Time Series of a Forest Canopy: Detecting Changes using the Visible Atmospherically Resistant Index and a low-cost Drone

by

Samuel Emard

Ryerson University

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Abstract

The drone industry has expanded as the technology has become more affordable in the last few years. The use of drone images in remote-sensing research became an increasingly attractive alternative to other methods such as satellite imagery as it allows for a faster, more efficient method to capture spatial phenomenon. Unfortunately, drones are often costly and require additional sensors and lenses to capture multispectral data, making the technology difficult to access without financial support. However, modern drones designed for more casual flights are now affordable and equipped with high-quality cameras. This major research paper aims to find out whether the combination of a low-cost (< $1000 CAD), lightweight (< 249 grams) drone such as the DJI Mavic Mini is an adequate tool to monitor and detect subtle changes in forest canopy. The Visible Atmospherically Resistant Index is utilized to assess vegetation changes and monitor vegetation growth while minimizing research costs. After capturing a forest canopy for three months, the results show that the DJI Mavic Mini is an adequate tool for research purposes, given that the study area is relatively small and has temperate weather. In addition, the Visible Atmospherically Resistant Index showed mixed results when detecting fine changes in the canopy of the study area. It showed inconsistencies and significant variances in terms of the acquired images. For the index to detect subtle changes in the canopy accurately, the study area needs to be under the same weather conditions and similar sunlight at the time of capture, which is not a realistic expectation.

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List of Acronyms

GLI: Green Leaf Index

MRP: Major Research Project

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Index

RBG: Red, Blue, Green

UAV: Unmanned Aerial Vehicle

VARI: Visible Atmospherically Resistant Index

Chapter 1: Introduction

Remote sensing as a field of research has continuously grown over the past few decades, from images taken from a plane or a balloon to a satellite capturing entire countries from space. One of the latest evolutions in remote sensing is the drone. These small flying machines enabled researchers in the field to capture spatial phenomena easily and quickly without relying on publicly available satellite images or other, more expensive means. Drones also enabled the observation of spatial occurrences in finer detail. For example, monitoring the growth of a wheat field or the tracking packs of wild animals across the wilderness are two things that drones made easier to study for researchers. They also allow for accurate observation of vegetation growth over a specific period by taking images daily and creating time series with relative ease, which would be difficult to do with satellite imagery with their somewhat rigid temporal resolution. However, drones designed for academic research are usually expensive and heavily legislated by the Canadian government. The additional sensors and lenses that research drones are equipped with to capture multispectral data cost thousands of dollars (Dronefly, 2021). As drone technology becomes more efficient and better at capturing data, it also becomes more affordable to the population. Consumer-grade drones are designed for casual flights, acquiring images, videos, and panoramas, but they are also equipped with high-resolution cameras. Using those low-cost drones for academic research instead of casual landscape images is a real possibility that becomes increasingly more realistic as the technology improves. This research aims to understand if such a low-cost, consumer-grade drone can perform adequately in academic research. In addition to using a low-cost drone in this paper, the research will also apply the Visible Atmospherically Resistant Index (VARI), a vegetation index that strictly uses the visible light spectrum to highlight vegetation vigour. Combining both the low-cost drone and the VARI would allow for a lower cost alternative to monitor a spatial phenomenon in the form of a time series. As such, this research aims to answer two questions:

I. Is a lightweight (< 249g), consumer-grade (< $1000 CAD) drone an excellent tool to capture the growth of a forest canopy over three months for academic research purposes?

II. Is the Visible Atmospherically Resistant Index an effective tool for detecting subtle changes in forest canopy growth?

The combination of the two would minimize research costs while maintaining the efficiency of drones and the powerful nature of vegetation indices.

1.1 Study Area

The Covid-19 pandemic has limited population movement in many countries, including Canada, where this research took place. While the restrictions were lifted in June (2021) for the Province of Quebec, it was not the case back in March, when the research started. The pandemic prohibited traveling across regions in the province, limiting the study area's choice to those within the immediate region. The study area is a stretch of forest in the Sorel Islands, an archipelago about 60 kilometres north of the Island of Montreal. Figures 1 and 2 show an overview of the Sorel Islands and a closer view of the actual study area. Figure 1 gives a clear context of the study area's region. As it is in an archipelago in the middle of the St. Lawrence River, the northern half of the islands get flooded annually. Those floods are caused by the snow melting upstream. They usually occur at the end of March/beginning of April and rarely extend to May. In 2021, the flooding was light but still caused the soil of the study area to be temporarily flooded. Figure 3 demonstrates

Figure 1: Overview of the Sorel Islands.

such floods happening three days before the first flights completed in this research. The water receded rapidly, but it was captured in the first few images taken for this paper. Initially, it was feared that the presence of water in the images would affect the VARI calculations, but that was not the case. In Figure 4, the orthomosaic images for the flight on April 2nd clearly show water in the north end of the study area. However, the VARI of the same images, also in Figure 4, does not return any significant changes caused by the presence of water.

Figure 2: Overview of the Study Area (Island of Dupas in the Sorel Islands).

As seen in Figure 2, the forest canopy studied in this research paper is a thin stretch of forest measuring 600 metres in length and about 80 metres wide. The shape of this forest makes it easier to be captured by a drone as it can capture the entire width in one image, which allows lower altitude flights for greater image resolution. The starting altitude for the flights was 100 metres. When measured, each pixel of the images captured by the drone had a spatial resolution of 2.7 centimetres. The forest itself is mainly composed of maples (Government of Quebec, 2021). This composition of leaf trees is crucial to this project, and the minimal presence of needle trees makes the study area ideal for capturing canopy growth.

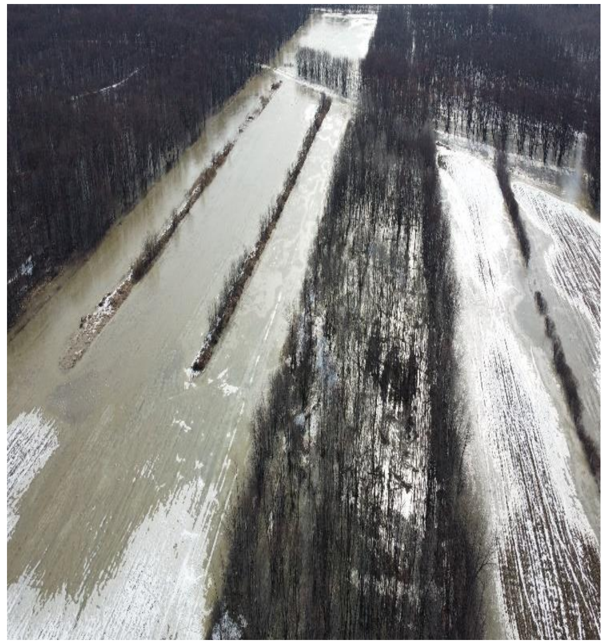

Figure 3: Study area experiencing light floods 3 days before first flights.

Figure 4: Orthomosaic images of the April 2nd flight both in natural colour and with the VARI applied.

Chapter 2: Literature Review

2.1 Visible Atmospherically Resistant Index (VARI)

The literature review of this research project will focus on two topics specifically. The first being the academic usage of the Visible Atmospherically Resistant Index (VARI) as a potential vegetation index, and the second concerns the potential for low-cost drones in academic research. The latter is often tested to determine whether it is a viable alternative to capture spatial phenomenon and increase the efficacy and the cost of research (Zhang et al., 2019). The former is seen as an interesting method used to identify vegetation information and is often compared to other similar indices that exclusively use the visible light bands (Soon Eng et al., 2019).

