Spring 2022

UAV remote sensing approaches to mapping glacier ablation and snow algae radiative forcing in the North Cascades.

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UAV remote sensing approaches to mapping glacier ablation and snow algae radiative forcing in the North Cascades.

By

Shannon Healy

Accepted in Partial Completion of the Requirements for the Degree Master of Science

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Master’s Thesis

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Shannon Healy

February 9, 2022
UAV remote sensing approaches to mapping glacier ablation and snow algae radiative forcing in the North Cascades

A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science

by
Shannon Healy
March 2022
ABSTRACT

The stability of our cryosphere relies on highly reflective snow surfaces that reflect solar radiation, thereby maintaining the energy balance of the earth. The advances in Uncrewed Aerial Vehicle (UAV) technology allow for researchers to assess snow surfaces in remote terrain at unprecedented scales. With this thesis, we demonstrate the range of UAV applications to assess glacier ablation and map snow algae in the North Cascades. The first chapter employs a low-cost, light-weight UAV to measure ablation of the Sholes Glacier using Structure-from-Motion technology and validates the measurements with outlet stream discharge data collected by the Nooksack Indian Tribe. We spectrally classified the orthomosaics to reveal that the glacier transitioned from 75% snow-covered to 43% snow-covered from August 17, 2021 to September 5, 2021. Digital Elevation Model differencing reveals that the glacier lost an average thickness of $-0.132 \text{ m per day (m d}^{-1}\text{)}$ and contributed a total of $550,161 \pm 45,206 \text{ m}^3$ water equivalent whereas the stream gauge station measured a total discharge of $350,023 \text{ m}^3$. The second chapter utilizes a high-end, multispectral UAV to map snow algae within the Bagley Lakes basin using two different spectral approaches, under two distinct bloom conditions, and calculates the radiative forcing (RF) of the snow algae. This chapter found that the success of the classification approaches depends heavily on the snow algae bloom intensity. We calculated the RF of the snow algae and found an average instantaneous RF (IRF) of $158.8 \text{ W m}^{-2}$ with a maximum IRF of $360.0 \text{ W m}^{-2}$. Extrapolating the IRF over the mapped snow algae extent and scaled linearly over the 29 days between the surveys, we calculate that snow algae contribute a total of $1,508 \text{ m}^3$ of snowmelt in the $0.1 \text{ km}^2$ basin. These results demonstrate the potential to map snow algae and assess the RF over expansive areas of the cryosphere using UAV technology.
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The highly reflective nature of Earth’s cryosphere is integral to maintaining the planet’s energy balance by reflecting solar radiation. As temperatures increase, the reflective properties of the snowpack will serve to protect our glacier ecosystems. Glaciers respond to changes in both temperature and precipitation, making them sensitive indicators of global climate (Oerlemans, 1986). Glacier mass loss and retreat has been documented across the world (Gardner et al., 2013), including in the North Cascades where all 47 of the monitored glaciers have experienced terminus retreat as of 1991 (Pelto and Riedel, 2001). The North Cascades is the most heavily glaciated region in the contiguous United States and the meltwater from these glaciers supports the regional agricultural and hydroelectric industries. Understanding the stability of these glaciers in a warming climate will greatly aid our ability to prepare for the future.

Glacier monitoring through remote sensing allows researchers to examine glaciers at larger scales and across inaccessible regions. There is great interest in the scientific community to utilize remote sensing techniques to advance glacier research. However, satellite coverage in many areas of the cryosphere can be limited by spatial, spectral, and temporal resolution. The recent advances in Uncrewed Aerial Vehicles (UAVs) can fill these gaps in resolutions and allow researchers to customize the properties and timing of the aerial data that is collected in order to better suit their specific research needs.

UAV imagery processing generates high resolution Digital Elevation Models (DEM) from standard, RGB aerial imagery through Structure-from-Motion (SfM) technology. The generated DEMs has been used in glaciological research to study glacial calving (Ryan et al., 2015; van Dongen et al., 2021) and mass loss (Bash et al., 2018; Fugazza et al., 2018; Bash and Moorman, 2020; Healy and Khan, 2022). UAV-based studies also enable researchers to coincide
field observations and sampling with the collection of aerial imaging. This coupling of ground data can be used to develop more rigorous indices that can later be upscaled to satellite images. Previous studies have utilized the UAV to derive a variety of spectral properties including measuring albedo, the measure of reflected solar radiation relative to absorbed solar radiation, over the Greenland Ice Sheet (Ryan et al., 2017). Albedo plays a key role in the rate of snowmelt of a glacier and therefore the stability of the glacier. Many things can impact the albedo of a glacier including snow grain size and the presence of light-absorbing impurities.

Light-absorbing impurities darken snow surfaces and cause them to absorb solar radiation instead of reflecting it, resulting in increased snowmelt (Cook et al., 2016). This snow darkening phenomenon has received great focus in the scientific community and the public after studies linked the darkening of snow in the Arctic to the massive loss of Greenland ice in 2012 (Benning et al., 2014; Tedesco et al., 2016). Extensive albedo models have attempted to predict surface melting of the ice sheets. However, the measured melting of the ice sheets is exceeding what the models predict (Tedesco et al., 2016). This discrepancy could be due to the lack of accounting for biologically active impurities, such as snow algae, as factors when predicting albedo. Including snow algae in the global albedo models is challenging since the snow algae grow in remote places, where collecting in situ measurements can be nearly impossible. Not much is known about the distribution patterns and phenology of snow algae, making their blooms difficult to predict.

The ability to effectively map snow algae using remote sensing will greatly enhance our understanding of the organisms. However, satellite images rarely correspond exactly with field studies, inhibiting the validation capabilities of the studies. The UAV provides the opportunity to
couple multispectral imagery with *in situ* sampling and allows for direct validation with the ability to upscale the validation to satellite images.

Reports of snow algae date back to 400 BC when Aristotle noted colored snow in his History of Animals (Aristotle, 400 BC). Snow algae persist in snow covered ecosystems all over the globe, with heavy documentation in the Arctic, Antarctica, and nearly all alpine glacial regions in between (Hoham and Duval, 2001). In these frozen landscapes snow algae, primarily algae from the Chlamydomonadaceae family, are the dominant primary producers, providing the foundation of the ecosystem for all other organisms living among them (Anesio et al., 2017). Snow algae thrive in areas of wet snow, where the interstitial water within the snow allows the algae to navigate to the surface of the snow to photosynthesize (Jones, 2001). In the summer months, when there is meltwater present, the snow algae bloom in the top 10 centimeters of the snowpack where *Chlamydomonas nivalis* develop secondary pigments, coloring the snow red or pink and lowering the albedo of the snow by around 20% (Hoham, 1980; Lutz et al., 2014; Khan et al., 2021). The algae are thought to have developed these red astaxanthin secondary pigments as a protective adaptation to reduce the damage of the high UV radiation present at the surface of the snow (Thomas and Duval, 1995). The decrease in albedo associated with the abundance and spread of snow algae accelerates the melting rate of snow and ice (Lutz et al., 2016; Khan et al., 2021). Snow algae are theorized to be expanding their habitat as the climate warms and the melt season lengthens (Benning et al., 2014).

Effective remote sensing methods will be important for assessing the stability of mid-latitude alpine glacial regions, where climate change is causing faster than average snow and glacier melt (Mote et al., 2008). Alpine glaciers have more light-absorbing impurities inherent in them due to their position within mountain valleys, surrounded by nunataks, than expansive,
isolated ice sheets. In most natural systems, snow algae are nutrient and liquid water limited (Ganey et al., 2017). Therefore, the snow algae in alpine regions are at a relative advantage in comparison to the arctic and Antarctic ice sheets because of the nutrients available to them from rock dust from the mountains that allow them to grow in larger quantities, accelerating the melt of the local water reservoirs held within alpine glaciers.

This thesis is broken into two chapters that address separate aspects of UAV remote sensing to assess glacier melt and snow algae in the Mount Baker region. Chapter 1, titled *Mapping glacier ablation with a UAV in the North Cascades: A Structure-from-Motion approach*, demonstrates the feasibility of the UAV to spectrally distinguish snow from ice and measure their independent contributions to ablation. The UAV derived ablation measurements are then compared with the outlet glacier stream discharge dataset collected by the Nooksack Indian Tribe. Chapter 2, titled *Approaches to remotely detect snow algae with a UAV and the radiative forcing responses in the North Cascades*, focuses on using the UAV to detect and quantify snow algal blooms in the Bagley Lakes snowfield near Mount Baker during differing bloom conditions. The snow algae extent is then used to quantify the radiative forcing implications on snowmelt across the study area.
CHAPTER 1
Mapping glacier ablation with a UAV in the North Cascades: A Structure-from-Motion approach.

1.1. INTRODUCTION

The North Cascades is the most heavily glaciated region in the contiguous United States, providing water to support the regional agricultural and hydroelectric industries. The meltwater from the glaciers in this area create the cold-water ecological habitat that fish and other riparian species depend upon. Increasing air temperatures have had great effects on glaciers across the cryosphere, including in the North Cascades where all 47 of the monitored glaciers have experienced terminus retreat as of 1991 (Pelto and Riedel, 2001). This decrease in size is associated with a 25% reduction in the late summer streamflow that salmon depend on for prosperous spawning (Riedel and Larrabee, 2016).

Mount Baker, a heavily glaciated stratovolcano within the North Cascades range, is of particular importance to both human and salmon populations downstream. The Sholes Glacier is located on the northeast flank of Mount Baker within the Indigenous territory of the Nooksack Indian Tribe. The meltwater from this glacier feeds into the North Fork Nooksack River where glacier runoff typically contributes over 25% of summer discharge (Bach, 2002) and as much as 60 to 90% during especially hot and dry summers, such as in 2015 (Pelto, 2016; Grah, 2019). The addition of glacier melt into the watershed supports the rich agricultural land downstream in Whatcom County and provides an influx of cold glacier melt water in the late summer dry season that sustains salmon habitat, which are of particular importance to the Nooksack and Lummi Tribes. The Sholes Glacier has experienced terminus recession of approximately 1,400 meters since the end of the Little Ice Age in the late 1890’s (Grah, 2019).

Many glaciers are physically inaccessible for mass balance field studies and if accessible, require considerable time and specialized glacier travel skills. Satellite remote sensing of glacier
mass balance and surface properties can ease the logistical challenge of glacier travel, and if publicly available, lessen the cost to researchers. However, satellite images are often thwarted by sensor spatial and temporal resolution, as well as shadows of steep surrounding mountains causing satellite imagery to be an inadequate tool in examining small, high alpine glaciers (Gaffey and Bhardwaj, 2020). Satellite coverage in many areas of the cryosphere is limited in repeat pass over rates and when the satellite does pass over the region, there is high likelihood of clouds, reducing the number of usable satellite images (Wigmore and Mark, 2017). Additionally, the few satellites that offer stereo images can be difficult to acquire (Bhattacharya et al., 2021) and do not offer sufficient temporal resolution to assess the rapid elevation changes caused by climate change.

With the recent advances in Uncrewed Aerial Vehicle (UAV) technology and the reduction in the price of this technology, there is huge potential for improving the spatial and temporal resolution of ablation data with limited field effort or cost. The availability and affordability of UAV technology has spurred interest in the field of glacier dynamics, with numerous studies applying UAV derived data to assess glacier dynamics at high spatial resolutions. Researchers have employed UAVs as tools to assess glacier calving (Ryan et al., 2015; van Dongen et al., 2021), track glacier motion (Immerzeel et al., 2014a; Che et al., 2020), and measure mass loss (Bash et al., 2018; Fugazza et al., 2018; Bash and Moorman, 2020) in remote regions. The majority of UAV-based cryosphere studies have been focused in Antarctica (Westoby et al., 2015, 2016; Florinsky and Bliakharskii, 2019), the polar regions (Ewertowski et al., 2016; Tonkin et al., 2016; Bernard et al., 2017b, 2017a; Cimoli et al., 2017), the European Alps (Mauro et al., 2015; Boesch et al., 2016; De Michele et al., 2016; Fugazza et al., 2018; Rossini et al., 2018; Vivero and Lambiel, 2019), and High Mountain Asia (Immerzeel et al.,
2014b; Brun et al., 2016, 2018; Kraaijenbrink et al., 2016; Vincent et al., 2016). However, to the authors knowledge, no previous peer reviewed studies have utilized the UAV to assess glacier dynamics in the Pacific Northwest.

