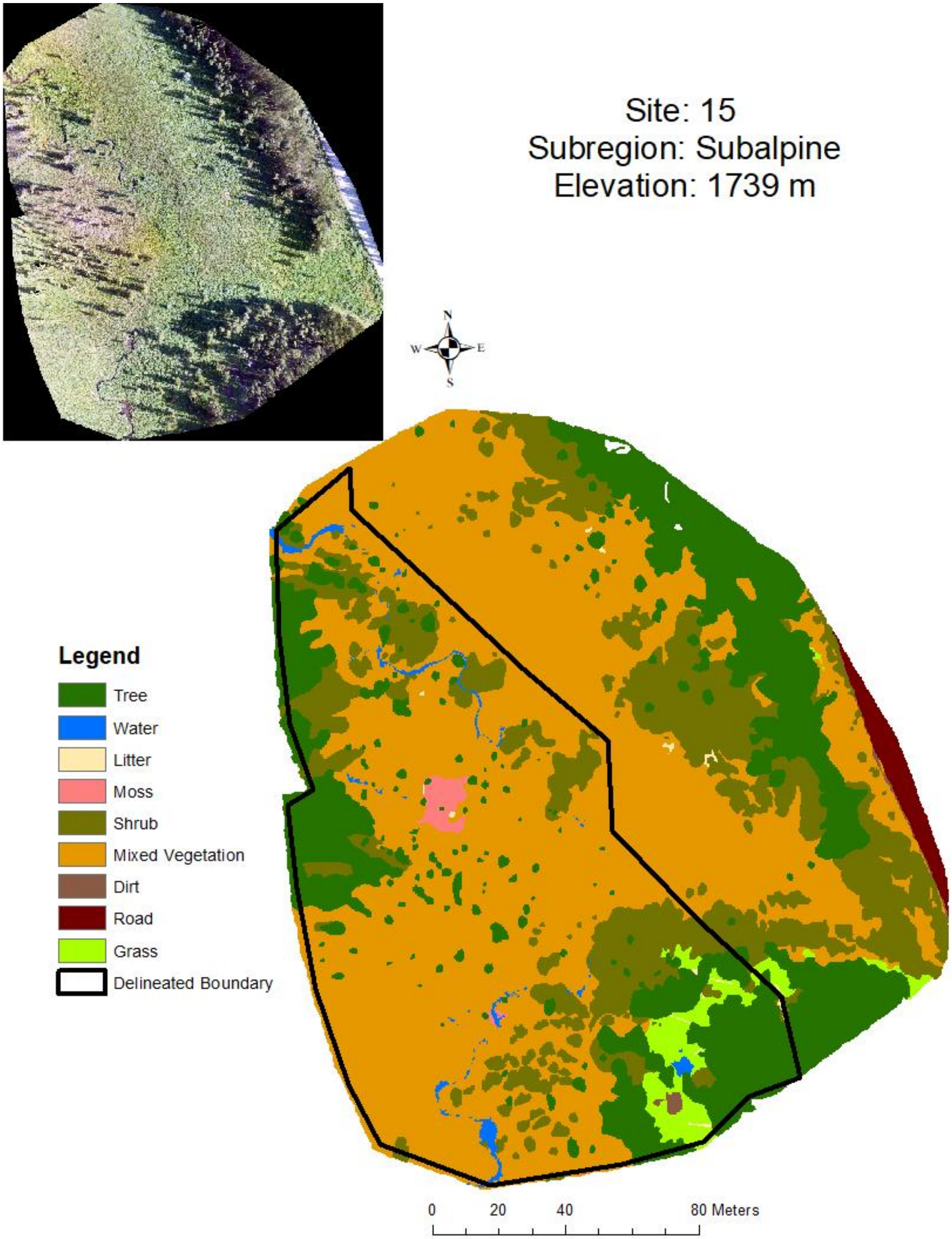


A8.10:



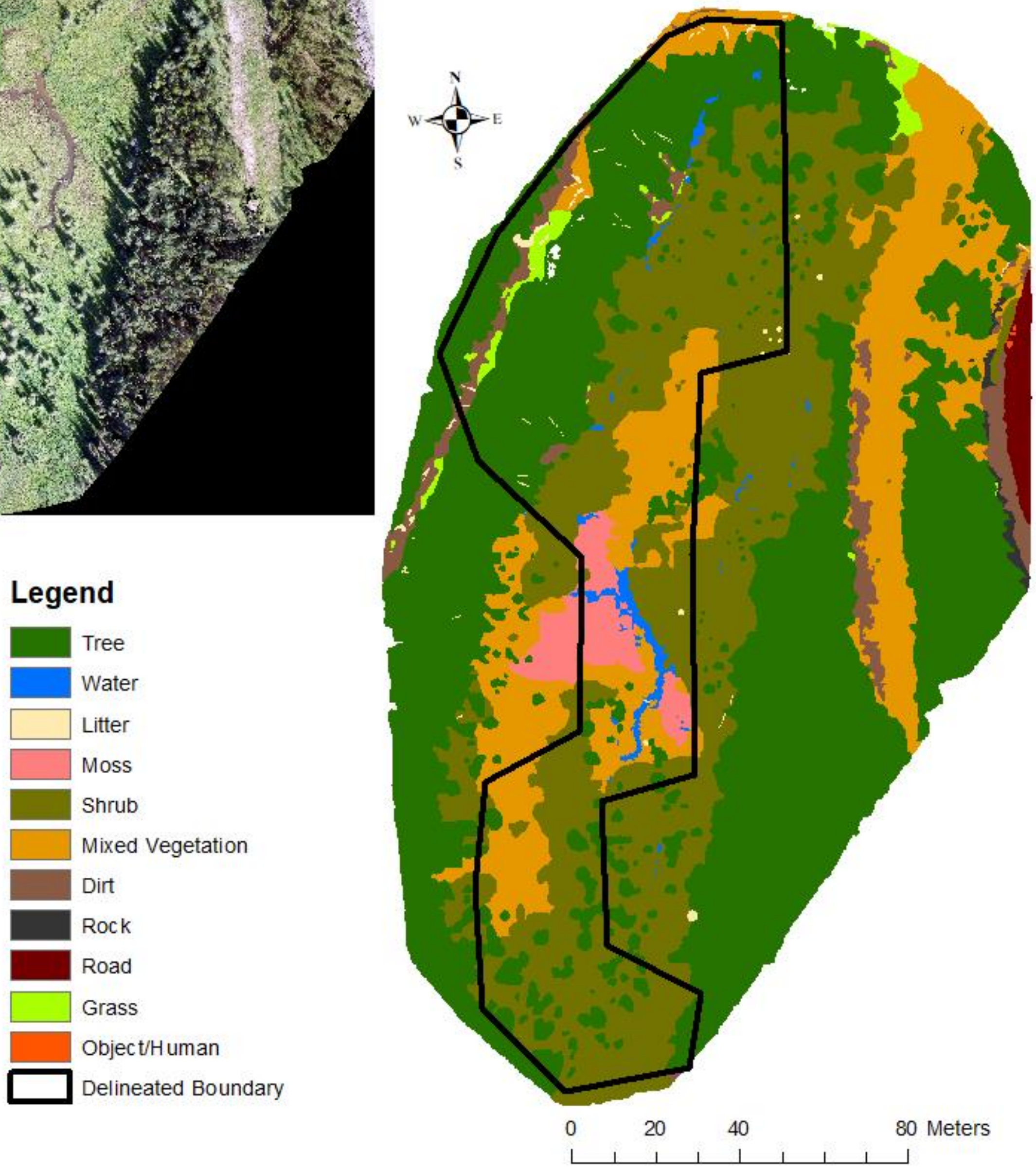
Site: 2
Subregion: Subalpine
Elevation: 1718 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Culvert
Mixed Vegetation
Dirt
Rock
Road
Grass
Object/Human
Delineated Boundary
0
15
30
60 Meters