One good example of research using the VARI is Soon Eng et al. (2019), where they compare the VARI with the Green Leaf Index (GLI) and the Vegetation Index Green (VIgreen). They use different methods to compare the three indices, such as the total number of pixels per class, what each index identified as vegetation, the variance in pixel values, and even the error differences between the indices. They conclude that the VARI and the VIgreen can be troublesome when used in urban areas and that the VARI has a significantly larger value difference than the other methods (Soon Eng et al., 2019). This paper used a methodology that is not too dissimilar from the methods used in this major research paper. Soon Eng et al. (2019) used the number of pixels per class, and this research will count the number of pixels in two ways: the count of pixels with negative and positive values and the number of pixels with a high value (> 0.3). The goals of such methodologies are to capture canopy growth over time and verify whether the VARI can capture subtle changes in vegetation.

Another significant usage of the VARI is from Rokhmatuloh & Hernina (2020), where they use the VARI to estimate the health of palm oil trees. Their study used images from an unmanned aerial vehicle that were processed to create the VARI. They did not deem the VARI results alone enough to estimate trees' health, so they extracted the average pixel value of the VARI in a circular polygon to create different classes for the health of the palm oil trees (Rokhmatuloh & Hernina, 2020). They concluded by explaining that using drone imagery and the VARI is an accurate way to monitor the health of palm oil trees and that it is an efficient method to do so (Rokhmatuloh & Hernina, 2020). Initially, this paper aimed to use a very similar methodology by computing the average pixel value of a polygon to capture the growth of a forest canopy. However, instead of using a polygon to measure the average value of the pixels within, it was decided to use a segment of the study area to monitor the subtle changes in the forest canopy by observing the changes in the pattern of high-value pixels in the final stages of canopy growth.

A third paper that displays a great example of the benefits of the VARI and its potential downfall is Sakamoto et al. (2011). Their project consisted of monitoring the growth of rice plants using the VARI during the day and the Nighttime Relative Brightness Index overnight. They also used different measurements such as plant length and the leaf area index to understand better the "*temporal relationship between the vegetation indices and the biophysical parameters of rice*." (Sakamoto et al., 2011). Their conclusions on the VARI showed a high correlation with the Leaf Area Index, but the results could be heavily affected if a yellow flower appeared in the field of view (Sakamoto et al., 2011). Similar findings were found in this paper. Due to the VARI being limited to the visible light spectrum, the index could easily see its results impacted by different objects of colour, such as the shadows from the trees or any objects of any colour other than green.

A great example of the issues of the VARI encountered in this paper is the research of Stow et al. (2005). Their paper aimed to create a time series using different indices to monitor fuel moisture content for fire risk purposes (Stow et al., 2005). The two main indices their paper focused on were the VARI and the Normalized Difference Water Index (NDWI). They detailed how the VARI had great co-variability in its results. This paper did not complete any comparison to other indices, but it also concluded that the VARI displayed high variability in the range of its results.

One last example where the VARI has shown promising results is in the paper of Jay et al. (2019). They aimed to experiment with many methods using unmanned aerial vehicle imagery and find a new way of retrieving canopy variables that would improve the estimations of leaf and canopy variables in sugar beet crops (Jay et al., 2019). While their research also focused on vegetation canopy growth to a certain extent, they used a multitude of vegetation indices, including multispectral ones such as Normalized Difference Vegetation Index (NDVI), which this paper does not. However, their results using the VARI to detect sugar beet canopies were found to be accurate. They also mention that the most accurate method of using the VARI was to combine it with the NDVI afterward, as they were highly correlated when computed over vegetation pixels (Jay et al., 2019). Interestingly, the VARI is best used in combination with another vegetation index that uses multispectral bands. While it goes against one of the objectives of this paper, it may have improved the results of this research.

Overall, the Visible Atmospherically Resistant Index is used in many papers where it identifies vegetation growth accurately as observed by Jay et al. (2019). The VARI also demonstrated a lot of variance in its results. However, compared to other similar indices, the VARI was shown to be less reliable as a vegetation index as it can be easily influenced by a plethora of factors, such as objects of different colours, shadows, and buildings. The VARI is still a suitable method for monitoring vegetation growth, but the academic literature review shows that it might be better to use the VARI in combination with a multispectral vegetation index (e.g., NDVI) to supplement its results.

2.2 Low-cost drones

The academic literature on the usage of drone imagery is abundant, but the focus for many of them is on how the data from the images can be manipulated for a particular end rather than the utility of the drones themselves. In Tang and Shao's review article from 2015, they outline the strengths of drones for remote sensing purposes. They explain that remote sensing using drones is still in its infancy, and they do mention some benefits of it, such as the low operational cost and its flexibility (Tang and Shao, 2015). However, there is a recurrent pattern in the literature on drones that concerns multispectral sensors equipped on the drone's camera, which goes against this MRP's objective of using a low-cost, consumer-grade drone limited to a high-resolution camera with no additional multispectral sensors. For example, the MicaSense Red Edge Sensor is a sensor capable of detecting the Red Edge and the Near Infrared wavelength that costs about five thousand dollars, which is almost ten times the price of the drone used in this Major Research Paper (MRP).

However, many studies specifically look at the possible use of low-cost drones, like the research of Ventura et al. (2016). The authors evaluate the possible usage of a low-cost drone and compare multiple cameras to capture images of marine ecology (Ventura et al., 2016). The drone they used was a light quadcopter using an automatic flight system and two different cameras to find a more efficient way to identify and characterize fish nursery grounds (Ventura et al., 2016). Ultimately, they concluded by recognizing that drone-assisted methodologies have an excellent potential for monitoring and assessing different coastal nursery areas (Ventura et al., 2016). Even though their research focuses on a different topic than this paper, it is interesting to note the versatility of drones when it concerns monitoring phenomenon over time. If anything, a low-cost drone makes it extremely easy, affordable, and efficient to capture a specific occurrence.

Another example of research using a low-cost drone was conducted by Kellaris et al. (2019). Their paper focused on using a drone, the Phantom Pro P3 model, which costs about two thousand dollars, to monitor seaweed (Kellaris et al., 2019). They explain that drones, with their centimetre-scale, are potentially more valuable to capture images of seaweed ecosystems than satellites or piloted aircraft as their spatial resolutions are inadequate for the task (Kellaris et al., 2019). The researchers conclude their paper by explaining that drones are an excellent tool to use, but it can be challenging to monitor seaweed habitats, especially in deeper waters (Kellaris et al., 2019). Interestingly, one of the most significant challenges of the utilization of a drone they faced was the weather. Wind, clouds, and sun glint were significant factors that affected the drone surveys (Kellaris et al., 2019). Environmental factors were also a significant component that would affect the length and the quality of the drone flights for this major research paper. Too much wind would make it difficult for the drone to fly. The wind would also drain the drone's battery faster because the drone would constantly attempt to stabilize itself and remain in place. Additionally, it would create a constant movement in the canopy of the study area, which makes it difficult for the software to build orthomosaic images. The cold would also severely decrease battery life, and the presence of clouds and sunlight would affect the images' brightness, which ultimately affected the results of the vegetation index.

Duffy et al. (2018) is an older but very similar paper to Kellaris et al. (2019). Their research also focused on the usage of drones to study seagrass ecosystems as a potential novel method to the typical approaches. They used a multi-rotor drone with a high-resolution camera and processed the images taken to answer five research questions, some of which are similar to those asked in this paper. To demonstrate, their paper aims to understand whether a consumer-grade camera and a lightweight drone can be used to collect remote observations of intertidal seagrass meadows. This goal is closely linked to this paper's examination of the ability of a lightweight drone to monitor canopy growth.

A great example of the potential usage of low-cost Unmanned Aerial Vehicles (UAV) can be found in Zhang et al. (2019). Their paper focused on the utility of UAVs for collecting data on turfgrass fields. They used a 3DR Solo Quadcopter equipped with a GoPro Red Green Blue (RBG) camera and a Parrot Sequoia multispectral camera (Zhang et al., 2019). They concluded that UAV-based images were a reliable and powerful tools to monitor turfgrass. Their research is a good example of the usage of UAV-based imagery to assess vegetation growth and demonstrate the potential the VARI possesses as a vegetation index (Zhang et al. 2019).