The use of Structure-from-Motion (SfM) technology in reconstructing glacier surfaces has been extensively validated (e.g. Bash et al., 2020). UAV-based measurements of snow depth change have even been shown to exceed the accuracy of traditional in situ methods (Fernandes et al., 2018). Additionally, photogrammetric approaches have outperformed systematic in situ methods of measuring snow depth when assessing small scale spatial variability (Redpath et al., 2018). Monitoring the rapid retreat of small mountain glaciers has been greatly enhanced by the use of UAVs, allowing researchers to capture the heterogeneity of glacier change that would not be possible through the analysis of satellite imagery (Wigmore and Mark, 2017). While the abilities of SfM have been tested thoroughly elsewhere in the world, they have never been tested in the Mount Baker region where there is an associated long-term glacier discharge dataset to draw comparisons. The Sholes Glacier is unique in that it is the only glacier in the North Fork Nooksack River watershed that has been studied in detail over a relatively long period of time using both glaciological and hydrological methods, allowing for validation and comparison of methodologies.

The Nooksack Indian Tribe, located in Deming, WA within the Nooksack River watershed, has been monitoring the mass balance and outlet flow of the Sholes Glacier weekly during the late summer snow and ice melt season since 2012. The Tribe is interested in understanding the glacier’s health and behavior to assess the Tribe’s ability to continue to harvest sustainable populations of salmon. The Tribe measures the glacier discharge as well as snow and ice depth changes throughout the melt season. The natural weir at the toe of the glacier makes
this specific glacier an ideal study site for mass balance work and glacier runoff observations (Supplementary Image 1).

There is movement in the scientific community towards developing more co-produced science that incorporates local communities and Tribal Nations who have a vested interest in understanding the vulnerability of their ecosystems to climate change (e.g. Lemos et al., 2012; Wynecoop et al., 2019; Turnhout et al., 2020; Oshun et al., 2021). The Nooksack Indian Tribe has generously shared their 2020 season data for this study in the interest of scientific collaboration.

Here we compare the glacier mass balance assessment of the Nooksack Indian Tribe with a SfM UAV-based approach. This study shows that the UAV can be used to derive glacier ablation and estimate the volume of water moving from the glacier into the Nooksack River. Additionally, we present the use of multispectral imagery collected from a UAV to differentiate snow and ice area of the glacier surface.

1.2. MATERIALS AND METHODS

1.2.1. Study area

The Sholes Glacier is located on the northeast flank of Mount Baker in the Mount Baker Wilderness area of the Mount Baker-Snoqualmie National Forest, Washington, United States (121.770032°W, 48.8141614°N). The glacier resides in a temperate maritime climate associated with mild year-round temperatures, high winter precipitation, and low summer precipitation. The glacier is predominantly fed by direct accumulation and wind drifting with minimal loss due to calving or avalanching events (Pelto, 2018). The glacier has a northern aspect and spans 0.56 km², descending from an elevation of 1,900 to 1,600 meters above sea level. The glacier melt
drains out of two streams at the toe of the glacier, Wells Creek and Sholes Creek, both of which feed into the North Fork Nooksack River.

The Nooksack River watershed is primarily rainwater and snowmelt dominated for the majority of the year. During the mid to late summer months, the area is quite dry, and the river system is supplemented by the flow of cold snow and glacier meltwater from May through September, which contributes over 25% of daily discharge to the watershed (Bach, 2002) and as high as 60 to 90% during particularly hot dry periods in the summer, such as in 2015 (Grah 2019, Pelto 2016).

2.2.2. **UAV surveys**

The Sholes Glacier was surveyed twice throughout the melt season with permission from the U.S. Forest Service, once on August 17, 2020 and again on September 5, 2020. The surveys were conducted using a DJI Phantom 3 Standard quadcopter equipped with the inherent, off-the-shelf DJI camera, as well as an additional MAPIR Survey3 three-band multispectral camera. The DJI camera was set to capture images every 2 seconds with ISO set at 100 and shutter speed set at 1/8000 s. The MAPIR camera captures imagery in the red (660 nm), green (550 nm), and near-infrared (850 nm) wavelengths (www.mapir.camera). This camera captured RAW (12 bit) and JPG (24 bit) images every 2 s with an ISO set at 100 and a 1/2000 shutter speed. Prior to take off for each survey flight, an image of the MAPIR camera calibration panel was taken to later facilitate conversion of the MAPIR imagery to reflectance values.

The UAV was powered with DJI LiPo 4S 15.2 V batteries. Only 4 batteries were available on the August 17 flight, while 6 batteries were available on the September 5 flight. Each battery provided approximately 20 minutes of flight time. Therefore, there is slightly more coverage on the September 5 flight compared to the August 17 flight.
Prior to each flight, 13 ground control points (GCPs) were laid out over the glacier. The GCP coordinates were acquired with an EMLID Reach RS2 RTK GNSS receiver, or rover, and corrected with another stationary receiver, or base, both of which logged continuously throughout the survey. The base receiver was stationed adjacent to the glacier, within 1 km of the rover, where it could have a clear view of the sky. Data logs of the base station were post-processed against the rover in the open-source RTKLIB software in kinematic mode (Takasu and Yasuda, 2009).

The UAV flight plan was created and executed in DroneDeploy. The glacier was flown in six flight segments with 75% sidelap and 75% frontlap at an above ground altitude of 73 m. The flights were completed between 12:00 and 16:00 Pacific Time. Both surveys were conducted following the same flight line angle to minimize shadow differences between the flights (Fernandes et al., 2018). Due to the large survey area and the constraint of flight time per battery, the six flight segments were conducted from three different launch locations located progressively towards the glacier terminus.

1.2.3. Image processing

The DJI and MAPIR images were refined to only include in-survey images. Images acquired during take-off, landing, and transit were removed from the analysis. The raw MAPIR survey images were processed and calibrated to reflectance using the MAPIR Camera Control software and the calibration target images that were captured pre-flight. The resulting MAPIR images represent the calibrated surface reflectance values and were used in the rest of the imagery processing steps.

The DJI and MAPIR images were processed separately. The images for each camera were grouped by their take-off location and the altitudes were adjusted with an open-source
Python script to represent meters above sea level based on the launch elevation and the flight altitude (Agisoft LLC, 2017). The flights were then loaded into Agisoft Metashape software where the Image Quality, or sharpness, was estimated and blurry images, defined as those with a quality below 0.5, were removed from the rest of the analysis to improve photogrammetric processing following the guidelines in the Agisoft Metashape Professional Edition User Manual (Agisoft LLC, 2021). Each flight subsection was aligned separately with high accuracy, 500,000 key point limit, and 0 tie point limit. All points with a reprojection error greater than 0.5 pixels and any obvious outlier points were removed from the sparse point cloud.

The GCPs and ground validation points (GVPs) were manually marked in at least 6 images where the target was most visible. The target coordinates were loaded, and the sparse point cloud was updated. The camera positions were optimized before constructing the dense point cloud with high quality and aggressive depth filtering. The DEM was constructed based on the dense point cloud and the orthomosaic was constructed based on the DEM.

Through the process described above, an orthomosaic and a DEM for both the DJI and the MAPIR camera were produced for each survey date. The MAPIR orthomosaic was used for conducting snow and ice classification and the DJI DEM was used to calculate the surface height change between survey dates. The DJI images had a higher spatial resolution than the MAPIR images and therefore produced a smoother and more accurate elevation model.

1.2.4. MAPIR image classification

The MAPIR orthomosaics, composed of green (550 nm), red (660 nm), and near-infrared (850 nm) bands, were used to conduct IsoData unsupervised classification of the glacier surface spectral properties on both August 17, 2020 and September 5, 2020 in ENVI version 5.6 (Exelis Visual Information Solutions, Boulder, Colorado). The default ENVI parameters were used
except for the number of classes, which was changed to a maximum of 50 classes, and the maximum iterations, which was increased to 10. The resulting spectral classes were then refined to represent the following three information classes: Snow, Ice, and Rock.

The accuracy of the classified images was assessed by assigning a minimum of 100 check points randomly stratified across the three information classes. These ground truth check points were then manually classified into Rock, Ice, and Snow using the MAPIR and DJI orthomosaics as references. The resulting ground truth points were compared to the IsoData classification to generate a confusion matrix. The confusion matrix demonstrates the accuracy of the classification with respect to user and producer accuracy. Here, user accuracy refers to how reliable the classification map is, for example, how often a check point location classified as Ice on the map is actually ice. Producer accuracy here, tells us how accurate our classification is, for example, how often ice will be classified as Ice in the map.

The classified images from each survey date were then clipped into image sections that were ice for both survey dates (Ice-to-Ice), snow for both survey dates (Snow-to-Snow), and sections that transitioned from snow to ice between the survey dates (Snow-to-Ice). These classifications were used to differentiate the DEM surface height changes that should be attributed to Snow-to-Snow melt, Ice-to-Ice melt, or a transition from Snow-to-Ice.

1.2.5. Ablation assessment

The late summer snowpack in the North Cascades region is highly homogenous and isothermal over the large scale. This allows us to calculate the water equivalent of snow and ice volume loss using constant density measurements. The snow density value used for our calculation of Snow-to-Snow areas was 600 kg m$^{-3}$ (Pelto and Riedel, 2001) and the ice density value used for our calculation of Ice-to-Ice areas was 850 kg m$^{-3}$ (Huss, 2013). The water
equivalent of the Snow-to-Ice classified areas that transitioned from snow to ice between the survey dates were calculated using a density of 725 kg m$^{-3}$, the average of the snow and ice densities.

The difference between the DEMs was clipped to only include areas of negative height change. The areas that resulted in a positive height change were examined separately and proved to be a result of shadow, cliff, and edge effects (Supplementary Figure 1). These areas were removed from the analysis. To mitigate any other possible edge effects that could create errors in the surface height changes, all survey edges were clipped out of the analysis.

Ablation measurements were calculated for the entire surveyed glacier area and also for a subsection of the glacier, the Wells Creek drainage area. Since only one of the two outlet creeks from the glacier is gauged, to compare the UAV derived discharge to the measured stream discharge we must separate the glacier area that drains into the gauged Wells Creek from the glacier area that drains into the ungauged Sholes Creek. This delineation was conducted based on the glacier surface topography that is observed in the UAV imagery and in the field. The medial moraine of the glacier divides the two drainage areas and can be followed from the terminus of the glacier to the ablation area using the stratigraphy of the glacier as a guide (Supplementary Figure 2).

1.2.6. Discharge measurements

The Nooksack Indian Tribe has an established monitoring system for measuring the discharge of the Sholes Glacier. At the beginning of the melt season, they install a Solonist Levelogger 5 accompanied with a Solonist Barologger 5 to record water level, water temperature, air temperature, and barometric pressure at 30-minute intervals. Additionally, the Tribe visits the monitoring site weekly to measure stream velocity with a Xylem Flowprobe
which was integrated over the cross-sectional area to determine discharge. A discharge rating curve was then developed for each creek in order to model continuous discharge over the field season from late July through mid-September (Grah and Beaulieu, 2013).

These data were compiled and trimmed to include only the measurements acquired between the two UAV surveys. This dataset was then integrated to calculate the total discharge in cubic kilometers that the glacier released over the course of the survey period.

1.3. RESULTS

1.3.1. Positional accuracy

The accuracy of the SfM image processing was assessed based on 8 GCPs and 4 ground validation points (GVPs) for the August 17, 2020 flight and 9 GCPs and 4 GVPs for the September 5, 2020 flight. The August 17, 2020 flight covered a smaller area, 0.8 km$^2$, than the September 5, 2020 flight, 1.0 km$^2$, and had a higher positional accuracy based on the GCPs and GVPs. The GVPs used during the September 5, 2020 flight had a total positional error more than 3 times greater than that of the August 17, 2020 flight, 60.5 cm and 16.1 cm respectively (Table 1). Based on these accuracy assessments, the DEMs used for the rest of this study were resampled using the nearest neighbor method to 1 m pixels to compensate for any lateral positional error. The vertical error for the August 17, 2020 flight was 9.15 cm and the vertical error for the September 5, 2020 flight was 10.20 cm. Propagating the vertical errors through to the differenced DEM results in an error of 0.19 m, which was used through the rest of the calculations.
Table 1. Control point errors where X represents Longitude, Y represents Latitude, and Z represents Altitude. Ground control points (GCPs) were used in the aligning of the orthomosaic while the ground validation points (GVPs) were omitted and used to assess the reconstruction accuracy.