A8.11:



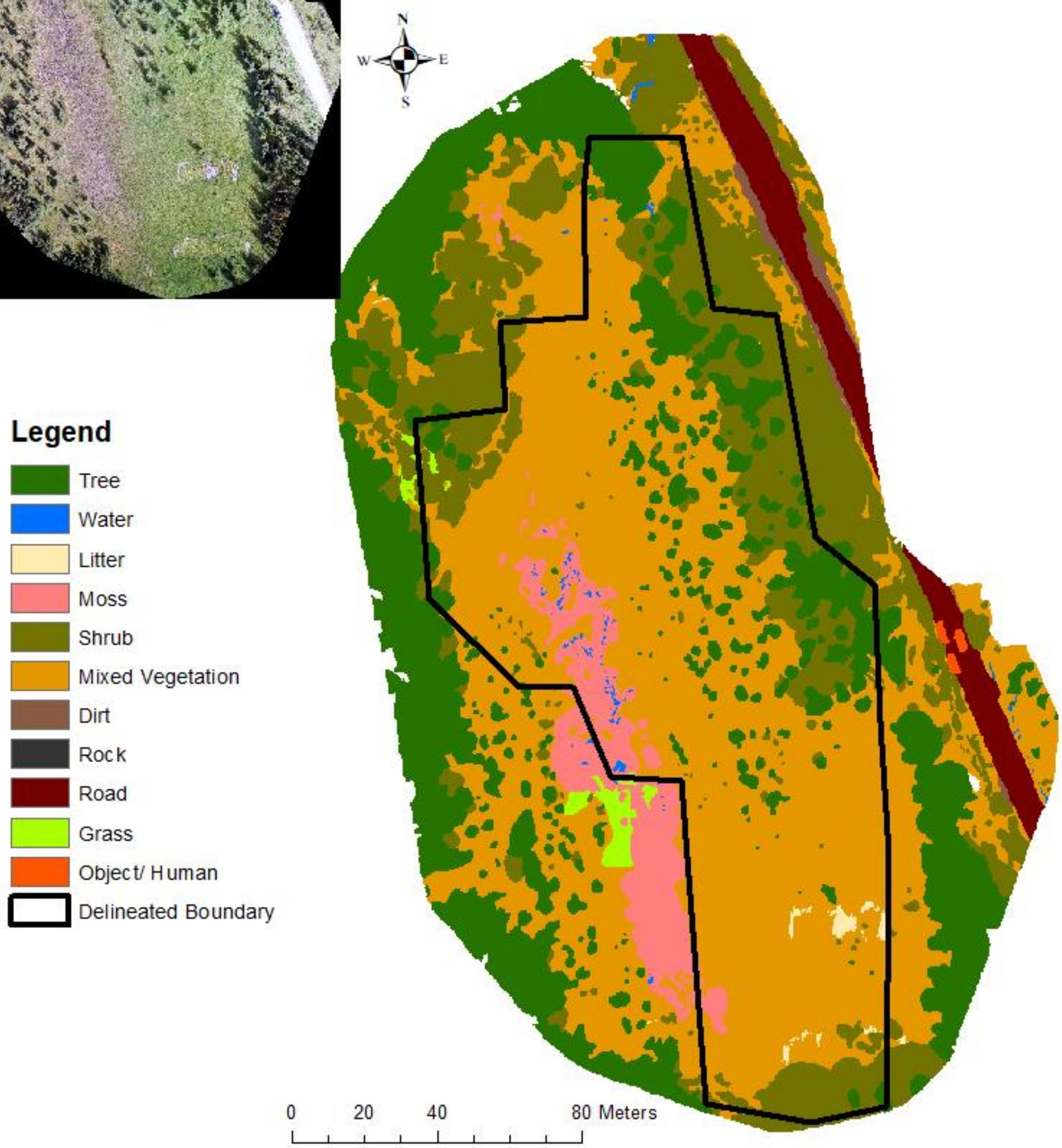
Site: 15
Subregion: Subalpine
Elevation: 1739 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Road
Grass
Delineated Boundary
0
20
40
80 Meters