The overall conclusions on the capacity of remote-sensing using low-cost drones agree that while using UAV makes it more efficient and provides images with a higher resolution than the other alternatives, there are some issues. Those problems mainly concern the weather conditions at the moment of the flight, which correlates with the findings in this research. Some concerns relate to specific topics, such as the seaweed in deeper water (Kellaris et al., 2019). However, the consensus on the usage of drones in academic research seems to agree that their usefulness outweighs any potential problems.

Chapter 3: Data and Methods

3.1 Field Data

The data used in this paper consists mainly of the images taken with the drone. The model of the drone is the DJI Mavic Mini (Figure 5). It is a small and compact drone weighing only 249 grams and has a diagonal distance of 213mm. Any drone weighing more than 250 grams requires a permit to fly in Canada (Transport Canada, 2020), so the DJI Mavic Mini is a machine specifically designed to be flown without a permit. It is also an affordable drone that cost about $700 CAD at the time of purchase (Feb. 2021). It is a drone made for casual flights, landscape images, and panoramic videos (DJI, 2019). The drone has a battery life allowing for 30 minutes of in-flight time, limiting the time spent surveying the study area. It can easily be affected by the weather, be it wind or temperature, which reduces the already limited battery life. The Mavic Mini uses the DJI FC7203 as a camera, with a resolution of 4000x2250 pixels with no multispectral sensors (DJI, 2019). It takes high-quality images that are restricted to the visible light spectrum, which perfectly fits the goals of this research paper. It is essential to mention that all flights using the DJI Mavic Mini were completed manually instead of using a software to create and schedule the flight. Autonomous flights using the DJI Mavic Mini would have required additional software to schedule and plan the flight paths to be completed by the drone. However, autonomous flights completed with such an app (e.g. DroneLink) were ineffective with the DJI Mavic Mini. Furthermore, the ability

Figure 5: DJI Mavic Mini Drone used for data gathering.

to perform autonomous flights became only available in late May, which meant that more than half the flights were already completed manually. Therefore, to stay consistent, all the flights were piloted manually. In hindsight, making all the flights autonomous would have been a better alternative to manual flights because they would have been more consistent in terms of image acquisition, image overlap and image quality. Furthermore, the lack of experience with operating the drone meant that the data collection process would be a learning experience. Therefore, manually operating the drone resulted in inconsistent flights that improved as the operator improved over time. So, flying the drone automatically would prevent any issues originating from inexperience with drone operation and would remain consistent for the entire data collection period. The Mavic Mini was flown at an altitude of 100 metres above ground initially but had to increase as the canopy grew. When the canopy started growing, the number of images taken and the altitude flown were unable to capture the study area's sides adequately. To remediate that issue, the drone had to be flown at an increased altitude of 120 metres for the remainder of the study. Drone2Map and ArcGIS Pro were utilized to measure the pixels of each orthomosaic image in order to verify the resolution change caused by the altitude increase. At the initial altitude of 100 metres, the resolution was of 2.7 centimetres per pixel. Increasing the altitude to 120 metres changed the resolution to 4.3 centimetres per pixel. Figure 6 compares images from the flights on April 27th and June 17th and exemplifies the resolution change caused by the altitude increase. The April 27th flight was completed at an altitude of 100 metres and the June 17th at 120 metres. It demonstrates the changes from 2.7 centimetres per pixel to 4.3 centimetres per pixel. Both display highly detailed images, but the April 27th image does show finer details.

An important factor to note is that while this paper focuses on reducing the costs of research by using a low-cost drone, the software packages used in this paper are quite expensive. Drone2Map alone costs $3500 for a yearly subscription, and ArcGIS Pro can cost from $1250 to $6850 annually, depending on which package is chosen (Esri, 2021). The licenses for these packages used in this paper were provided by Ryerson University. However, to truly cut the price of research and data collection using alternate software packages that are freely available such as QGIS would be perhaps desirable.

Figure 6: Zoomed-in images of the flights performed on April 27th and June 17th to compare the change of resolution caused by the increased altitude.

3.2 Raster Processing

The DJI Mavic Mini recorded an average of 69 images per flight for all recorded flights from April to June. The drone captured JPEG images equipped with geographic coordinates in their metadata. The images were then combined in Drone2Map to create orthomosaic images. When the orthomosaic map of the drone images was created, they were transferred into ArcGIS Pro in order to apply the VARI's calculation. The VARI originated from the Leaf Area Index (LAI) and Vegetation Fraction (VF) and is based on the visible wavelengths' reflectance values (Rokhmatuloh & Hernina, 2020). Equation 1 displays the VARI formula.

$$\text{VARI} = \frac{(\text{Green} - \text{Red})}{(\text{Green} + \text{Red} - \text{Blue})} \tag{1}$$

The VARI can be calculated by taking the values of the red-green-blue (RGB) wavelengths of a random pixel in the 2nd of April flight (seen in Figure 4). That pixel has a red value of 167, a blue value of 157, and a green value of 160. By using the equation above, the VARI returns a value of -0.041. By default, the VARI will turn the pixels with a positive value to white and those with a negative value to black. In other words, the higher the VARI results, the brighter the pixel, and the lower the VARI, the darker the pixel.

The VARI is unique from the other vegetation indices that are also limited to the visible light spectrum, such as the GLI and the VIgreen, because of how it minimalizes the atmospheric effects that could potentially impact an image. The inclusion of the blue band in Equation 1 is to minimize the atmospheric impacts (Soon Eng et al., 2019). It is unique in that aspect because the VIgreen does not include blue-band data and while the GLI does. Therefore, it does not serve a critical role in the index's equation. For the VARI, the inclusion of blue-band data is critical and necessary for the index to work as intended (Soon Eng et al., 2019). However, at an altitude of 120 metres, the atmosphere would have very little impact on the images. Still, this unique feature of the VARI is why it was chosen for this paper over the other indices.

3.3 Methods

The methods utilized in this paper all aim to answer the questions asked in the introductory segment. They will test and evaluate the capacity of a low-cost drone as a potential tool for research with an academic focus. They will also examine the results given by the VARI and its ability to detect fine changes in the forest canopy. When evaluating the DJI Mavic Mini as a potential tool for academic research, the methodology will mostly rely on a visual analysis of the natural colour images the drone produced and the orthomosaic images that resulted from those images. The quality and the reliability of the drone's images, the drone's performance in various weather, and the issues encountered with the data collection will all be the main points of the drone's evaluation.

The first method used to test and observe the capacities of the VARI to detect fine changes in forest canopy is similar to the one used to evaluate the drone. It consists of a visual analysis of the orthomosaic images after the VARI calculation was applied. This allows for observation of if and how the VARI identifies vegetation and whether it does it consistently and accurately. It also helps understand what the VARI considers as vegetation at different stages of canopy growth. It will also show how the VARI performs over three months.

The second method used to test the VARI is to observe the average pixel values it returns for all orthomosaic images. As the canopy grows, the average values of the pixels within the study area should also increase since the VARI identifies vegetation as positive values. A steady increase over three months in the pixels' average values should indicate that the VARI detects canopy changes.

Then, the following method will involve pixel manipulations to identify subtle changes in the forest canopy. This method involves reclassifying the values of the pixels into different categories. At first, the pixels will be separated into two groups: the pixels with negative and positive values. As VARI identifies vegetation with a positive value, isolating the pixels with positive values should isolate what the index considers as vegetation. Observing the changes in the pattern of the pixels with a positive value will test the VARI's ability to perceive subtle change in the forest canopy.