<table>
<thead>
<tr>
<th>Survey date</th>
<th>Type</th>
<th>Count</th>
<th>X error (cm)</th>
<th>Y error (cm)</th>
<th>Z error (cm)</th>
<th>XY error (cm)</th>
<th>Total (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>August 17, 2020</td>
<td>GCP</td>
<td>8</td>
<td>2.72</td>
<td>2.86</td>
<td>1.79</td>
<td>3.95</td>
<td>4.34</td>
</tr>
<tr>
<td></td>
<td>GVP</td>
<td>4</td>
<td>10.28</td>
<td>8.30</td>
<td>9.15</td>
<td>13.21</td>
<td>16.07</td>
</tr>
<tr>
<td>September 5, 2020</td>
<td>GCP</td>
<td>9</td>
<td>11.54</td>
<td>37.09</td>
<td>4.95</td>
<td>38.84</td>
<td>39.16</td>
</tr>
<tr>
<td></td>
<td>GVP</td>
<td>4</td>
<td>34.66</td>
<td>48.51</td>
<td>10.20</td>
<td>59.62</td>
<td>60.48</td>
</tr>
</tbody>
</table>

1.3.2. Glacier surface changes

From August 17, 2020 to September 5, 2020, DEM differencing revealed that the Sholes Glacier lost an average thickness of 2.5 ± 0.19 m (Table 2). The majority of the pixels resided within the 0 to -5 m range, with only crevasse openings and edge effects extending beyond -5 m. Since these pixels do not represent mass loss, they were removed from the analysis to more accurately capture the ablation. The Snow-to-Snow class covered the largest area (0.193 km²) and had the greatest total volume lost (-477,226 ± 37,054 m³) when compared to Snow-to-Ice (-362,263 ± 27,601 m³) and Ice-to-Ice (-217,359 ± 16,612 m³) (Table 2).
Table 2. Surface height differences between the DEMs of the Sholes Glacier on August 17, 2020 and September 5, 2020. The surface height changes are separated into three surface type classes based on the IsoData unsupervised classification. Statistics were calculated based on each surface type class.

<table>
<thead>
<tr>
<th>Glacier surface change</th>
<th>Area (km²)</th>
<th>Minimum height change (m)</th>
<th>Maximum height change (m)</th>
<th>Range of height change (m)</th>
<th>Mean height change (m)</th>
<th>Standard deviation of height change (m)</th>
<th>Volume lost (m³)</th>
<th>Water Equivalent of volume lost (m³ w.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow-to-Ice</td>
<td>0.144</td>
<td>-4.96</td>
<td>-0.01</td>
<td>4.95</td>
<td>-2.52</td>
<td>0.82</td>
<td>-362,263</td>
<td>-263,228 ± 20,055</td>
</tr>
<tr>
<td>Ice-to-Ice</td>
<td>0.087</td>
<td>-4.96</td>
<td>0.00</td>
<td>4.96</td>
<td>-2.51</td>
<td>0.61</td>
<td>-217,359</td>
<td>-185,168 ± 14,151</td>
</tr>
<tr>
<td>Snow-to-Snow</td>
<td>0.193</td>
<td>-4.96</td>
<td>-0.03</td>
<td>4.93</td>
<td>-2.47</td>
<td>0.62</td>
<td>-477,226</td>
<td>-286,976 ± 22,282</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td><strong>0.424</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>-735,372</strong></td>
<td><strong>-1,056,848 ± 56,488</strong></td>
</tr>
</tbody>
</table>

Snow-covered area declined from 75.5% to 43% with ice-covered area increasing by 0.16 km² over the 19 days between survey flights (Figure 1). Snow-covered areas and ice-covered areas lost surface thickness at similar rates, -0.130 m d⁻¹ and -0.132 m d⁻¹, respectively.

For areas that remained snow covered between the two survey dates (Snow-to-Snow), the surface height loss of 2.47 ± 0.19 m is equal to 1.48 ± 0.11 meters water equivalent (m w.e.) whereas for areas that remained ice covered between the two survey dates (Ice-to-Ice), the surface height loss of 2.51 ± 0.19 m is equal to 2.14 ± 0.16 m w.e.
Figure 1. (A) Displays Mount Baker with an inset showing the location of the mountain within Washington state in the contiguous United States and a callout box highlighting the Sholes Glacier. (B) The Sholes Glacier (-121.770032°W, 48.8141614°N) as seen in the true color DJI orthomosaic from the September 5, 2020 UAV survey. IsoData classification of the Sholes Glacier on (C) August 17, 2020 where the total glacier extent is 0.484 km² with 75.5% of the
Glacier surface height change appeared relatively uniform across the extent of the glacier with the most extreme height changes occurring in the upper section of the glacier (Figure 2). This section of the glacier is associated with a much steeper slope, faster moving ice, and more crevassing. The opening of crevasses and the collapsing of a snow or ice cave in this lower section resulted in DEM surface height differences greater than 14 m.

**Figure 2.** Surface elevation change of the Sholes Glacier between August 17, 2020 and September 5, 2020. The DEMs for each survey date were differenced to reveal the surface elevation change.
1.3.3. *IsoData classification*

The IsoData classification generated 9 unique spectral classes that were combined into the 3 information classes: Rock, Ice, and Snow. Accuracy assessment performed on each survey revealed that the spectral classification of the August 17, 2020 and the September 5, 2020 imagery had overall accuracies of 79.7% and 78.1% respectively (Table 3). The Rock class had the worst user accuracy (51.5% on August 17 and 58.5% on September 5) yet the highest producer accuracy (96% on August 17 and 100% on September 5) for both survey dates, meaning that the classification overpredicted rock and only 51.5 or 58.5% of the places classified as Rock were really rock (Table 3). The Snow class had the best user accuracy for both survey dates (90.6% on August 17 and 87.8% on September 5) (Table 3). Kappa values for the August 17, 2020 and the September 5, 2020 surveys were 0.665 and 0.664 respectively (Table 3).

**Table 3.** Confusion matrix for the MAPIR IsoData classification of the Sholes Glacier on August 17, 2020. User data for the 177 and 137 stratified random ground truth points were manually classified using the DJI and MAPIR orthomosaics as references.

<table>
<thead>
<tr>
<th>Survey date</th>
<th>Rock</th>
<th>Ice</th>
<th>Snow</th>
<th>Total</th>
<th>User Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>August 17, 2020</td>
<td>24</td>
<td>17</td>
<td>6</td>
<td>47</td>
<td>0.511</td>
<td>0.665</td>
</tr>
<tr>
<td>Rock</td>
<td>1</td>
<td>30</td>
<td>3</td>
<td>34</td>
<td>0.882</td>
<td></td>
</tr>
<tr>
<td>Ice</td>
<td>0</td>
<td>9</td>
<td>87</td>
<td>96</td>
<td>0.906</td>
<td></td>
</tr>
<tr>
<td>Snow</td>
<td>25</td>
<td>56</td>
<td>96</td>
<td>177</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Producer Accuracy</td>
<td>0.96</td>
<td>0.53</td>
<td>0.906</td>
<td>0.797</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.665</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>September 5, 2020</th>
<th>Rock</th>
<th>Ice</th>
<th>Snow</th>
<th>Total</th>
<th>User Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rock</td>
<td>24</td>
<td>15</td>
<td>2</td>
<td>41</td>
<td>0.585</td>
<td>0.664</td>
</tr>
<tr>
<td>Ice</td>
<td>0</td>
<td>47</td>
<td>8</td>
<td>55</td>
<td>0.855</td>
<td></td>
</tr>
<tr>
<td>Snow</td>
<td>0</td>
<td>5</td>
<td>36</td>
<td>41</td>
<td>0.878</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>24</td>
<td>67</td>
<td>46</td>
<td>137</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Producer Accuracy</td>
<td>1</td>
<td>0.702</td>
<td>0.783</td>
<td>0.781</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td></td>
<td>0.781</td>
<td>0.830</td>
<td>0.781</td>
<td></td>
<td>0.664</td>
</tr>
</tbody>
</table>
1.3.4. Glacier discharge

Wells Creek discharge data collected by the Nooksack Indian Tribe revealed an average discharge rate of 0.203 m$^3$ s$^{-1}$ between August 17, 2020 and September 5, 2020 (Table 4). The discharge remained within the 0.05 to 0.45 m$^3$ s$^{-1}$ for all days in this time period except on August 21, 2020 when there was a spike in discharge up to 0.7 m$^3$ s$^{-1}$, which could be due to a regional surface temperature increase observed on August 16, 2020, according to the Global Historical Climatology Network-Daily database (Menne et al. 2012; version 3). The hydrology of the lower Sholes glacier includes small moulins and englacial conduits, which may serve as reservoirs for meltwater leading to the discharge spike observed 4 days later. The residence time of supraglacial and englacial meltwater on the Sholes has not yet been exhaustively studied.

Based on the UAV results, the majority, 0.342 km$^2$, of the 0.424 km$^2$ glacier drains into Wells Creek. DEM differencing reveals that this drainage basin area lost an average surface height of -2.33 ± 0.19 m for a total of -550,161 ± 45,206 m$^3$ w.e. discharged into Wells Creek between the survey dates (Table 5). In comparison, the Wells Creek stream gauge station measured a total discharge of 350,023 m$^3$ between the survey dates (Table 4). The two measurements differ by 200,138 m$^3$.

Table 4. Wells Creek discharge data from August 17, 2020 through September 5, 2020, shared by the Nooksack Indian Tribe in the interest of scientific collaboration.

<table>
<thead>
<tr>
<th>Average Air Temperature (°C)</th>
<th>Standard deviation</th>
<th>Average Stream Temperature (°C)</th>
<th>Standard deviation</th>
<th>Average rate of discharge (m$^3$ s$^{-1}$)</th>
<th>Standard deviation</th>
<th>Total discharge volume (m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.838</td>
<td>4.988</td>
<td>2.496</td>
<td>1.018</td>
<td>0.203</td>
<td>0.084</td>
<td>350,023</td>
</tr>
</tbody>
</table>
Table 5. Surface height differences between the DEMs of the Wells Creek drainage basin portion of the Sholes Glacier on August 17, 2020 and September 5, 2020. The surface height changes are separated into three surface type classes based on the IsoData unsupervised classification. Statistics were calculated based on each surface type class.