A8.12:

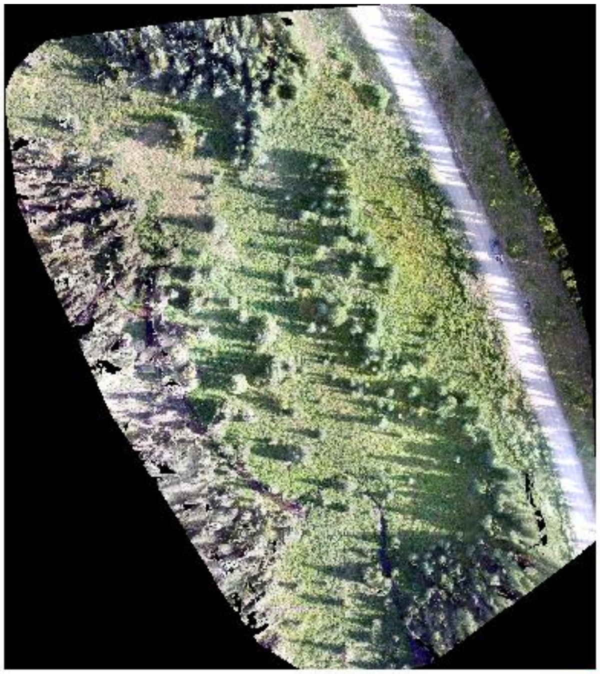


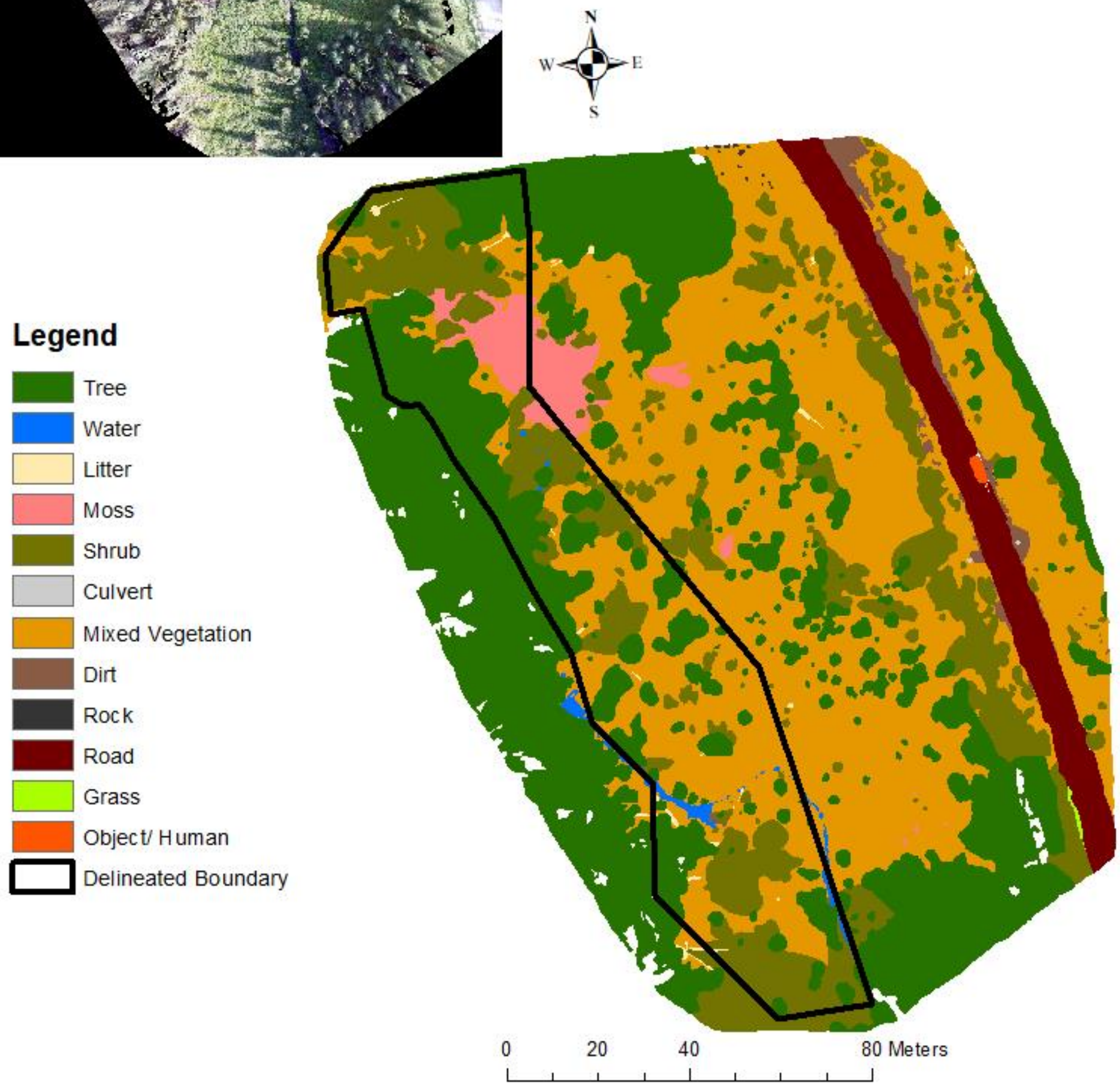
Site: 11
Subregion: Subalpine
Elevation: 1744 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Road
Grass
Object/Human
Delineated Boundary
0
20
40
80 Meters