The last part of the methodology testing the VARI is similar to the previous one. Instead of separating the pixels with a positive value, this method will isolate those the VARI returned with a value higher than 0.3. The value of 0.3 was determined to be a high-value based on two different observations of the data. First, the value of 0.3 is above the pixel average of every flight, making it an above average value across all orthomosaic images. Second, the value of 0.3 is 'present' in every flight. In other words, each orthomosaic image possesses at least a few thousands pixels with the value of 0.3, which makes it an ideal lower limit for what is considered a high-value pixel. If, for example, the lower limit of the high-value pixels was of 0.5 instead, some images would not have any high-value pixels. Reclassification was performed on every flight, but only the June flights are considered for this part of the analysis. This method aims to compare how the VARI detects slight changes in forest canopy when it is in its final stages of growth. It will also test the consistency of the VARI because the canopy, by that point, will almost be fully grown, so only very subtle changes should occur in it. The number of high-value pixels should stay similar from one flight to the other and show small increases as the canopy grows fully. At this point, any significant variance in the results of the VARI would be indicative of the index's inability to detect subtle changes or of the influence of external factors such as the sun's brightness and the presence of shadows.

Chapter 4: Analysis

4.1 Visual Analysis of orthomosaic images in natural colour

The preliminary analysis of the orthomosaic images in natural colour can be seen in Figure 7. It shows the flights performed from April to June of 2021 with an interval of about two or three weeks. There is a striking difference in forest canopy from April to June, where it is barren in April and fully grown in June. It is only in May that the first leaves start to become noticeable. Then, from the 14th of May to the 6th of June, there is a significant growth in which the canopy blooms to its final growth stage. The DJI Mavic Mini captured the study area quite accurately at a steady altitude of ~100 metres above ground and a resolution of 2.7 cm per pixel. However, in the orthomosaic of the 14th of May, data corruption can be seen in the edge of the forest, appearing as white areas. These contain no data, and those issues originated as the canopy grew in thickness and size. Figure 8 shows a close-up image of these corrupted zones that unfortunately appeared in multiple flights completed in the second half of May. At the time, it was difficult to pinpoint the origin of the issue and required multiple experts weighing on the matter to figure out the solution. As the canopy grew, the original altitude of the flights was insufficient as it could not accurately capture the sides of the study area, hence why they appeared as no data areas. To remediate this issue, the drone had to fly at an increased altitude of 120 metres above ground and complete multiple passages above the study area when only one passage was previously required. In hindsight, the solution and its logic make sense and could have been remediated easily. As the canopy grew, the software did not have enough data at the edge of the study area to generate an orthomosaic map based on the images taken by the drone. That is why multiple passes with the drone were required to capture these areas accurately.

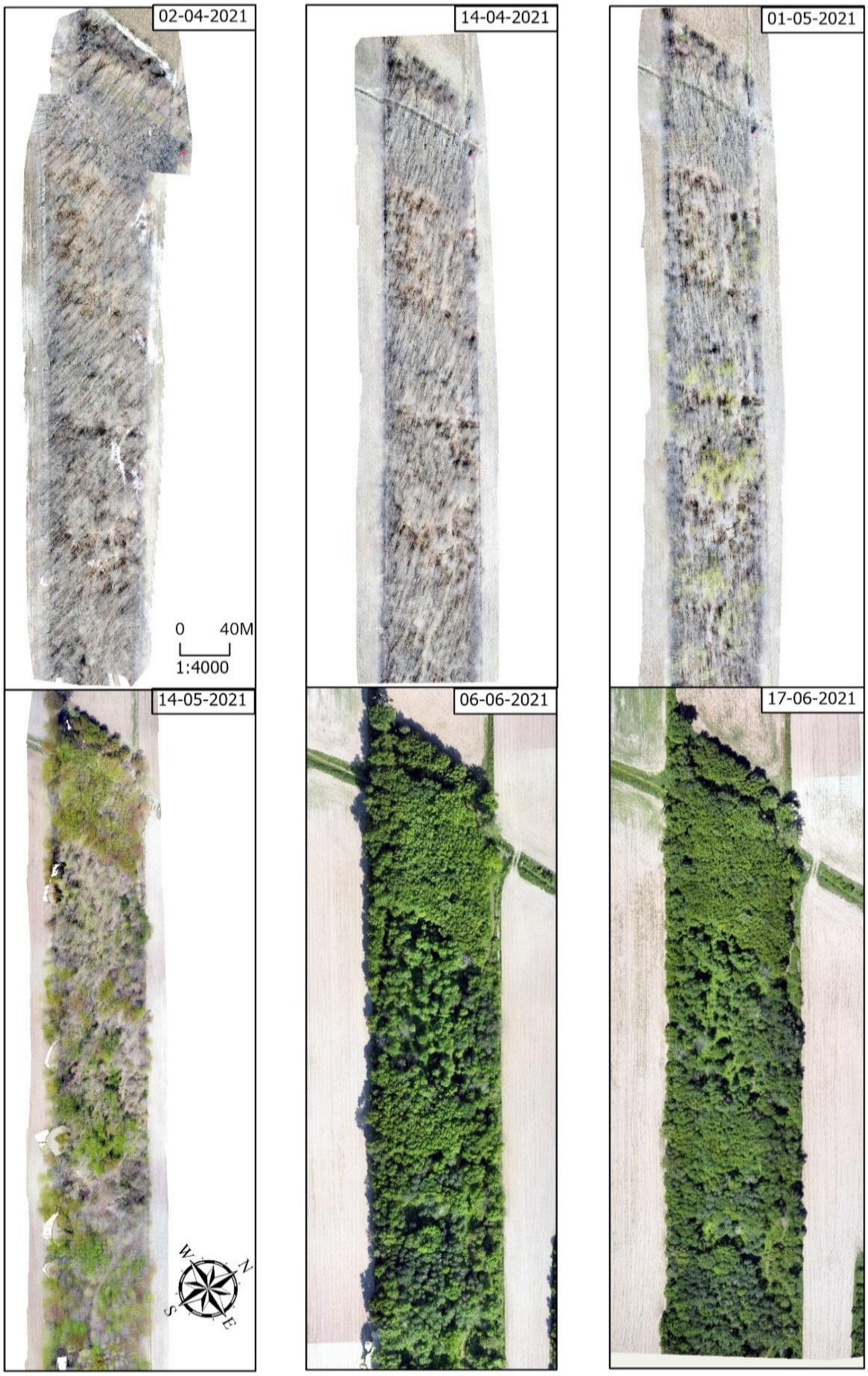

Figure 7: Orthomosaic images in natural colour of the flights with a 2-3 weeks interval from April to June.

However, completing multiple passes over the study area with the drone required a battery change, which meant the data capture period was longer, especially in windy weather where the drone consumes more power to operate. Also, raising the altitude slightly reduced the quality of the images (Figure 6). The resolution went from 2.7 centimetres per pixel to 4.3 centimetres. The difference might not seem staggering, but it can influence how the subsequent analyses detect fine changes. It took about two weeks to pinpoint the issue, which means that May's remaining flights were not adequate to be used in this research. The specks of corrupted data were only the beginning of the issue. As the canopy grew and the altitude remained at 100 metres, the orthomosaic images became warped, and it was impossible to recognize the study area. Figure 9 shows such a flight. Completed on the 18th of May, the software could not construct an orthomosaic map based on the images taken. The study area is unrecognizable, and this flight could not be used for the next step of the analysis. This issue was only fixed for the flights of June, meaning that a critical period of canopy growth was not accurately captured. While this issue probably originated in the inexperience of the drone pilot, it is hard to imagine that a more expensive drone purposefully built for research would have resulted in the same errors. As mentioned, the altitude of the drone had to be raised to 120 metres. Fortunately, 120 metres is the maximum legal height at which a drone can fly, according to the Canadian government (Transport

Figure 8: Zoomed-in image exemplifying data corruption in the May 14th flight.