<table>
<thead>
<tr>
<th>Glacier surface change</th>
<th>Area (km²)</th>
<th>Minimum height change (m)</th>
<th>Maximum height change (m)</th>
<th>Range of height change (m)</th>
<th>Mean height change (m)</th>
<th>Standard deviation of height change (m)</th>
<th>Volume lost (m³)</th>
<th>Water Equivalent of volume lost (m³ w.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow-to-Ice</td>
<td>0.110</td>
<td>-4.81</td>
<td>-0.01</td>
<td>4.80</td>
<td>-2.32</td>
<td>0.79</td>
<td>-255,749 ± 15,355</td>
<td>-185,832 ± 15,355</td>
</tr>
<tr>
<td>Ice-to-Ice</td>
<td>0.066</td>
<td>-4.88</td>
<td>-0.32</td>
<td>4.57</td>
<td>-2.35</td>
<td>0.57</td>
<td>-154,674 ± 12,598</td>
<td>-131,766 ± 10,732</td>
</tr>
<tr>
<td>Snow-to-Snow</td>
<td>0.166</td>
<td>-4.96</td>
<td>-0.03</td>
<td>4.93</td>
<td>-2.33</td>
<td>0.54</td>
<td>-386,740 ± 31,794</td>
<td>-232,563 ± 19,119</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td><strong>0.342</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>-797,163 ± 65,524</strong></td>
<td><strong>-550,161 ± 45,206</strong></td>
</tr>
</tbody>
</table>

1.4. DISCUSSION

This paper demonstrates the application of low-cost UAV survey equipment to resolutely map short time scale glacier dynamics. The total cost of the UAV set up was less than $2,000 USD and did not require complicated rigging or modification. While the MAPIR camera is not designed for calculating research level spectral indices, the spectral capabilities are more than sufficient to conduct spectral classification. The ability to divide the survey area into Snow, Rock, and Ice using IsoData unsupervised classification greatly aided in our ability to analyze the glacier ablation based on surface type. This classification approach could be useful in a variety of UAV applications, including in the classification of supraglacial lakes or sea ice melt ponds (Tschudi et al., 2008).
The summer snow melt of a glacier is a dynamic process where the snowline does not necessarily move linearly up the glacier in elevation. On the Sholes Glacier in particular, there are patches above the snowline that reveal ice much earlier in the season and patches below the snowline that remain snow covered until much later in the season. Therefore, manually digitizing the snow- and ice-covered extent would likely misrepresent the contributions of snow and ice melt to the total discharge. In this way, the IsoData unsupervised classification enabled us to parse out snow versus ice more accurately and interpret their respective surface height changes.

Though the IsoData unsupervised classification performed effectively when classifying spectrally distinct features, such as snow and rock, the performance decreased when classifying more spectrally similar surfaces like ice and rock. This causes issues in sections of the Sholes Glacier where the ice is covered by debris and gets classified as Rock in the process. Since the areas classified as Rock were not included in the analysis, the contribution of ice melt was likely underestimated. Previous studies have also encountered this issue when attempting to spectrally distinguish between debris covered glacier features and the surrounding rock faces (Kraaijenbrink et al., 2016). This misclassification could potentially be reduced in future studies by the addition of a thermal sensor on the UAV that could distinguish debris on top of ice from the surrounding rock, allowing the approach to be applied to studying rock glaciers or debris covered glaciers more effectively (Brun et al., 2016; Vincent et al., 2016; Wigmore and Mark, 2017; Vivero and Lambiel, 2019; Che et al., 2020).

This study did not venture to conduct ground validation across the entire glacier extent and instead sought to assess the glacier as a whole. In this regard, we were able to compare the total surface height changes measured with the UAV to the total glacier discharge measured by one of the glacier outlet creeks. The UAV derived discharge overestimated the measured stream
discharge by 200,138 m$^3$. This discrepancy is likely due to the manual digitization of the Wells Creek drainage basin, as described in the methods. Processes like sublimation, snow compaction, and meltwater drainage to groundwater should also be considered as potential sources of error. Additionally, the Snow-to-Ice class assumes that only the wet, intermediary snow melted and that after it melted away, no underlying ice melted. While we attempted to compensate for this by using a density halfway in between that of snow and ice, there could have been a larger portion of snow rather than ice that melted away and contributed to our overestimation of water equivalent. Future studies should gauge the secondary outlet stream, Sholes Creek, in addition to the Wells Creek, to capture all of the glacier discharge.

Due to the remote and rigorous terrain of the field site, we were only able to set up 13 ground control targets over the glacier, all of which had to be restricted to low angle, snow-covered regions of the glacier for the targets to be placed safely and effectively. Placing GCPs evenly across the snow-covered and snow-free areas of the glacier would have improved lateral and vertical accuracy of the data (Gindraux et al., 2017), however there was no way to safely place GCPs in the heavily crevassed areas of the glacier. The approach still produced a sufficiently low RMSE in the orthomosaics and DEMs (Table 1) to be able to compare between the two survey dates. Additionally, the lateral error in the orthomosaics and DEMs was accounted for by resampling the products to a pixel size that exceeds the positional error in the imagery. In the future, the surveys could be set up to correspond with more traditional times of data collection at the snow maximum and minimum. However, our goal was to test the methodology in reference to the Nooksack Tribe’s discharge data, which is collected through the late summer season.
1.5. CONCLUSION

The development and application of UAV research to cryosphere science is creating new opportunities for increased spatial and temporal monitoring of glacier mass balance and surface properties. Many areas of the cryosphere are changing so rapidly that frequent temporal revisit is necessary to document and understand them (Rossini et al., 2018). The increasing affordability of UAVs provides a distinct advantage over satellite remote sensing and traditional field surveys by allowing researchers to exert greater control over the collected data without being limited by the availability and affordability of satellite data or the manual labor required for field campaigns.

With the addition of a multispectral camera mounted on the UAV there is great potential to connect the observed rates of snowmelt to the influence of light absorbing impurities. In particular, there is great interest to connect the spectral properties of snow algae to the measured snow melt in sensitive ecosystems (Khan et al., 2021). Additionally, there is potential to collect albedo measurements of glacier surfaces at unprecedented spatial resolution and over previously inaccessible glacier areas by mounting upwelling and downwelling solar radiation sensors on the UAV (Ryan et al., 2017).

The approach presented in this study could also be used to assess the impacts of short but intense warming events on snow and ice melt, such as the 2021 Pacific Northwest heatwaves. The ability to assess snow and ice ablation in small alpine glaciers is of great importance to downstream communities, such as the Nooksack Indian Tribe. The Tribe seeks to understand the magnitude and timing of the influx of glacier melt into the Nooksack River so that they can better protect their essential salmon populations. With this study we have demonstrated the feasibility of using the UAV in the North Cascades region to assess glacier ablation and the
addition of UAV data to the Tribe’s established dataset could substantially enhance the overall understanding of the glacier’s health. By surveying with the UAV at the snow maximum and minimum we can obtain robust mass balance measurements while also capturing any influence of light absorbing impurities that will influence the glacier’s long-term stability and, therefore, the Tribe’s ability to harvest salmon. With this paper, we provide a baseline for future glacier monitoring and the potential to connect the snow surface properties with the rate of snow melt into a warming future.
CHAPTER 2
Approaches to remotely detect snow algae with a UAV and the radiative forcing responses in the North Cascades.

2.1. INTRODUCTION

The highly reflective snow surfaces of the world contribute substantially to maintaining the energy balance of the earth. Clean snow surfaces reflect as much as 99% of incoming solar radiation, protecting our atmosphere from warming (Hudson et al., 2006). Even small-scale reduction in snow cover extent or snow albedo will drastically reduce the protective properties of the cryosphere and contribute to a warming climate (Flanner et al., 2007; Flanner & Zender, 2006).

Snowpacks across the cryosphere support the growth of a variety of microorganisms including bacteria (e.g. Carpenter et al., 2000; Thomas & Duval, 1995), annelids (e.g. Shain et al., 2011; Tynen, 2011), chytrids (e.g. Naff et al., 2013), fungi (e.g. Gunde-Cimerman et al., 2003), and algae (e.g. Brown & Tucker, 2020; Davey et al., 2019; Engstrom et al., 2020; Fujii et al., 2010; Müller et al., 1998). Snow algae bloom on the surface of the snowpack during the summer months, developing colored photoprotective pigments to protect the cells from intense solar radiation (Bidigare et al., 1993; Remias et al., 2005). The photoprotective pigments, primarily astaxanthin, color the snow red where they bloom and cause the albedo of the snow to decrease by around 20% (Hoham, 1980; Khan et al., 2021; Lutz et al., 2014). Quantifying the impacts of this reduced albedo across glaciers and snowfields would be prohibitive with in situ studies. With the increasing capabilities of Uncrewed Aerial Vehicles (UAV), we can evaluate the prevalence and albedo influence of snow algae across large, inaccessible areas.

Previous studies have utilized UAVs to evaluate a variety of research questions in the cryosphere. The advances in Structure-from-Motion (SfM) technology allow researchers to construct high resolution Digital Elevation Models (DEM) from the UAV imagery. This
principal has been applied as a means to evaluate snow and glacier ablation (Bash et al., 2018; Bash & Moorman, 2020; Healy & Khan, 2022; Rossini et al., 2018), assess glacier dynamics (Bash & Moorman, 2020; Che et al., 2020; Immerzeel et al., 2014; Jouvet et al., 2017; Kraaijenbrink et al., 2016; Ryan et al., 2015), and retrieve snow depth (Boesch et al., 2016; Cimoli et al., 2017; De Michele et al., 2016; Fernandes et al., 2018; Gunn et al., 2021; Harder et al., 2016; Jacobs et al., 2021; Lendzioch et al., 2019). While there have been studies that use the UAV to study ice algae on the Greenland Ice Sheet (Cook et al., 2020; Tedstone et al., 2020), to the author’s knowledge, the remote detection of snow algal blooms in mid-latitudes using a UAV has not been previously demonstrated.

The current research on the remote detection of snow algae has largely been focused on using satellite images (Gray et al., 2020, 2021; Hashim et al., 2016; Huovinen et al., 2018; Painter et al., 2001; Takeuchi et al., 2006). One of the most prevalent indices developed thus far is the red (610-680 nm) to green (500-590 nm) SPOT satellite reflectance ratio developed by Takeuchi et al. (2006). The Takeuchi index has been applied to other satellites, including Landsat (Hisakawa et al., 2015) and Sentinel-2A (Huovinen et al., 2018). However, satellite images are less likely to have closely corresponding ground validation data and usually have limited spectral or spatial resolutions sufficient to capture the snow algae. One study by Tovar-Sánchez et al. (2021) was able to observe a snow algae bloom in UAV imagery collected for environmental and wildlife research in Antarctica, yet the bloom was secondary to their research purposes, and they did not attempt to use the imagery to classify the snow algae. This study seeks to downscale the red/green index utilized in previous satellite remote sensing of snow algae studies to the UAV level and validate the approaches with coupled in situ snow algae data.
The snowpack of the North Cascades has been declining as a result of climate change with the average spring snowpack projected to decrease by 38 to 46% by 2050 (Roop et al., 2020). This reduction in snow cover will cause glacier ice to be exposed to solar radiation for longer periods of time, exacerbating glacier melt. Snow algae are likely contributing to this increased snow melt by decreasing the albedo of the snow (e.g. Cook et al., 2016; Khan et al., 2021). Additionally, the habitat extent of snow algae is expected to expand with a warming climate and a lengthened melt season (Benning et al., 2014). Understanding and evaluating the extent and impacts of the snow algae at a large scale will aid our ability to predict the stability of the North Cascades snowpack.

Radiative transfer models have been previously established for clean snow, such as the Two-stream Radiative Transfer in Snow (TARTES) developed by Libois et al. (2013). However, modelling the influence of biologically active snow algae on the albedo of the snow has only recently been established. The SNow, ICe, and Aerosol Radiative (SNICAR) model developed by Flanner and Zender (2006) has been well validated as a tool to model the spectral albedo of snow with light absorbing impurities and has been used in IPCC assessments (Adolph et al., 2016; Meredith et al., 2019; Shao et al., 2019; Zhong et al., 2017). This model has been updated as the first of its kind to include the contribution of snow algae to albedo in a unified code base (Flanner et al., 2021).

In this study, we utilize the high-spectral and -spatial resolution MicaSense Dual camera system mounted on a UAV to map snow algae in a basin in the North Cascades under differing bloom conditions and employing two distinct approaches. Firstly, we reduced the 10-band multispectral imagery into three layers by conducting a Principal Components Analysis and classifying the snow algae with the resulting components. Secondly, we tested a spectral
indexing approach using the red and green bands to map the snow algae and correlate the cell concentration to the proposed index. We used our in situ snow algae data to model the spectral albedo of the snow algae using the SNICAR model and compare the modelled spectra to the UAV derived spectra. Finally, we quantified the radiative forcing of the snow algae across the entire study area using the UAV derived snow algae map.