A8.13:

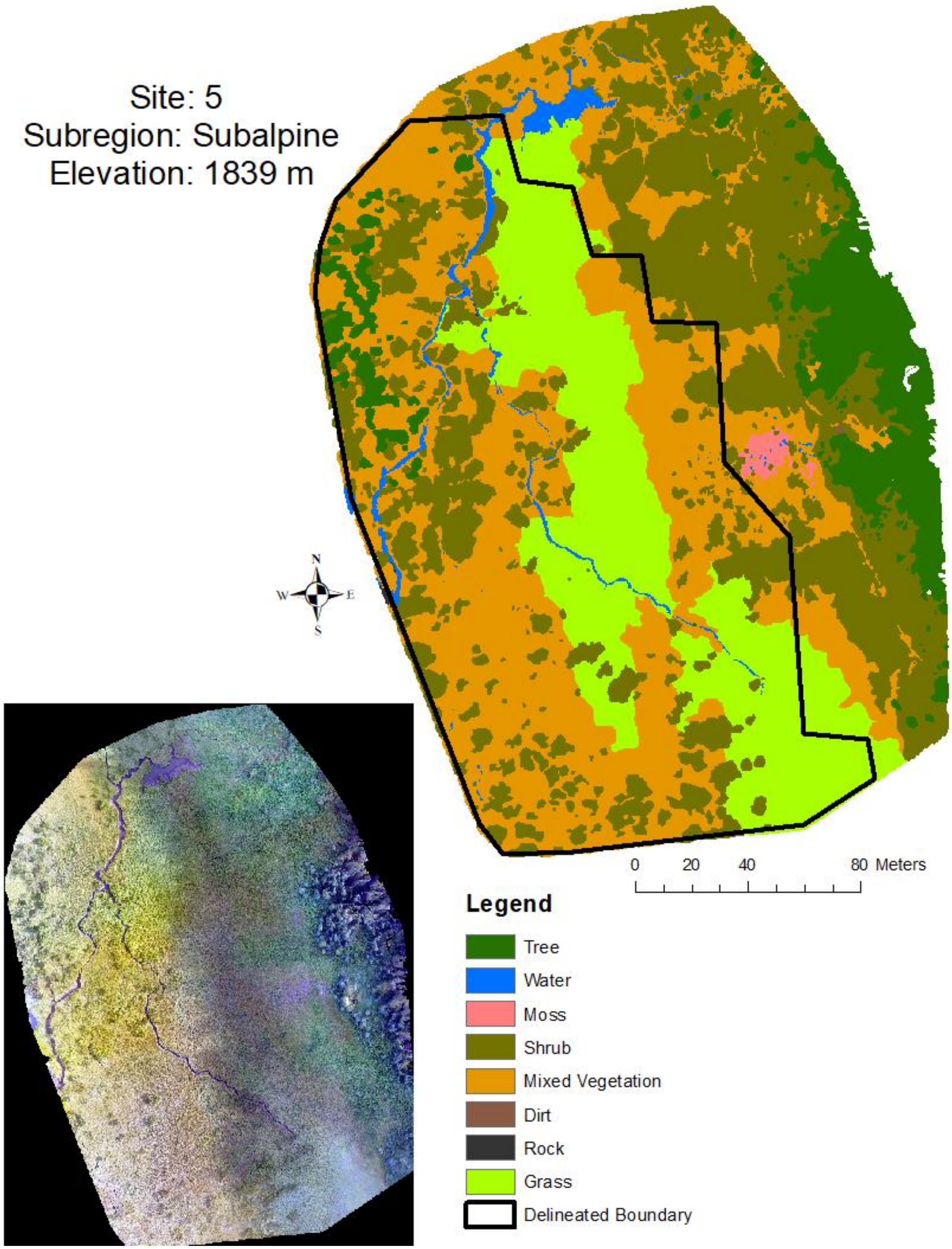

Site: 14
Subregion: Subalpine
Elevation: 1795 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Road
Grass
Object/ Human
Delineated Boundary
0
20
40
80 Meters

A8.14:

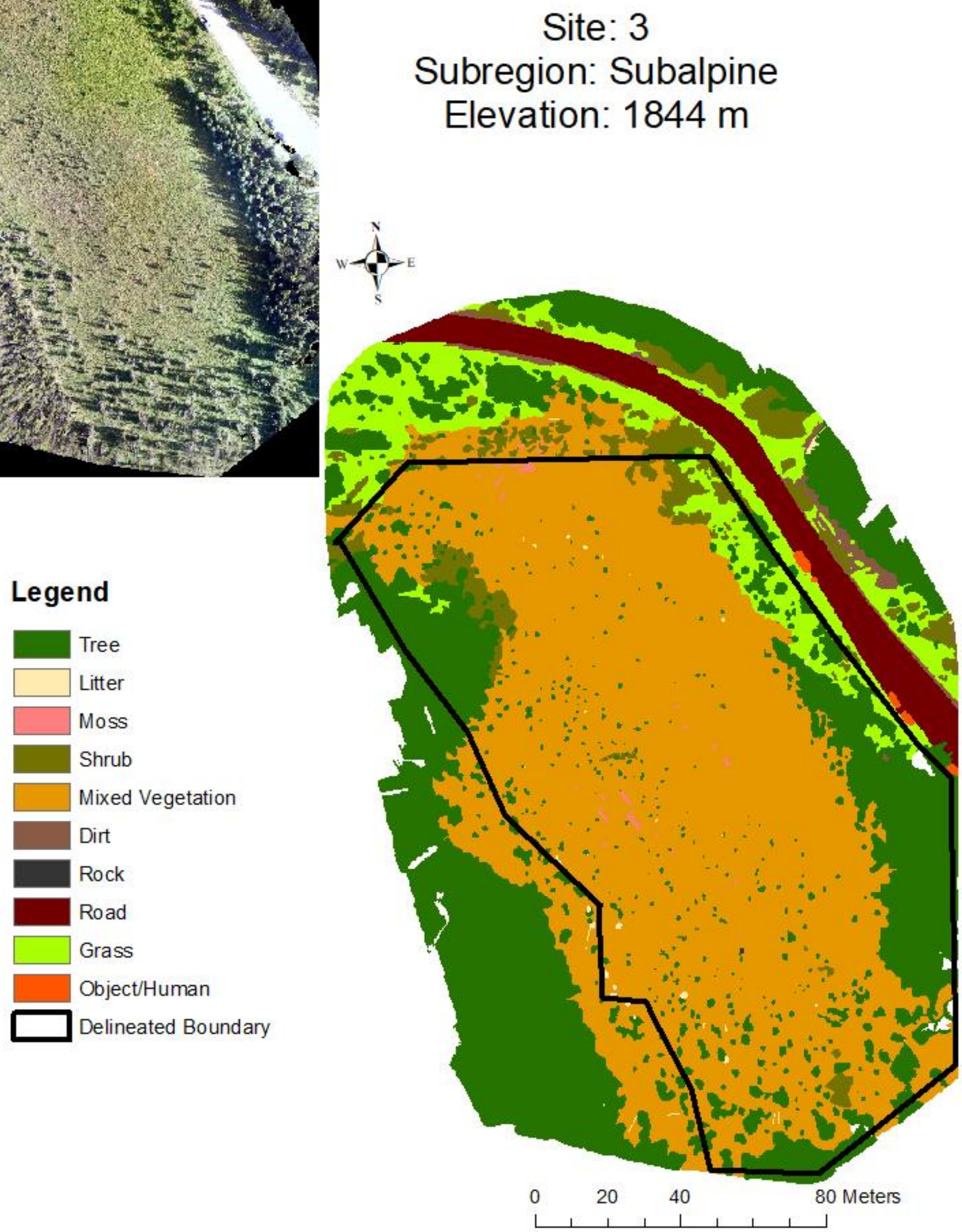



Site: 18
Subregion: Subalpine
Elevation: 1800 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Culvert
Mixed Vegetation
Dirt
Rock
Road
Grass
Object/ Human
Delineated Boundary
0
20
40
80 Meters

A8.15:

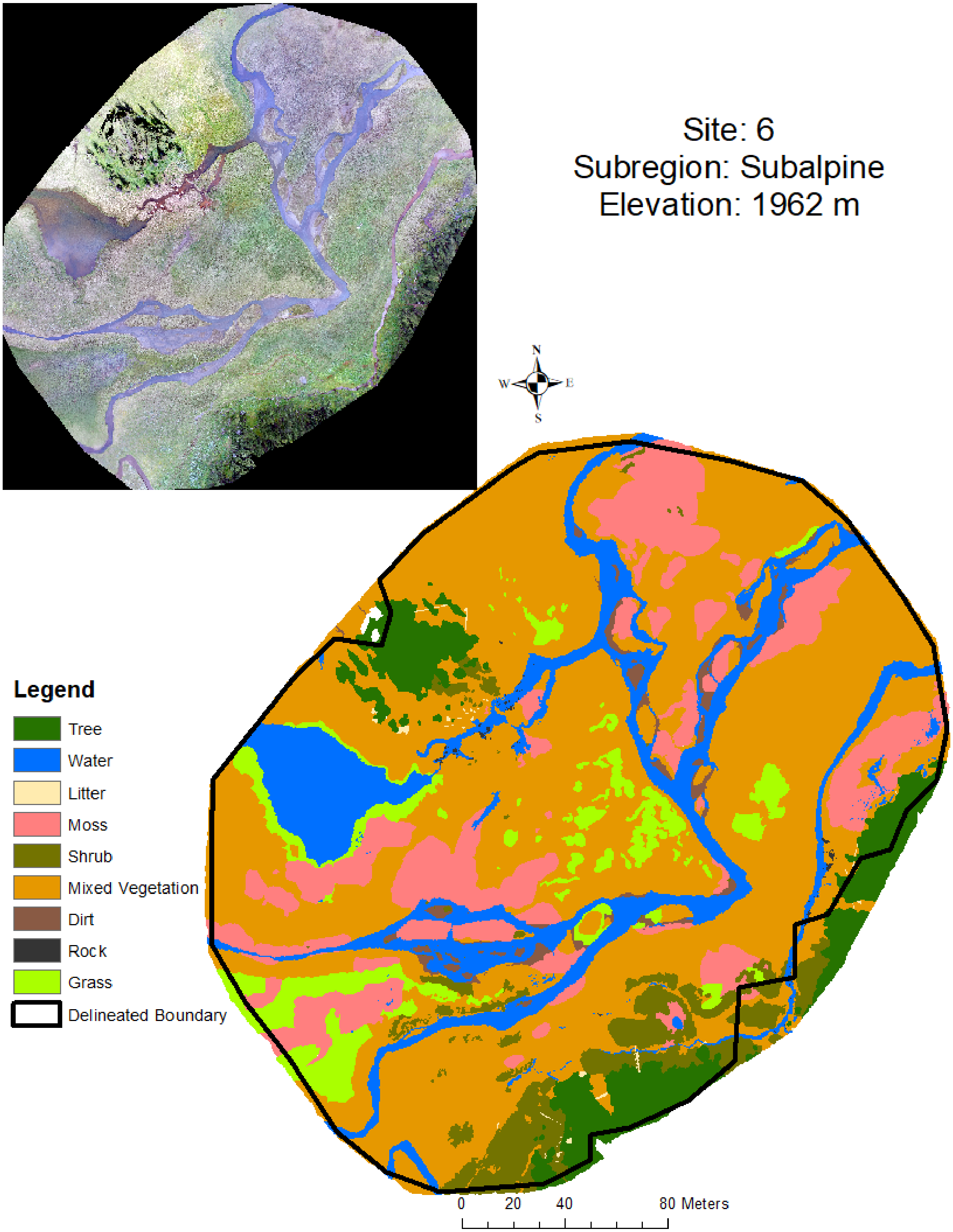

Site: 5
Subregion: Subalpine
Elevation: 1839 m
N
W
E
S
0
20
40
80 Meters
Legend
Tree
Water
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Grass
Delineated Boundary

A8.16:



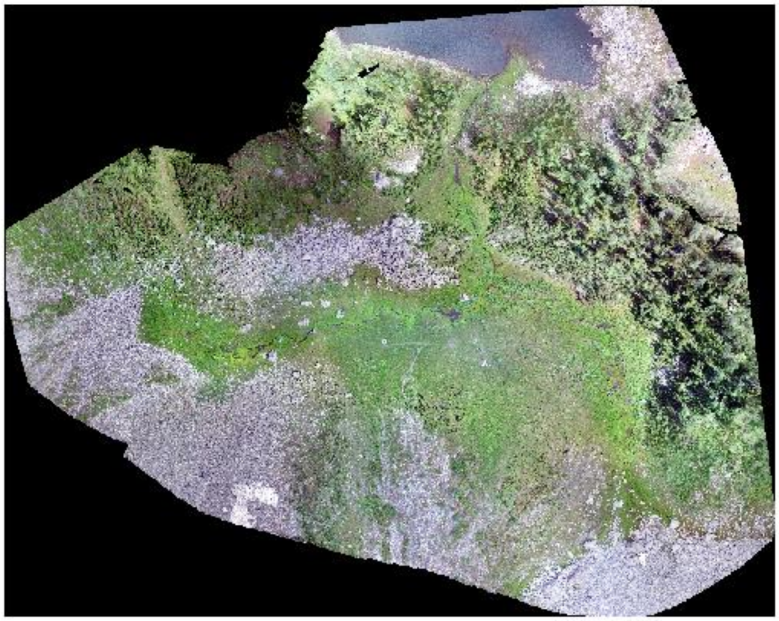
Site: 3
Subregion: Subalpine
Elevation: 1844 m
N
W
E
S
Legend
Tree
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Road
Grass
Object/Human
Delineated Boundary
0
20
40
80 Meters

A8.17:



Site: 6
Subregion: Subalpine
Elevation: 1962 m
N
W
E
S
Legend
Tree
Water
Litter
Moss
Shrub
Mixed Vegetation
Dirt
Rock
Grass
Delineated Boundary
0
20
40
80 Meters

A8.18:



Site: 8
Subregion: Subalpine
Elevation: 2106 m