Canada, 2020). Therefore, the drone had to be flown at the legal limit in Canada to capture the forest canopy correctly. Overall, however, except for the period in late May where the orthomosaic images were distorted, the natural colour images clearly show a progression of canopy growth. Thanks to the highly detailed images taken by the DJI Mavic Mini, it is possible to examine the canopy of the study area in more detail. For example, the canopy growth pattern over time. Figure 7, the 1st of May flight, shows that the first leaves in the canopy to be captured are near the centre of the forest. Then, on the 14th of May flight, both ends of the canopy started to grow. Finally, the rest followed suit until the canopy was fully grown. The reasons behind such a growth pattern are difficult to pinpoint as it could be due to the tree species, soil moisture, or many other explanations relating specifically to the study area. The natural colour images have shown the canopy growth in a time series made easily while minimizing research costs and efforts thanks to a low-cost drone. The only major issue encountered at this stage was the change in altitude to the legal limit required as the canopy grew and thickened. It created a problem due to inexperience with drone imagery and orthomosaic mapping and resulted in multiple flights being discarded for the next steps of this analysis. It can be safely concluded that a low-cost drone such as the Mavic Mini is indeed an adequate tool for forest canopy monitoring, if the drone is flown at an altitude of at least 120 metres consistently. Another issue the drone faced was the weather conditions, such as high winds and the cold temperatures that were present during the early stages of this project.

Figure 9: Example of distorted flight caused by low altitude. Flight of May 18th.

Those drained the batteries faster, which either limited the capture of the study area or lengthened the process by requiring a battery change.

4.2 Visual Analysis of VARI orthomosaic images

The following method is another visual examination of the orthomosaic images generated in Drone2Map from the drone images, but with a different purpose. The examination will focus on the orthomosaic images after applying the VARI calculations (See Equation 1 for detailed calculations). The results of the calculations can be seen in Figure 10, where the same orthomosaic images showed in Figure 7 had the VARI applied to them. By default, the index turns the pixels with a positive value to white and a negative value to black. Therefore, the brighter the pixel, the higher the value assigned by the VARI. High-value pixels are what the index identifies as vegetation. In Figure 10, starting with the flight completed on the 2nd of April, the entire study area shows very few black pixels or darker areas. This is due to the entire area showing minimal variance in its colour palette of the natural colour images. Since the weather was still cold, the plants, leaves, and grass were all in similar shades of yellows and browns. Such a similarity in the colours of the canopy translated in the VARI as not showing any very high or very low values. Visually, it resulted in a multitude of greys instead. There are only a few white pixels in the April 2nd flight located at the north edge of the study area. Those pixels have a high value because of the presence of snow, which had yet to melt away at the time. When translated in the VARI calculation, the whiteness of the snow made the pixels very bright. This is a clear example of one of the main issues of the VARI, its strict reliance on the visible light spectrum. That reliance on red, blue, and green bands is one of the main reasons the VARI was chosen for this research, but it also results in some issues.

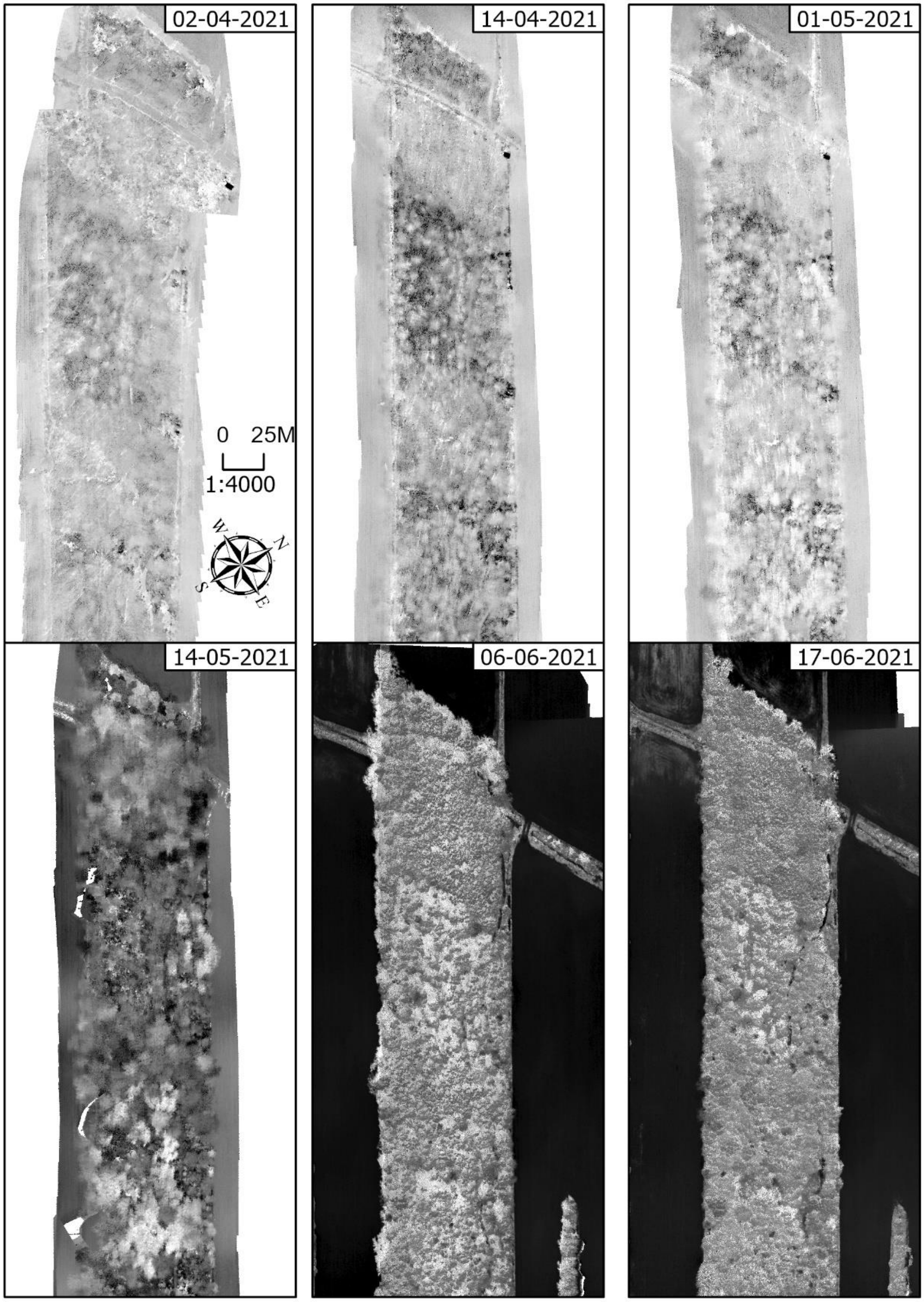

Figure 10: Orthomosaic images of the flights with VARI for the flights from April to June, 2021.

Another example of a similar issue can be seen in the 14th of April flight. However, the white pixels in the orthomosaic are neither vigorous vegetation nor snow. In this case, it is the shadows from the trees. Figure 11 depicts the issue more clearly by showing what it incorrectly identified as vegetation. Furthermore, the shadows were often shown as high value in the VARI in many flights because of the lack of leaves, especially in April. The spectral profiles of the pixels located within the shadows of the trees return values with a low red band value, a high green band value, and a high blue band value. For example, On the 14th of April flight, the spectral profile of the tree shadows returns a red band value of 69.59, a green band value of 76.68, and a blue band value of 79.01. The VARI calculations return a result of 0.105412, which may seem low, but it is relatively high with an average pixel value of -0.03457346. This problem introduced another factor to the research: the time of day. As the shadows are heavily dependent on the sun's position, the time of day had to be considered in order to have as few shadows as possible. In this paper, all flights were completed in the late morning between 10 AM and 12 PM so that, at least, all shadows would have similar angles and locations. Nonetheless, snow and shadows created an issue for the VARI as it would identify "vigorous vegetation" mainly on the outer edges of the study area. Snow was only an issue in the first two flights since it melted away. The shadows,