2.2. MATERIALS AND METHODS

2.2.1. Study site

The Bagley Lakes are a set of snowmelt fed lakes located in the Mount Baker-Snoqualmie National Forest (48.85416537°N, -121.69186266°W, 1277 m above sea level). The basin area remains snow covered until late in the summer and has consistent blooms of red snow algae. The basin covers an area of 0.1 km² consisting of a flat marshy expanse and a large lake nestled in a cirque with steep rocky sides. Beneath the larger, upper lake is a connected, smaller lake that flows into a tributary of the North Fork Nooksack River. The snowmelt fed Nooksack River supports agricultural irrigation, drinking water, and salmon spawning in the region. The local Tribes have relied on the snowmelt from the North Cascades to replenish the rivers and support the salmon populations since time immemorial. After the winter of 2020 to 2021, the area had an early May snowpack thickness of 4.06 m (Northwest Avalanche Center, 2022). The basin receives its snowpack both through direct precipitation and through avalanching events from the steep walls of the basin that deliver snow and debris to the bottom of the basin. The area is reasonably accessible from the road during the late summer months, making it an ideal site for repeat surveys. A portion of the study area lies within an avalanche runout zone and, due to numerous winter avalanching events, there is a great amount of deposited debris and trees in this area. For this analysis, we chose to remove the avalanche runout zone from the study due to the
steepness of the terrain, as well as the complex spectral properties that would make it unlikely to
detect snow algae in the patches of snow within the debris covered area. This also focused our
algorithms specifically on snow covered with snow algae.

Figure 1. (A) The Bagley Lakes basin study area as viewed from above hiking down into the
basin. (B) A patch of snow algae that was sampled for this analysis.

2.2.2. UAV surveys

Over the summer of 2021, three survey flights were completed of the Bagley Lakes basin. The
first two surveys were flown to collect data during the snow algae bloom, one on 2 July 2021 and
a second survey on 30 July 2021. The third survey was flown on 24 September 2021 to acquire
snow free ground elevation data. The UAV surveys were conducted with a DJI Matrice 210
equipped with a MicaSense Dual camera system comprised of both the RedEdge MX and the
RedEdge MX Blue sensors. Combined, the two sensors acquire data in the coastal blue (430 -
The cameras captured RAW (12-bit) images every 1 s. Prior to UAV take off, the MicaSense cameras captured an image of the MicaSense camera calibration panel to later convert the imagery to reflectance. The DJI Matrice 210 was flown following a flight plan designed and executed in the DJI Pilot application. Flight altitude was set at 90 m above ground level and the flight lines were set for a 75% sidelap and frontlap, generating a ground resolution of 7 cm/pixel. The survey area flight took approximately 20 minutes to complete with the Matrice and required 2-3 batteries.

On the same survey days, the basin was also flown with a DJI Phantom 3 Standard quadcopter equipped with a MAPIR Survey3 three-band multispectral camera. The MAPIR camera captures imagery in the red (660 nm), green (550 nm), and near-infrared (850 nm) wavelengths (www.mapir.camera). The camera captured RAW (12 bit) and JPG (24 bit) images every 2 s with an ISO set at 100 and a 1/2000 shutter speed. The DJI Phantom 3 UAV was flown following a flight plan designed and executed in Pix4D. Flight altitude was set at 90 m above ground level and the flight lines were set for a 75% sidelap and frontlap, generating a ground resolution of 4 cm/pixel. The survey took 14 minutes on average to complete and required one battery. Immediately prior to UAV launch, an image of the MAPIR camera calibration panel was taken to later convert the imagery to reflectance values.

Prior to take off for each survey flight, a base station was established with an EMLID Reach RS2 RTK GNSS receiver in RTK mode that logged its location for the entirety of the field survey and communicated GPS corrections to the rover GPS. The base was stationed where it would have a clear view of the sky and within range of the rover to transmit corrections. Targets
to be used as Ground Control Points (GCPs) and Ground Validation Points (GVPs) were spread out over the entire survey area and the GPS coordinates were collected with the rover EMLID Reach RS2 RTK GNSS receiver in RTK mode.

2.2.3. Sample collection

Immediately following each UAV survey, snow algae blooms were located and the GPS coordinates were acquired with the rover GPS receiver. The samples were collected from a 10 cm by 10 cm square to a depth of 2 cm using a metal spatula and stored in WhirlPak bags. The samples were immediately placed in a black trash bag to prevent continued photosynthesis. The coordinates of the center of the sample locations were acquired and the samples were melted in the dark at ambient temperature over 24 hours. The next day, the melted samples were processed for pigment composition, cell concentration, and Ash-Free Dry Mass (AFDM).

The pigment and ash-free dry mass samples were vacuum filtered through pre-ashed and -weighed 0.47 µm glass fiber filters. The filters were folded in half, wrapped in tin foil, and stored at -20°C until they were ready to be processed for further analysis.

2.2.4. Pigment analysis

The frozen filters were processed for analysis on the HPLC-QTOF following a modified method based on Remias and Lutz (2007). The filters were shock frozen in liquid nitrogen for 10 minutes before being ground in a mortar and pestle until disintegrated. The ground filter was then resuspended in 1 mL dimethylformamide (DMF) and shaken on a vortex mixer for 10 minutes with 1.0 mm glass beads. The samples were centrifuged for 10 minutes at 4,700 rpm and the resulting supernatant was extracted and filtered through a 0.2 µm Nylon filter. The internal standard, trans-beta-Apo-8'-carotenal, was added to the sample to a constant concentration. The
samples were stored frozen and run on the HPLC-QTOF within 24 hours of processing. Samples were analyzed for the following pigments: astaxanthin, lutein, chlorophyll \( a \), and chlorophyll \( b \).

2.2.5. Cell concentration

Melted snow algae samples were homogenized and a 12 mL aliquot of whole sample was collected. The sample was fixed with 50% glutaraldehyde to 2% final concentration and stored at -20\(^{\circ}\)C. The samples were run on a Guava easyCyte flow cytometer equipped with a blue laser. Bead checks were conducted at the beginning of each sample run to ensure consistency between run dates. Four replicates of 200 \( \mu \)L were analyzed for total of 800 \( \mu \)L per sample and cells with high red fluorescence and high forward scatter were counted as red snow algae as validated by optical microscopy. The sample was run through the Guava for 120 seconds.

2.2.6. Ash Free Dry Mass

The AFDM of the snow algae samples was determined following the method described in Water on the Web (2003). The frozen filters were dried for 1 hour at 104\(^{\circ}\)C and left to cool in a desiccator before being weighed. The filters were then combusted in the muffle furnace for 1 hour at 550\(^{\circ}\)C and left to cool in the desiccator before being weighed again. The AFDM was calculated as the difference between the weight of the filter before and after combustion divided by the sample volume to reveal the AFDM as mg organic material per liter.

2.2.7. Image processing

The flight images were refined to only include in-survey images. Images acquired during take-off, landing, and transit were removed from the analysis. The raw MAPIR survey images were processed and calibrated to reflectance using the MAPIR Camera Control software and the calibration target images that were captured pre-flight. The resulting MAPIR images represent
the calibrated surface reflectance values and were used in the rest of the imagery processing steps.

The MicaSense images were calibrated to surface reflectance based on the calibration panel images within the Agisoft Metashape Professional Software version 1.6.4 following MicaSense processing procedures (Agisoft LLC, 2021). For both the MicaSense and the MAPIR images, the altitude of the images was adjusted with an open-source Python script to represent meters above sea level based on the launch elevation and the flight altitude (Agisoft LLC, 2017). The Image Quality, or sharpness, was estimated and blurry images, defined as those with a quality below 0.5, were removed from the rest of the analysis to improve photogrammetric processing following the guidelines in the Agisoft Metashape Professional Edition User Manual (Agisoft LLC, 2021). Each set of images was aligned separately with high accuracy, 500,000 key point limit, and 0 tie point limit. All points with a reprojection error greater than 0.5 pixels and any obvious outlier points were removed from the sparse point cloud.

The GCPs and GVPs were manually marked in at least 6 images where the target was most visible. The target coordinates were loaded, and the sparse point cloud was updated. The camera positions were optimized before constructing the dense point cloud with high quality and aggressive depth filtering. The DEM was constructed based on the dense point cloud and the orthomosaic was constructed based on the DEM.

With the resulting 10-band orthomosaics, we applied two approaches for the detection of snow algae: (1) the principal component thresholding approach and (2) the optimized red/green band indexing approach. The area of snow algae covered snow is compared with both approaches and validated using the in situ snow algae samples along with 100 random points classified into Snow and Other classes.
2.2.8. Principal Components Analysis

The first approach reduced the 10-band MicaSense orthomosaic to three principal component bands using the Forward PCA Rotation New Statistics & Rotate tool in the ENVI software version 5.6. The efficacy of the ordination was tested with 100 randomly located points that were visually classified as Snow or Other (i.e., rock, water, vegetation) in addition to the in situ snow algae locations that were collected in the field. These points were plotted with respect to the first three principal component bands to assess which combination of bands best distinguishes the snow algae from clean snow. Threshold limits were developed based on these points and applied to the entire orthomosaic.

2.2.9. Red/green band index development

In the second approach, snow algae detection indices were developed based off the MicaSense bands for both the 2 July and the 30 July 2021 surveys. The 100 training points for each day were used to assess the efficacy of the indices and determine which MicaSense band pairs separated the snow algae from the snow the best for both survey dates. The developed indices were chosen based on literature proposed indices and based on the bands that most closely aligned to those of satellite platforms.

2.2.10. MAPIR image processing

The survey area was also flown on the same days with a DJI Phantom 3 Standard quadcopter equipped with a MAPIR Survey3 three-band multispectral camera. The MAPIR camera captures imagery in the red (660 nm), green (550 nm), and near-infrared (850 nm) wavelengths (www.mapir.camera). This camera captured RAW (12 bit) and JPG (24 bit) images every 2 s with an ISO set at 100 and a 1/2000 shutter speed. Prior to take off for each survey flight, an
image of the MAPIR camera calibration panel was taken to later convert the MAPIR imagery to reflectance values using the MAPIR. Camera Control software. These reflectance images were processed following the same methods laid out for the MicaSense imagery.

2.2.11. Albedo and radiative forcing

The albedo of the snow algae covered snow and clean snow was simulated using the SNICAR model. The snow algae cell and pigment concentration data collected in the field was used as input parameters for the model. Our pigment dry mass fractions, calculated following Flanner et al. (2021), fell below the allowable range set by the SNICAR model. To fit SNICAR model parameters, pigment dry mass fractions were scaled by a factor of 0.05 to reach the low end of the allowable range. Average cell diameter was set at 15 µm based on optical microscope analyses conducted on snow algae samples collected from the same study area the previous year. The solar zenith angle was estimated using the NOAA Solar Zenith Calculator based on the sample date, time, and location (gml.noaa.gov/grad/solcalc/azel.html). Snowpack thickness was derived by differencing the UAV generated Digital Elevation Models (DEMs) from the snow algae UAV surveys with the snow free UAV survey and snowpack density was set to 600 kg/m$^3$ based on the literature values for the North Cascades region (Pelto & Riedel, 2001). The snow grain shape was set to spheroids and the rest of the parameters, including the dust parameters, were set as the default or zero. As the output of this model, the broadband snow albedo is calculated as well as the albedo and fraction of incident irradiance within each spectral band at 10 nm spaced intervals. Clean snow albedo was modelled using the same parameters described above, but without any of the snow algae inputs.
The instantaneous radiative forcing (IRF) of the snow algae was calculated as:

\[
IRF \approx \sum_{350}^{850} E_d(\lambda) \left( R_{\text{clean}}(\lambda) - R_{\text{algae}}(\lambda) \right) \Delta \lambda
\]

where IRF is calculated as the sum of the wavelength-specific downward flux, \( E_d \), multiplied by the wavelength interval and the difference between clean snow reflectance, \( R_{\text{clean}} \), and snow algae covered snow reflectance, \( R_{\text{algae}} \), over the wavelengths 350 to 850 nm. The downward flux was retrieved from https://www.pvlighthouse.com.au (last access: 2 February 2022; Ganey et al., 2017; Khan et al., 2021).

### 2.3. RESULTS

#### 2.3.1. Positional accuracy

The orthomosaic image accuracy is derived from the GCP and ground validation points (GVPs) for each survey date. On the 2 July survey there were 12 total targets, 9 that were used as control points and 3 as validation points. This resulted in a total GVP accuracy of 37.07 cm (Table 1). The 30 July survey only used 10 targets instead of 12 that were divided into 7 GCPs and 3 GVPs. Even though there were only 7 GCPs to guide the SfM image processing, the total error of the GVPs was less than that of the 2 July survey at 20.69 cm (Table 1). Across the two survey dates and the GCPs and GVPs of each, the Z error was the largest in comparison to the error of X and Y. The orthomosaics produced in the SfM process generated pixel sizes of 7 cm. Since the XY error is less than the pixel size, 1.64 cm for 2 July and 1.36 cm for 30 July, the lateral error is encompassed within the pixel.
Table 1. Control point errors where X represents Longitude, Y represents Latitude, and Z represents Altitude. Ground control points (GCPs) were used in the aligning of the orthomosaic while the ground validation points (GVPs) were omitted and used to assess the reconstruction accuracy.

<table>
<thead>
<tr>
<th>Survey date</th>
<th>Type</th>
<th>Count</th>
<th>X error (cm)</th>
<th>Y error (cm)</th>
<th>Z error (cm)</th>
<th>XY error (cm)</th>
<th>Total (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 July 2021</td>
<td>GCP</td>
<td>9</td>
<td>0.48</td>
<td>0.24</td>
<td>0.62</td>
<td>0.54</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>GVP</td>
<td>3</td>
<td>1.15</td>
<td>1.16</td>
<td>37.03</td>
<td>1.64</td>
<td>37.07</td>
</tr>
<tr>
<td>30 July 2021</td>
<td>GCP</td>
<td>7</td>
<td>0.62</td>
<td>0.72</td>
<td>0.93</td>
<td>0.95</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td>GVP</td>
<td>3</td>
<td>1.13</td>
<td>0.75</td>
<td>20.64</td>
<td>1.36</td>
<td>20.69</td>
</tr>
</tbody>
</table>

2.3.2. Principal component thresholding development

The ordination process reduced the variation in the 10-band imagery to explain 99.67% of the variation with the first principal component (PC), 0.30% with the second PC, and 0.01% with the third for the 2 July survey (Supplementary Table 1). For the 30 July survey, the ordination reduced the 10-bands with the first PC explaining 99.78% of the variation, the second PC explaining 0.19%, and the third PC explaining 0.01% (Supplementary Table 1).

The first principal component of the 2 July survey contains all the information of the 10 bands weighted equally and positively correlated to create the first eigenvector (Table 2). This is simply an index to the overall brightness of the image across all bands. The second component has negative correlations with the red edge and near-infrared bands and positive correlations with the rest of the bands (Table 2). This eigenvector contrasts the brightness in the visible bands with the red edge and near infrared wavelengths. These first two eigenvectors provided clear separation between the snow algae and the snow classes (Figure 2).
The ordination of the 30 July survey created a first eigenvector that is composed of all 10 bands equally weighted and negatively correlated (Table 2). This first PC contains all the information of the 10 bands weighted equally but negatively. The second component has a strong positive correlation with the near-infrared band and the red edge bands that is balanced by negative correlations with the visible bands. This eigenvector contrasts the visible wavelengths with the infrared wavelengths while weighting the near-infrared and the blue bands the strongest and in opposite directions. Note that the sign of the loadings for the first and second PCs for July 2 and July 30 are reversed but the loading pattern is the same. The third PC positively weights the blue band, green-2 band, and red edge-3 band, while negatively weighting the red-1, red-2, and red edge-1 bands (Table 2).

**Table 2.** Loadings of each MicaSense band for principal components 1, 2, and 3 from the 2 July 2021 and 30 July 2021 surveys.

<table>
<thead>
<tr>
<th></th>
<th>Coastal Blue</th>
<th>Blue</th>
<th>Green-1</th>
<th>Green-2</th>
<th>Red-1</th>
<th>Red-2</th>
<th>Red Edge-1</th>
<th>Red Edge-2</th>
<th>Red Edge-3</th>
<th>Near-Infrared</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>2 July 2021</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 1</td>
<td>0.318</td>
<td>0.313</td>
<td>0.311</td>
<td>0.310</td>
<td>0.316</td>
<td>0.317</td>
<td>0.317</td>
<td>0.318</td>
<td>0.318</td>
<td>0.326</td>
</tr>
<tr>
<td>PC 2</td>
<td>0.229</td>
<td>0.339</td>
<td>0.294</td>
<td>0.266</td>
<td>0.127</td>
<td>0.080</td>
<td>-0.065</td>
<td>-0.206</td>
<td>-0.307</td>
<td>-0.716</td>
</tr>
<tr>
<td>PC 3</td>
<td>0.436</td>
<td>0.401</td>
<td>0.080</td>
<td>0.092</td>
<td>-0.412</td>
<td>-0.419</td>
<td>-0.356</td>
<td>-0.139</td>
<td>-0.061</td>
<td>0.374</td>
</tr>
<tr>
<td><strong>30 July 2021</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC 1</td>
<td>-0.322</td>
<td>-0.320</td>
<td>-0.319</td>
<td>-0.317</td>
<td>-0.319</td>
<td>-0.320</td>
<td>-0.316</td>
<td>-0.313</td>
<td>-0.310</td>
<td>-0.305</td>
</tr>
<tr>
<td>PC 2</td>
<td>-0.224</td>
<td>-0.360</td>
<td>-0.213</td>
<td>-0.267</td>
<td>-0.142</td>
<td>-0.089</td>
<td>0.046</td>
<td>0.225</td>
<td>0.382</td>
<td>0.691</td>
</tr>
<tr>
<td>PC 3</td>
<td>-0.095</td>
<td>0.399</td>
<td>0.070</td>
<td>0.447</td>
<td>-0.320</td>
<td>-0.525</td>
<td>-0.285</td>
<td>-0.148</td>
<td>0.368</td>
<td>0.101</td>
</tr>
</tbody>
</table>

For the 2 July 2020 flight the first two PCs provide the best distinction between the snow algae and the clean snow (Figure 2). Based on the values for each PC, we developed an index to classify snow algae as pixels that have a PC 1 value greater than -90,000 and a PC 2 value less than -2,500 (Figure 2). This index indicated that 1.09% of the snow was covered in snow algae (Table 3).
For the 30 July 2020 survey, the first and the third PC were best able to separate the snow algae from the clean snow where pixels that had a value less than 50,000 for the first PC and a value less than -500 for the third PC were classified as snow algae (Figure 2). This classification seemed less distinct than that of the 2 July 2020 flight with less separation between the snow algae and the snow classification points (Figure 2). This index estimated that 2.47% of the remaining snow was covered in snow algae (Table 3).

Figure 2. Classification points for the (A) 2 July 2021 and (B) 30 July 2021 surveys with their associated principal component values. Dashed lines represent the threshold values used for snow algae classification, for 2 July these values were PC1 = -90,000 and PC2 = -2,500 and for 30 July 2021 these values were PC1 = 50,000 and PC3 = -500.

Table 3. Area of snow algae in the study area based on the principal component thresholding for the MicaSense orthomosaics on 2 July and 30 July 2021.

<table>
<thead>
<tr>
<th>Survey date</th>
<th>Area snow covered (m²)</th>
<th>Area algae covered (m²)</th>
<th>Snow with algae bloom (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 July 2021</td>
<td>116,226.95</td>
<td>1,174.25</td>
<td>1.01%</td>
</tr>
<tr>
<td>30 July 2021</td>
<td>40,593.57</td>
<td>834.91</td>
<td>2.06%</td>
</tr>
</tbody>
</table>
2.3.3. Optimized red/green band index development

On the 2 July 2021 survey there is a distinct separation between snow algae and clean snow with multiple band combinations providing sufficient separation for snow algae classification (Supplementary Figure 3). While there could potentially be more than one applicable band combination, we proceeded with the red (642-658 nm) to green (534-538 nm) ratio since that one cleanly distinguished the snow algae classification points from the others (Figure 3) and falls within the established red (610-680 nm) to green (500-590 nm) band ratio developed by Takeuchi et al. (2006) for snow algae mapping with the SPOT satellite.

Using the classified training points, a snow mask was developed and applied to the image so that only the snow-covered portions of the study area were analyzed. Snow-covered area was defined as pixels that meet the following requirements:

\[
\frac{R_{\lambda_{BS}} - 0.015}{1.02 \times R_{\lambda_{B3}}} < 1
\]

\[
AND
\]

\[
R_{\lambda_{BS}} > 0.3
\]

Similarly, an optimized red/green band index was developed based on the training points. The original red/green band index classifies snow algae as any pixel with a red/green ratio greater than 1.02 (Takeuchi et al. 2006). However, applying the original red/green band index to our training points captured the snow classified training points as well as the snow algae training points. We decided to develop an optimized red/green band index to find tune the classification where snow algae pixels were identified based on their reflectance in the red (\(R_{\lambda_{BS}}\)) and the green band (\(R_{\lambda_{B3}}\)) as follows:
\[ \frac{R_{AB5} - 0.015}{1.02 \times R_{AB3}} > 1 \]

\text{AND}

\[ R_{AB5} > 0.3 \]

On the 30 July survey with the MicaSense Dual camera system, the optimized red/green band index (Equation 2) that worked quite well on the 2 July survey seemed to be less effective in separating the snow algae from the rest of the snow in the 30 July survey (Figure 3).

\textbf{Figure 3.} MicaSense reflectance in Band 5 versus Band 3 for the classification training points on (A) 2 July 2021 and (B) 30 July 2021. The dashed line represents the equation: Band 5 = 1.02(Band 3) + 0.015.
Using the above optimized red/green band index (Equation 3) with the snow mask (Equation 2), the snow-covered area and the snow algae covered area was extracted from the survey orthomosaics. This process revealed that on 2 July 2021, 1.16% of the snow in the study area was covered in snow algae for a total of 1,352.18 m$^2$ (Table 4). For the 30 July survey, there is a visible reduction in snow coverage (Figure 4) from 116,226.95 m$^2$ of snow on July 2 to 40,593.57 m$^2$ on July 30 (Table 4). However, snow algae covered a slightly higher percent of the snow, 1.37%, on the 30 July survey for a total of 556.07 m$^2$ of snow algae (Table 4).

Figure 4. MicaSense true color orthomosaics on (A) 2 July 2021 and (B) 30 July 2021, where areas in pink represent snow algae detected using the Equation (3) optimized red/green band index.
Table 4. Area of snow algae in the study area based on the optimized red/green band index for the MicaSense orthomosaics on 2 July and 30 July 2021.

<table>
<thead>
<tr>
<th>Survey date</th>
<th>Snow covered area (m²)</th>
<th>Snow algae covered area (m²)</th>
<th>Percent of snow with algae bloom</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 July 2021</td>
<td>116,226.95</td>
<td>1,352.18</td>
<td>1.16%</td>
</tr>
<tr>
<td>30 July 2021</td>
<td>40,593.57</td>
<td>556.07</td>
<td>1.37%</td>
</tr>
</tbody>
</table>

2.3.4. Cell counts and pigment concentrations

There were large shifts in the snow algae cell and pigment compositions between the two study dates, with much higher cell counts and pigment concentrations associated with the earlier study date (Table 5). By the second survey date, the cells have a much higher astaxanthin to chlorophyll a ratio than they do on the first survey (Figure 5). This shift is also associated with a decrease in the ratio of lutein to chlorophyll a while the ratios of chlorophyll b and beta carotene to chlorophyll a remain similar between the two surveys (Figure 5).

Table 5. Snow algae cell and pigment concentration data for the samples collected on July 2 and 30 July 2021.