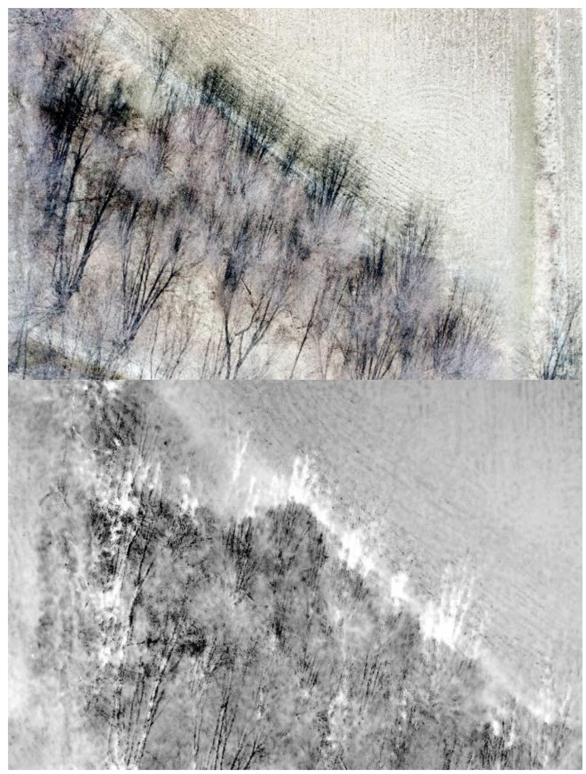

Figure 11: A zoomed-in image of the April 14th flight to exemplify how the VARI identifies the shadows of the trees as vegetation. Top is in natural colour and bottom is after the VARI was applied.

however, were a consistent issue across all flights that manifested in different ways as the canopy grew. The issues with the VARI where it incorrectly identified vegetation mainly were seen in the early flights. As time progressed, the number of high-value pixels grew and concentrated in the study area's canopy. As the pixels in the canopy started to brighten, the ones surrounding the study area started to darken. This is due to the increasing presence of the colour green in the colour palette of the images, which is significantly different from the brown tones that composed the images of the early flights. The VARI of the 14th of May flight shows the canopy being accurately captured by the index, but still not fully. It is only when the canopy is fully grown that the index consistently captures it.

One of the issues with the VARI that was detailed in other works such as Soon Eng et al. (2019), where they compared the VARI with other vegetation indices and found the VARI to have the largest variance in its data (Soon Eng et al., 2019). That was also the case in this paper, as the pixel values of the VARI were different from one flight to the next, especially in the range of the values. For example, for the April 2nd flight, the minimum pixel value was -21, and the maximum was 17. To compare, the 14th of April flight had a minimum of -3 and a maximum of 2. Such significant differences in the range of its values were observed across all April flights. The difference between the maximums and minimums started to decrease as the canopy grew during the flights of May. The maximum and minimum values stabilize between -2 and 2 and remain stable until the 20th of June. See Table 1 for information on all the flights completed for this paper. Further massive differences in the range of values of the VARI are exemplified in Figure 12, which shows the maximums and the minimums across all flights. Using the maximums and minimums was not viable to determine whether the VARI detected subtle changes as the results were different every time.

Table 1: All flights completed for this paper dated, the number of images taken, the VARI minimums and maximums and the pixel average value

Flight Number	Flight Date	Number-Of-Images-Taken	VARI-Min-Value	Vari-Max-Value	Pixel-Avg-Value
1	2021-04-02	63	-21	17	-0.032915657
2	2021-04-05	18	-7	7	-0.03517097
3	2021-04-07	35	-28	28	-0.03293536
4	2021-04-14	63	-3	2	-0.03457346
5	2021-04-24	47	-16	13	-0.0258347
6	2021-04-27	69	-1	3	-0.03153581
7	2021-05-01	70	-7	5	-0.04348751
8	2021-05-03	74	-0.51282054	0.5	-0.04802201
9	2021-05-06	46	-0.75	1	-0.04565663
10	2021-05-09	63	-0.69	0.69	-0.04470122
11	2021-05-13	59	-0.75362319	0.5067	-0.01549954
12	2021-05-14	59	-0.60869563	0.54098362	-0.02901087
13	2021-05-15	76	-0.5714286	0.7	-0.00621746
14	2021-05-17	60	-2	1.1667	0.04522067
15	2021-05-18	49	-0.38461539	1	0.06223702
16	2021-05-19	41	-0.38016528	0.93023258	0.12351288
17	2021-05-24	32	-0.48288974	6	0.16889656
18	2021-06-04	53	-0.42857143	0.800000001	0.09769139
19	2021-06-06	93	-0.25316456	2.16666675	0.09666
20	2021-06-08	94	-0.20634921	1.0833337	0.0755321
21	2021-06-11	107	-0.14851485	91666669	0.08799889
22	2021-06-13	115	-0.28431374	0.90909094	0.07498237
23	2021-06-16	92	-0.20930232	1.7777779	0.079551
24	2021-06-17	79	-0.25	3	0.06859517
25	2021-06-20	81	-9	17.66666603	0.28885843

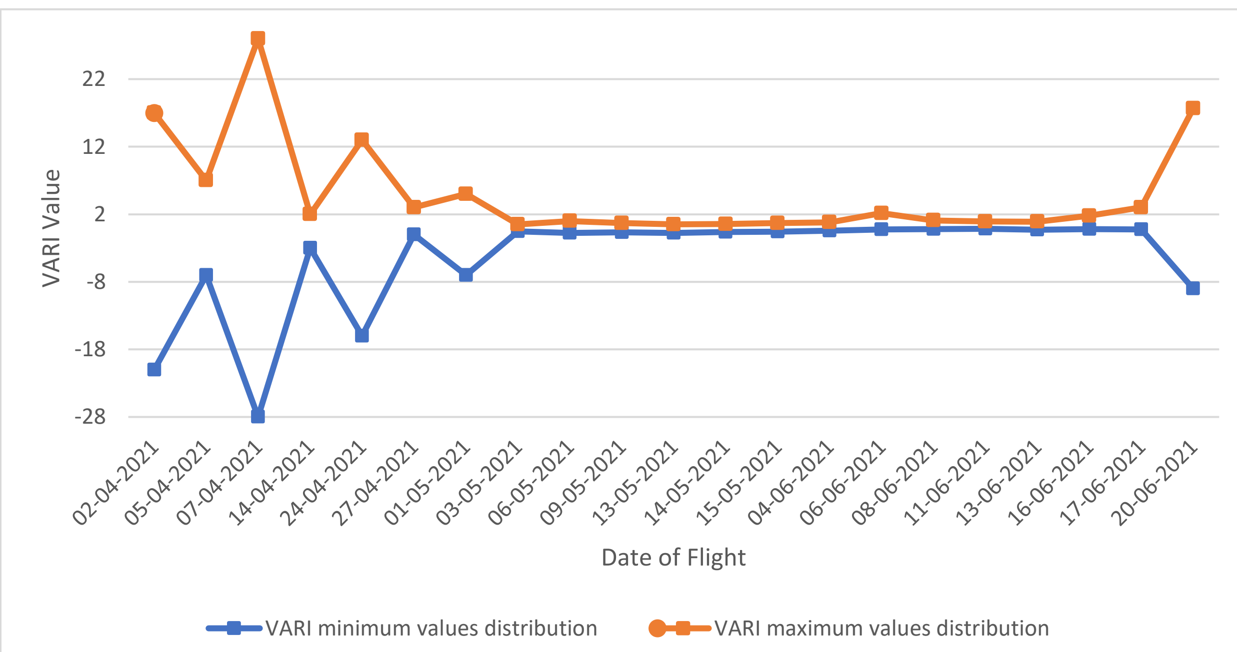

Figure 12: Graph showing the minimum and maximum values of the VARI across all flights.