<table>
<thead>
<tr>
<th></th>
<th>2 July 2021</th>
<th>30 July 2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell concentration</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>(cells/mL)</td>
<td>47,252 to 1,393,863</td>
<td>431,339 ± 397,869</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>55,124 ± 59,708</td>
</tr>
<tr>
<td>Astaxanthin</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>concentration (µg/L)</td>
<td>0 to 55.76</td>
<td>19.27 ± 20.61</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>4.39 ± 9.27</td>
</tr>
<tr>
<td>Lutein concentration</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>(µg/L)</td>
<td>0 to 114.21</td>
<td>51.23 ± 38.16</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>1.73 ± 3.23</td>
</tr>
<tr>
<td>Beta carotene</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>concentration (µg/L)</td>
<td>0 to 125.37</td>
<td>38.52 ± 42.93</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>3.36 ± 3.07</td>
</tr>
<tr>
<td>Chlorophyll a</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>concentration (µg/L)</td>
<td>1.72 to 195.75</td>
<td>67.55 ± 72.77</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>3.66 ± 6.02</td>
</tr>
<tr>
<td>Chlorophyll b</td>
<td>Range</td>
<td>Average ± SD</td>
</tr>
<tr>
<td>concentration (µg/L)</td>
<td>0 to 86.10</td>
<td>31.39 ± 33.02</td>
</tr>
<tr>
<td></td>
<td>Average ± SD</td>
<td>1.80 ± 2.21</td>
</tr>
</tbody>
</table>
2.3.5. Optimized red/green band index correlations

When regressing the optimized red/green band index with the snow algae cell concentrations there is a nonsignificant relationship between the index value and the natural log of the snow algae cell concentration, with the index value only explaining 16% of the variation in the cell concentration ($F_{1,17} = 3.232, p = 0.09, r^2 = 0.16$) (Figure 6). Separating out the two survey dates, the 2 July index explains more variation in the natural log of the cell concentration in comparison to examining both surveys together (30% and 16%, respectively), but the relationship is still nonsignificant ($F_{1,7} = 3.038, p = 0.13, r^2 = 0.30$) (Figure 6). The relationships are much stronger with the 30 July survey index. Examining only the 30 July data, there is a significant relationship
between the optimized red/green band index and the natural log of the snow algae cell concentration where the index explains 86% of the variation in the cell concentration ($F_{1,8} = 50.23, p < 0.001, r^2 = 0.86$) (Figure 6).

![Graph showing correlation between optimized red/green band index and natural log of cell concentration.]

**Figure 6.** Correlation between the optimized red/green band index with the natural log of the cell concentration by date. The black dashed line represents the linear regression of all the points where $\ln(y) = 4.488x + 6.188$ ($F_{1,17} = 3.232, p = 0.09, r^2 = 0.16$), the red solid line represents the linear regression of just the 2 July 2021 points where $\ln(y) = 8.185x + 3.038$ ($F_{1,7} = 3.038, p = 0.13, r^2 = 0.30$), and the blue solid line represents the linear regression of just the 30 July 2021 points where $\ln(y) = 5.0575x + 4.4519$ ($F_{1,8} = 50.23, p < 0.001, r^2 = 0.86$).

There is also a significant positive correlation between the optimized red/green band index and the ratio of astaxanthin to chlorophyll $a$, however the index only explains 24% of the
variation in the ratio of astaxanthin to chlorophyll $a$ ($F_{1,17}=5.30$, $p=0.034$, $r^2 = 0.24$) (Supplemental Figure 4). This relationship is not improved by analyzing the two survey dates separately.

2.3.6. Reflectance observations

The 10-band spectral resolution of the MicaSense imagery provides insight into the albedo shifts of the snowpack from 2 July to 30 July 2021. The Snow Algae classification points tend to absorb more strongly in the 400 to 600 nm range and reflect more in the 600 to 900 nm range (Figure 7). In comparison, the Snow class reflects more in the lower wavelengths and absorbs more in the higher wavelengths (Figure 7). To capture the snow algae spectral signature, the mean reflectance of the 444 to 560 nm MicaSense bands was calculated and compared to the mean reflectance in the 650 to 842 nm bands. In both survey dates, the mean reflectance of the Snow Algae class increases from the lower wavelengths to the higher and the Snow class decreases (Table 6). There is more separation between the Snow and the Snow Algae classes in the mean reflectance of the 650 to 842 nm bands in the 2 July survey than compared to the 30 July survey where they are both 0.62 (Table 6).
Figure 7. MicaSense reflectance values of the classification training points over their corresponding band wavelengths for (A) 2 July 2021 and (B) 30 July 2021. Lines represent the local polynomial regression with shaded areas representing the standard error.

Table 6. MicaSense reflectance statistics by class for the training points on the 2 July 2021 and 30 July 2021 surveys.

<table>
<thead>
<tr>
<th>Date</th>
<th>Class</th>
<th>Mean Reflectance (444 to 560 nm)</th>
<th>Mean Reflectance (650 to 842 nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 July 2021</td>
<td>Snow</td>
<td>0.91 ± 0.11</td>
<td>0.83 ± 0.10</td>
</tr>
<tr>
<td></td>
<td>Snow Algae</td>
<td>0.56 ± 0.10</td>
<td>0.69 ± 0.10</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.08 ± 0.05</td>
<td>0.11 ± 0.05</td>
</tr>
<tr>
<td>30 July 2021</td>
<td>Snow</td>
<td>0.69 ± 0.09</td>
<td>0.62 ± 0.08</td>
</tr>
<tr>
<td></td>
<td>Snow Algae</td>
<td>0.55 ± 0.12</td>
<td>0.62 ± 0.07</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.05 ± 0.04</td>
<td>0.08 ± 0.07</td>
</tr>
</tbody>
</table>
2.3.7. Albedo modeling

The SNICAR modeled albedo varies greatly with cell concentration in the visible part of the spectrum but converges after 750 nm (Figure 8). As to be expected, increasing the snow algae cell concentration is associated with a decrease in albedo within the visible portion of the spectrum, 200 to 750 nm. There is a much greater variation in the albedo and cell concentration within the first survey on 2 July, whereas on the 30 July survey the range of albedo and the cell concentration is much lower. Associated with the decrease in cell concentration between the survey dates, the average albedo increased within the 205 to 750 nm range of the spectrum shifting from $0.56 \pm 0.17$ on 2 July to $0.82 \pm 0.09$ on 30 July.

Figure 8. Spectral profile of the snow algae samples as simulated by the SNICAR model. Solid lines represent the samples from the 2 July 2021 survey and dashed lines represent the 30 July 2021 survey. The darker red the line, the higher concentration of snow algae cells were in the sample.
In comparison to the snow algae reflectance profile generated from the MicaSense data, the snow algae modelled albedo resembles the shape of the MicaSense measured spectra on both the survey dates (Figure 9). On the 2 July survey, the shape of the snow algae curve is much more exaggerated in the SNICAR output than in the MicaSense data. The snow algae SNICAR curve shape on the 30 July 2021 survey very closely matches that of the MicaSense, but with about a 0.25 vertical shift in reflectance (Figure 9).

**Figure 9.** SNICAR modeled albedo for the snow algae samples compared to the MicaSense measured reflectance values for the Snow Algae, Snow, and Other classes on (A) 2 July 2021 and (B) 30 July 2021. Lines represent the local polynomial regression with shaded areas representing the standard error.
2.3.8. Radiative forcing

Modelling the radiative forcing of the snow algae revealed an average IRF of 236.56 W m$^{-2}$ on 2 July and 88.86 W m$^{-2}$ on 30 July 2021 (Table 7). Taking the MicaSense index estimated snow algae covered area for each survey date and the IRF of the snow algae, we calculated an average daily RF by snow algae of 18,290 MJ on 2 July and 2,671 MJ on 30 July. If 334,000 J melts 1 kg of snow (Cohen, 1994), then we can calculate that the snow algae caused 91.27 m$^3$ of snowmelt on 2 July and 13.33 m$^3$ of snowmelt on 30 July.

In comparison to previous studies of snow algae radiative forcing, the calculated IRF values of the first survey in this study were greater than twice those calculated in previous studies of red snow algae (Table 7). The average IRF calculated in this study is comparable to the IRF of dust in the European Alps and the San Juan Mountains, U.S. (Di Mauro et al., 2015; Painter et al., 2013).

**Table 7.** Instantaneous radiative forcing of snow algae, dust, and other light absorbing impurities across the cryosphere from this study and previous studies.

<table>
<thead>
<tr>
<th>Study</th>
<th>Location</th>
<th>Impurity type</th>
<th>Date</th>
<th>Average IRF (W m$^{-2}$)</th>
<th>Maximum IRF (W m$^{-2}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healy et al. 2022</td>
<td>Washington, U.S.</td>
<td>Red snow algae</td>
<td>2 July 2021</td>
<td>236.56</td>
<td>359.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>30 July 2021</td>
<td>88.86</td>
<td>156.9</td>
</tr>
<tr>
<td>Khan et al. 2021</td>
<td>West Antarctic Peninsula, AN</td>
<td>Red snow algae</td>
<td>January 2018</td>
<td>88.0</td>
<td>185.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Green snow algae</td>
<td>January 2018</td>
<td>179.7</td>
<td>227.53</td>
</tr>
<tr>
<td>Di Mauro et al. 2015</td>
<td>European Alps</td>
<td>Dust</td>
<td>14 March 2014</td>
<td>128.6</td>
<td>153</td>
</tr>
<tr>
<td>Painter et al. 2013</td>
<td>Colorado, U.S.</td>
<td>Light absorbing impurities</td>
<td>15 June 2011</td>
<td>215</td>
<td>400</td>
</tr>
</tbody>
</table>
2.3.9. MAPIR comparison

The survey area was also flown with a MAPIR Survey 3N camera mounted on a DJI Phantom 3S UAV on the same survey dates that the MicaSense camera was flown. Applying the same classification training points used to develop the PCA and MicaSense indices to the MAPIR data we see that there is far less distinction between the snow algae and the snow classes on both survey dates, with the snow algae class not consistently clustering together in the same location (Figure 10). There is also quite a bit of overlap between the Snow Algae classes and the other two classes without distinguishing thresholds (Figure 10). The Snow Algae class seems to cluster more in the 30 July survey than in the 2 July survey where the points are spread above and below the Snow points (Figure 10).

![Figure 10. MAPIR reflectance values for the classification training points on 2 July 2021 in the upper right panels and 30 July 2021 in the lower left panels. Blue points represent the Snow class, pink represent the Snow Algae class, and grey represent the Other class (ie. rock, vegetation, water). B1 is the red band, B2 is the green, and B3 is the near-infrared.](image-url)
2.4. DISCUSSION

The two approaches presented in this study show great potential to remotely detect snow algae with a UAV. Both the principal component thresholding and the optimized red/green band indexing approaches provide clear separation between snow algae and the rest of the snowpack for the first survey date. By the second survey date, both approaches had less distinct separation between the classes that complicated the classification. Additionally, the variation in snow algae cell and pigment concentration enabled a comparison of the approaches for differing bloom intensities.

2.4.1. Principal component thresholding

PCA offers a valuable way to extract spectrally unique features from multispectral imagery, yet it has not been tested previously in snow algae remote sensing applications. This approach is most useful when there is associated classification training data. Without the training data it would be difficult to apply this approach at large scales unless the snow algae bloom is so distinct from the rest of the snowpack that it can be visually confirmed in the imagery. In this study, we had 9 samples of snow algae for the first survey and 10 for the second, both with associated GPS data. This dataset enabled us to develop the principal component thresholds used to map the snow algae.

The PCA method provided plenty of separation between the Snow Algae and the Snow and Other classes on the 2 July survey. During this survey, the majority of the study area was snow covered at an average depth of about 2 m. Where the snow algae were not blooming, the snow was considerably clean with very few visible impurities. In comparison, on the 30 July survey, the snowpack thickness was reduced with an average depth of less than 1 m. The snow that remained was much dirtier as the melting snow brought the impurities in the snowpack to
the surface. This dirtying of the snowpack likely contributed to the less distinct separation between the Snow Algae and the Snow classes in the PCA ordination process for the 30 July survey.

    The relatively less effective classification developed based on the ordination of the 30 July flight could also be due to the reduced snowpack coverage of the basin and increased vegetation coverage. The ordination process encompasses as much of the variation in the 10-band orthomosaic into as few principal components as possible. The orthomosaic of the 2 July survey was composed almost completely of snow and rocks, with some areas of water and minimal patches of vegetation. Whereas the 30 July orthomosaic consisted primarily of vegetation, rock, and water with less than half the image being snow-covered. For the 30 July survey the ordination process was driven by the variation in the vegetated portion of the survey area instead of the variation in the snow-covered portion of the image. Future studies that apply the PCA approach should attempt to mask the portions of the image that are not relevant to the analysis prior to ordinating the data.

2.4.2. Optimized red/green band index

While the MicaSense Dual camera system may be prohibitively expensive for widespread use, $9,600 for the camera system in addition to the cost of the UAV, it provides researchers with the ability to directly upscale the UAV derived and ground validated indices to satellite platforms. The wavelengths of the camera system align closely with those of the Sentinel 2A and Landsat 8 satellites. The similarity in spectral bands and the ability to closely couple ground validation samples with survey flights could greatly advance the capabilities of satellite remote sensing for detecting spectrally subtle features like snow algae.

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The MicaSense camera systems have been employed by previous studies that used the spectral capabilities to map a variety of research focuses, including mapping submerged vegetation (e.g. Taddia et al., 2020), wetland functions (Doughty & Cavanaugh, 2019), arctic vegetation (Thomson et al., 2021), and ice algae (Cook et al., 2020; Tedstone et al., 2020). However, to the author’s knowledge, this is the first dedicated application of the UAV and the MicaSense Dual camera system to map snow algae.

The 10-bands of the MicaSense imagery all gather useful information but parsing out which band combinations are superior depends on a robust ground validation data set. For this study, we sought to explore the band combinations that were already established in the literature to assess their efficacy from a UAV platform with coincident ground truth data. Our study found the most success by using an optimized red/green index, originally developed by Takeuchi et al. (2006). Based on our ground data, we added in a red band reflectance threshold and fine-tuned the index by incorporating multipliers into the ratio. Previous studies that have used the original red/green ratio have classified snow algae pixels as those that have a ratio greater than one (Hisakawa et al., 2015). Our results suggest that this approach would falsely classify snow pixels as snow algae, particularly in late melt season snow.

Similar to the PCA approach, the dirty, late season snowpack has close spectral similarities to the snow algae that make the snow algae difficult to distinguish in the later survey on 30 July. However on the 2 July survey, the index provided a clear distinction in the Snow and Snow Algae training points, likely because of the comparatively clean, early melt season snow that is spectrally distinct from any dark snow algae patches. The developed index did not clearly separate debris covered snow from snow algae. This could provide a challenge for future studies that seek to classify snow algae in heavily debris covered areas. However, the applications of
imagers with more bands, such as hyperspectral imagers, may have the ability to further discern snow algae in debris covered snow.

Both the principal component thresholding and the optimized red/green index approaches indicated that there was a slightly higher percent of snow algae covering the snow in the 30 July survey compared to the 2 July survey. The percentage of snow algae coverage was quite similar for the principal component thresholding and the optimized red/green index approach for the 2 July survey, 1.01% and 1.16% respectively. However, they slightly differed in their results on the 30 July survey where the principal component thresholding approach determined that 2.06% of the snow surface contained snow algae compared to 1.37% determined by the optimized red/green index approach.

The difference between the results of the two approaches supports the dependency of index development on the snow algae bloom conditions, where early season peak intensity blooms are easier to detect consistently than late season post-peak blooms. Future studies should acknowledge the influence that the algal bloom state and the age of the snowpack have on these remote sensing indices when attempting to map snow algae without ground data.

2.4.3. Snow algae properties

We developed a regression model to predict algal concentration from the UAV imagery with the goal of estimating the algal abundance over the entire survey area. However, this study showed that the ability of the optimized red/green index to predict snow algal concentration varies greatly depending on the time of the year. During the early summer season, the algal blooms have much greater range in cell and pigment concentrations that does not correlate well with the proposed index. Yet, later in the summer season, the algal blooms seem to stabilize with lower variation in the cell and pigment concentrations allowing for the proposed index to have greater
predictive power. When both surveys are combined, the optimized red/green index only explains 16% of the variation in the natural log of cell concentration – not enough to confidently apply the index at large scales without associated ground data.

Previous studies that have applied the original red/green index to satellite imagery and predicted snow algal abundance using snow algae samples that did not coincide closely in time with the satellite image (Takeuchi et al., 2006). However, the results of this study demonstrate that imagery and sampling must be closely coupled since over the three weeks between our two surveys, the predictive ability of the index shifts greatly. While the optimized red/green index can be used to capture the presence/absence of snow algae, the variation in cell and pigment concentration reveals the need for development of multiple indices in order to predict snow algae bloom intensity.

The increase in the ratio of astaxanthin to chlorophyll $a$, the decrease in the ratio of lutein to chlorophyll $a$, and the associated decrease in snow algae cell concentration suggest that the bloom is reducing its photosynthetic pigment production and increasing its photoprotective pigment production in the later survey. This indicates that the algae bloom during the early season survey of 2 July was considerably more intense than during the second survey when the peak bloom has passed.

2.4.4. Albedo implications

There is a distinct vertical shift between the snow algae SNICAR simulated spectral profile and the MicaSense measured profile on the July 30 survey. Since our algae pigment biomass ratios measured below the SNICAR input range, we scaled up our pigment concentration ratios to fit within the allowable value range set by the SNICAR model. This scaling would likely cause there to be a shift between the measured reflectance and the modelled reflectance, but we would
expect the shift to be in the opposite direction. Since we had to scale up our pigment ratios, we would presume the measured reflectance to be higher than the modelled reflectance. This difference indicates room for further refinement of the SNICAR model using in situ snow algae pigment and reflectance data from various regions across the cryosphere to generate an accurate representation of snow algae spectra.

Our RF calculations demonstrate the substantial impact that snow algae have on snowmelt in mid-latitude snow through their snow darkening effects. The snow algae patches can produce an IRF of up to 360 W m\(^{-2}\) during peak bloom, far greater than previous observations of red snow algae at higher latitudes that measured up to 186 W m\(^{-2}\) in Antarctica (Khan et al., 2021) and 88 W m\(^{-2}\) in Alaska (Ganey et al., 2017). We calculated the RF of the snow algae over the coinciding survey day, indicating that over the month of July snow algae contributed between 91 to 13 m\(^3\) of snowmelt each day. Assuming the snow algae RF scales linearly over the 29 days between the surveys, that would translate to a total of 1,508 m\(^3\) of snow algae caused snow melt in the 0.1 km\(^2\) basin, suggesting that these algae-covered regions have a substantial impact on the snowpack by increasing the snow melt.

2.4.5. MAPIR comparison

While this study did not conduct an in-depth comparison of the accuracy of the MAPIR snow algae classification with the MicaSense classification, it is clear that the narrow and specific band wavelengths of the MicaSense camera system allows for a better classification of the snow algae. The MAPIR camera is considerably more affordable than the MicaSense camera and can be mounted on smaller, lighter UAVs. This makes it an attractive option for rigorous field campaigns that need a compact system to collect spectral data in remote locations. While this camera does not provide the necessary spectral resolution to extract the subtle reflectance
differences between the snow algae and the rest of the snow, it can be used to classify more distinct features, like snow and ice (Healy & Khan, 2022).

2.5. CONCLUSION

This study demonstrates the ability of the principal component thresholding and the optimized red/green band indexing approaches to map snow algae with a UAV in a basin in the North Cascades. The goal of this study was to map snow algae extent utilizing the two approaches across two different bloom conditions. We found that the algal bloom state has a large impact on the efficacy of the band indexing and needs to be considered before this approach can be applied at large scales without extensive ground data. Further, we calculated the RF for snow algae and scaled this across the mapped snow algae extent to estimate the cumulative impact on RF. The RF implications of snow algae have been documented previously in Antarctica (Khan et al., 2021) and Alaska (Ganey et al., 2017), yet this is the first study to evaluate snow algae RF in the mid-latitude range of the North Cascades. Our results demonstrate the potential to map snow algae and assess the RF over expansive areas of the cryosphere using UAV technology.

The influence of snow algae on albedo in the cryosphere is not currently included in global climate models. Considering the substantial RF of snow algae demonstrated in this study, there is great need for the inclusion of snow algae into the global climate models. Not much is known about the extent of snow algae habitat, however, snow algae blooms are expected to expand in their range with warming temperatures (Benning et al., 2014). Being able to reliably map snow algae will greatly enhance our understanding of the RF implications caused by snow algae across the cryosphere.
THESIS CONCLUSION

This thesis demonstrates the versatility and customizability of the UAV in two distinct cryosphere applications. With the first chapter we explore the Structure-from-Motion capabilities of the UAV to derive glacier ablation. While the second chapter demonstrates the ability to spectrally distinguish snow algae with the UAV imagery and determine the radiative forcing of the snow algae on snowmelt.

There are many unique UAV systems that can be developed to address specific research applications. In the first chapter, we utilize a low-cost UAV system that is portable and durable for remote field campaigns. This system was effective in mapping glacier ablation and, while the spectral capabilities of the camera system were not great, they still allowed us to spectrally classify the glacial features. In comparison, the second chapter utilized a high-end, 10-band camera system to map snow algae. This system is costly and provides high quality spectral imagery, but the system is rather large and heavy, rendering it less usable in glacial field campaigns. These two differing systems each have their own benefits and drawbacks that must be weighed for each study. Here we utilized the lighter, more portable UAV system for the remote glacier research and then capitalized on an accessible snowfield so that we could use the heavier, more cumbersome UAV system.

The UAV should be considered a great tool to advance satellite remote sensing and ground-based studies as it allows researchers to capture imagery with unprecedented spatial resolution, to decide the desired dates and times of flights, to collect coinciding ground data, and to customize the data that the UAV captures based on the analysis. Future studies should utilize the UAV to validate existing satellite remote sensing approaches and develop novel techniques that can then be upscaled. Based on the research presented in this thesis, the techniques of the
two chapters could be combined in a future study to measure glacier ablation and snow algae radiative forcing over the same study site to validate the radiative forcing estimations with the UAV measured snow melt.
Works Cited


Appendix

Supplementary Image 1. Wells Creek stream gauge located at the terminus of the Sholes Glacier. The ground plateaus beyond the terminus of the glacier before descending steeply into the valley below. The stream gauge is located just before this drop off.
Supplementary Figure 1. This figure shows the areas of positive surface elevation change between the two UAV surveys colored in yellow to purple. The underlying image is the orthomosaic of the Sholes Glacier on September 5, 2021. The areas of positive change are located in the northwest portion of the glacier as a result of shadow and edge effects.
Supplementary Figure 2. The subsection of the Sholes Creek survey area that was used to calculate the Wells Creek discharge from the UAV DEMs. The Wells Creek drainage area was manually digitized based on the glacier surface topography that was observed in the UAV imagery and in the field. The medial moraine of the glacier divides the two drainage areas and can be followed from the terminus of the glacier to the ablation area using the stratigraphy of the glacier as a guide.
Supplementary Table 1. Eigenvalues from the PCA for each survey date and eigenvector.

<table>
<thead>
<tr>
<th>Eigenvector</th>
<th>July 2, 2021</th>
<th>July 30, 2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eig. 1</td>
<td>4864277125</td>
<td>8163241694</td>
</tr>
<tr>
<td>Eig. 2</td>
<td>14584757.42</td>
<td>15985887.2</td>
</tr>
<tr>
<td>Eig. 3</td>
<td>557019.0724</td>
<td>1036672.75</td>
</tr>
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<td>Eig. 4</td>
<td>322975.7243</td>
<td>358428.861</td>
</tr>
<tr>
<td>Eig. 5</td>
<td>249755.0241</td>
<td>161825.945</td>
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<td>Eig. 6</td>
<td>186933.0451</td>
<td>92756.7365</td>
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<td>Eig. 7</td>
<td>132605.1517</td>
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<td>102392.2995</td>
<td>48922.8692</td>
</tr>
<tr>
<td>Eig. 10</td>
<td>88617.90452</td>
<td>40219.9944</td>
</tr>
</tbody>
</table>
Supplementary Figure 3. MicaSense band combinations colored by training point classifications where red is snow algae, blue is snow, and grey is other (i.e. rock, water, vegetation). The top right panel is the data from July 2, 2021 and the bottom left panel is the data from July 30, 2021.
**Supplementary Figure 4.** Correlation between the optimized red/green band index with the ratio of astaxanthin to chlorophyll $a$ where $y \sim 1.5335x - 1.4928$ ($F_{1,17} = 5.30$, $p = 0.034$, $r^2 = 0.24$).