However, the average pixel value showed an interesting pattern. Figure 13 shows a graph of the average pixel values of the VARI across all flights. It shows two plateaus in the data pattern where, in the first half, the average pixel value was negative, meaning that the VARI had trouble identifying any vegetation. There was no vegetation to detect during that first half, so the VARI is correct in this case. It was still unable to detect subtle changes because the values of the flights completed in May, where the canopy was growing, should have been higher than those done in April. This shows the impact of the external elements such as the snow and the shadows. From the flight on May 3rd, there is a slow and unsteady increase in the average pixel value observed until the fifteenth, the last good flight of May. Then, it jumps to the June 4th flight, where the canopy is almost fully grown and, as such, the average pixel value is positive. The average values slowly decrease across the flights of June up until the last one on the 20th of June, where it suddenly jumps. Such a drastic change is also why the flights were stopped on that day, and no other flights were completed afterward. Figure 14 represents the VARI applied to the orthomosaic image of the

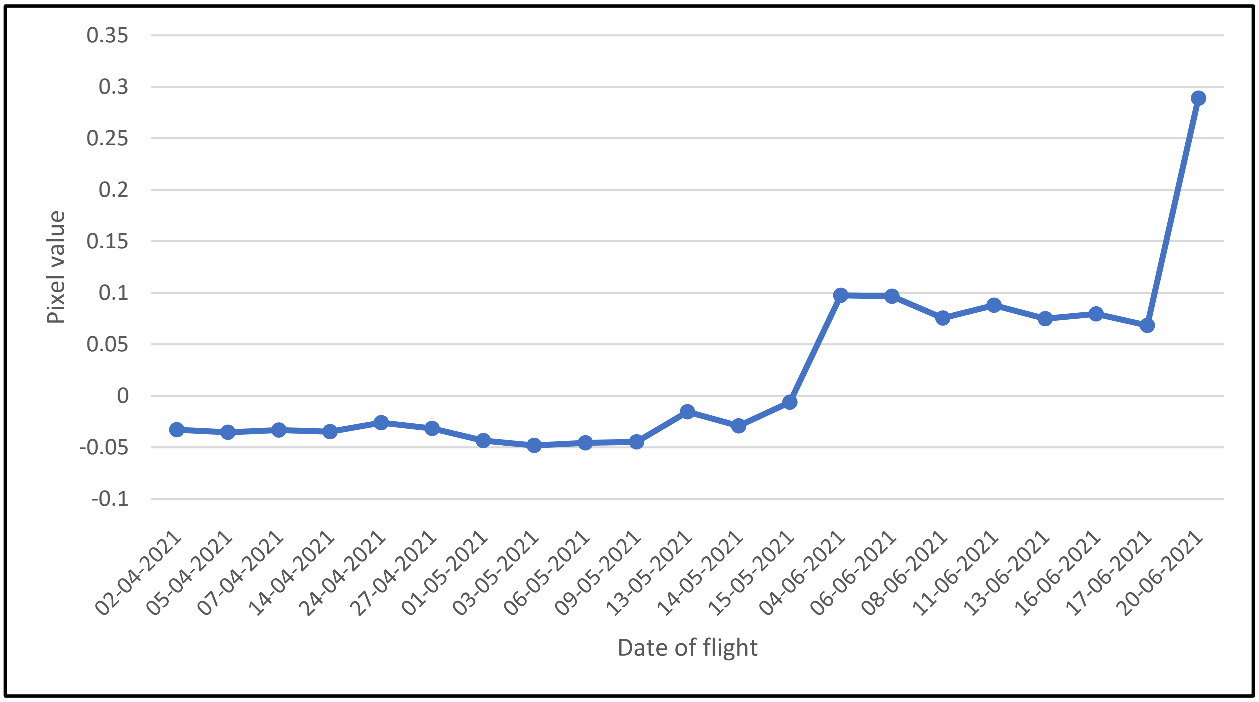

Figure 13: Graph showing the average pixel value of the VARI across all flights completed.

flight completed on the 20th of June, 2021, and represents the last flight completed for this research. The issue caught in this flight was not due to the VARI but due to increased altitude. As the canopy grew, the altitude had to be increased to better capture the study area. However, the surrounding fields were also captured in consequence of that increased altitude. Those fields were seeded in May and had yet to show any growth until the end of June. It is difficult to know if the growth of the soy plants in the fields is the only cause of the sudden jump in the average pixel value. After all, the soy plants were present in the 17th of June flight, which did not show any

Figure 14: Orthomosaic images of the June 20th flights in natural colour and the VARI.

spike in its average pixel value. In fact, the most logical explanation that caused the increase in positive pixels is most likely due to the fact that the June 20th flight is the only flight taken in the afternoon. This flight is the only one that occurred in the afternoon due to unfavourable flight conditions in the morning of that day. That would have caused the sun to be in its apex, which means a higher brightness and higher presence of shadows. It is most likely a combination of factors that impacted the 20th of June flight, such as the sun's brightness, the soy plants in the fields, and the more prominent presence of shadows that caused the June 20th flight to be so different from the other flights. This exemplifies perfectly how fickle the VARI can be with its identification. For the index to be used adequately, similar times and weather conditions are necessary to draw good results.

The Visible Atmospherically Resistant Index showed mixed results when it comes to purely visual analysis of the orthomosaic images. Even though it does identify vegetation clearly in some flights, it is only accurate when the canopy is fully grown. When the forest canopy is starting to be visible in natural colour, or when the canopy is in its early stages, the VARI is not reliable as it is easily tricked by the presence of things other than vegetation. A similar finding was detailed in the research of Soon Eng et al. (2019). They concluded that the VARI is not reliable in an urban environment because it had trouble differentiating vegetation from building and other urban landmarks. Even without the presence of urban features, the VARI faced difficulties identifying the early stages of the canopy. Only when it was fully grown could the VARI identify it. Sakamoto et al. (2011) paper also identified similar issues where the VARI showed satisfactory performance until an object of a colour other than green was capture in the images. A yellow flower in their case (Sakamoto et al., 2011). However, these conclusions are purely based on visual inspections of the orthomosaic images, which are not enough to judge the performance of the VARI.

4.3 Analysis of VARI Pixel Patterns

This first method of analyzing the VARI results will test the vegetation index and make it clearer whether it identifies subtle changes in the vegetation or not. As the VARI identifies vegetation as positive values and the rest as negative values, the first method is to reclassify the VARI results to show the positive and negative ones in a contrasting way. This will allow for a clearer and more objective way to visualize what the VARI identifies as vegetation. Figure 15 represents the method of contrasting the negative pixels from the positive ones. If the pixel is negative, the VARI identified it as non-vegetation; it is attributed to the green colour. Conversely, if it is a pixel with a positive value where there is supposed vegetation according to the VARI, the pixel is attributed the purple colour. The pattern of the positive pixels is similar to what was noted in the visual analysis. The positive pixels are mostly outside the study area in the April flights because they represent the trees' shadows. However, as time progresses, fewer positive pixels are found outside the study area and start to aggregate inside the study area. This corresponds nicely with the growth of the forest canopy. The vegetation index still identifies shadows as positive values, but now there is also the canopy being detected. The VARI still shows difficulties with the early flights and the early stages of the canopy growth. From the May 1st flight onward, the canopy was identified. This method shows its limitations with the flight completed on the 20th of June because the entirety of the image would be classified as positive. As mentioned above, this last flight of the study area shows a jump in the average pixel value. The reclassification of the pixel by their positive or negative values allowed for a clearer visualization of canopy growth. It shows that the VARI does capture the forest canopy as it grows.

In addition to the identification issues discussed prior, the vegetation index suffers from a consistency problem. The count of positive and negative pixels is inconsistent from one flight to another. Logically, as the canopy grows, the number of negative pixels should decrease, and the number of positive pixels should increase. The graph in Figure 16 displays the progression of the number of negative and positive pixels over time. It clearly shows how the number of pixels varies from one flight to the other in drastic ways. From the very first flight, there is a sharp decrease in the number of pixels followed by a significant increase in the count of negative pixels. Such a decrease can be influenced by the number of images taken, which differs slightly across all flights, averaging around 70 images taken per flight. Another incongruent pattern in Figure 16 would be that the flight on the 13th of May has more positive pixels than the 6th of June flight when it should not be. The canopy was significantly different in-between those two flights. On the 13th of May, the canopy was growing, but nowhere near the canopy level present on the 6th of June.

To further this point, the exact number of positive pixels for the 13th of May flight is 24,813,926 positive pixels. In the flight of the 6th of June, there are 24,634,437 positive pixels. That is a difference of 179,489 positive pixels between the two flights. In orthomosaic images with over sixty million pixels, it is a trivial difference. The difference of positive pixels should be much larger than that because of the significant difference in canopy growth.

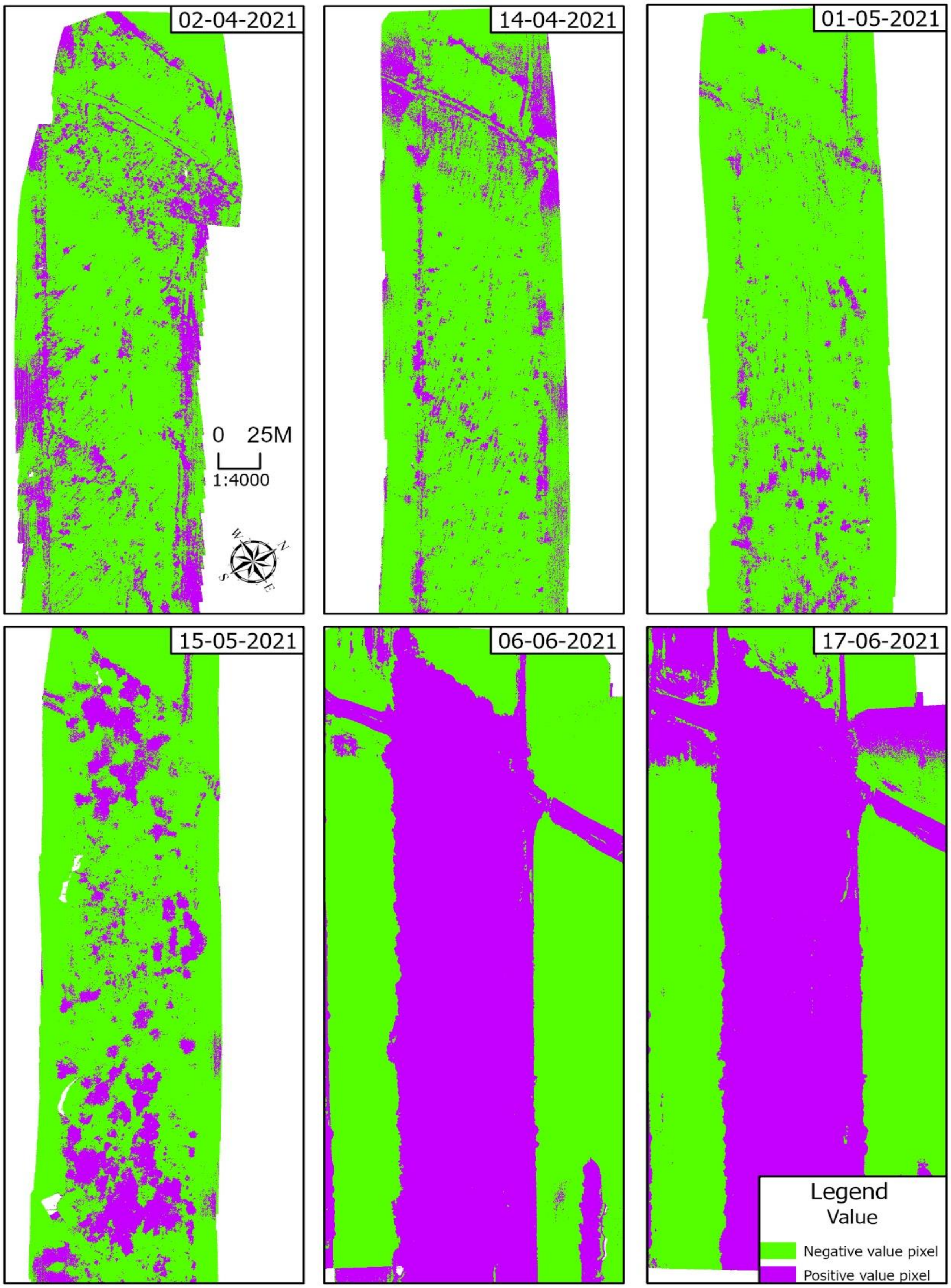

Figure 15: Orthomosaic images with VARI reclassified to contrast the positive and negative pixels from the flights of April to June, 2021.

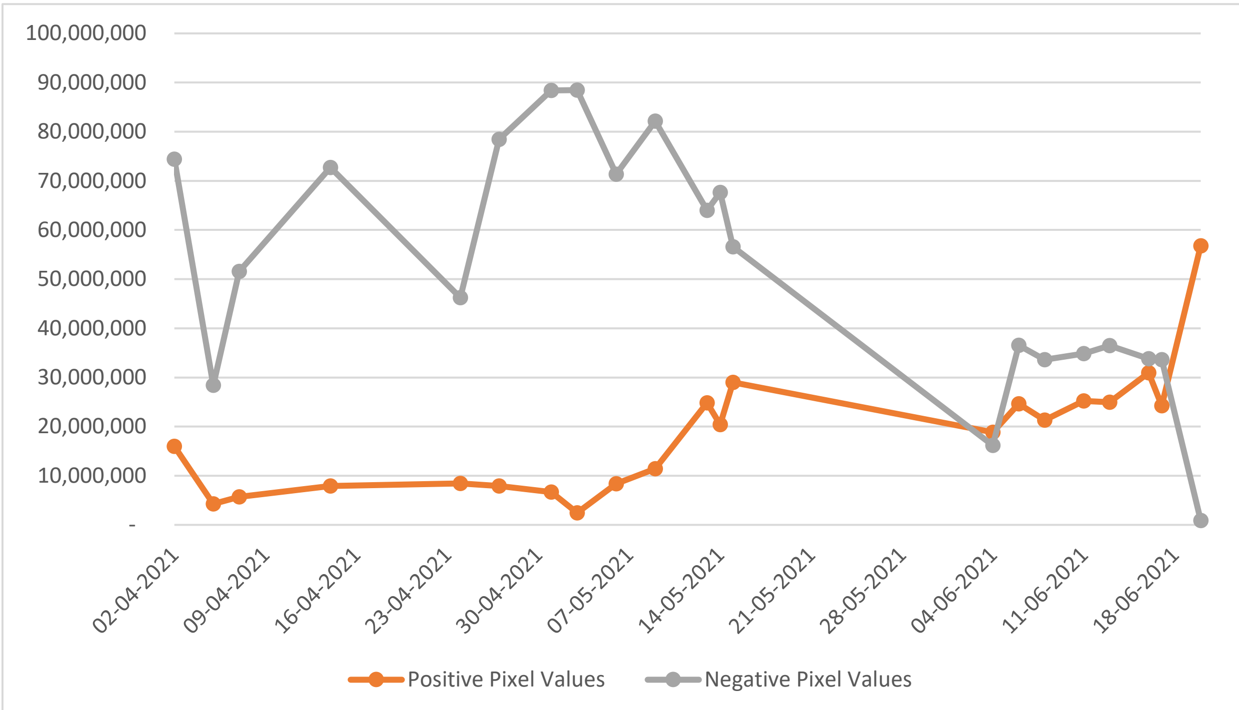

Figure 16: Graph of the number of positive and negative pixels across all flights from April to June 2021.

Figure 17 shows the orthomosaic images of the flights of the 1st of May and the 9th of May in both natural colour and the VARI reclassified by its positive and negative pixels. The natural colours images show canopy growth in the southern edge of the orthomosaic images, which the VARI seems to capture accurately as vegetation. There are more positive pixels in the south of the study area in the 9th of May images in the VARI reclassification. The 1st of May orthomosaic still detects shadows as vegetation, but those mostly disappear in the 9th of May orthomosaic images. So the VARI seems to detect subtle changes when the study area is captured in similar conditions and at similar times.

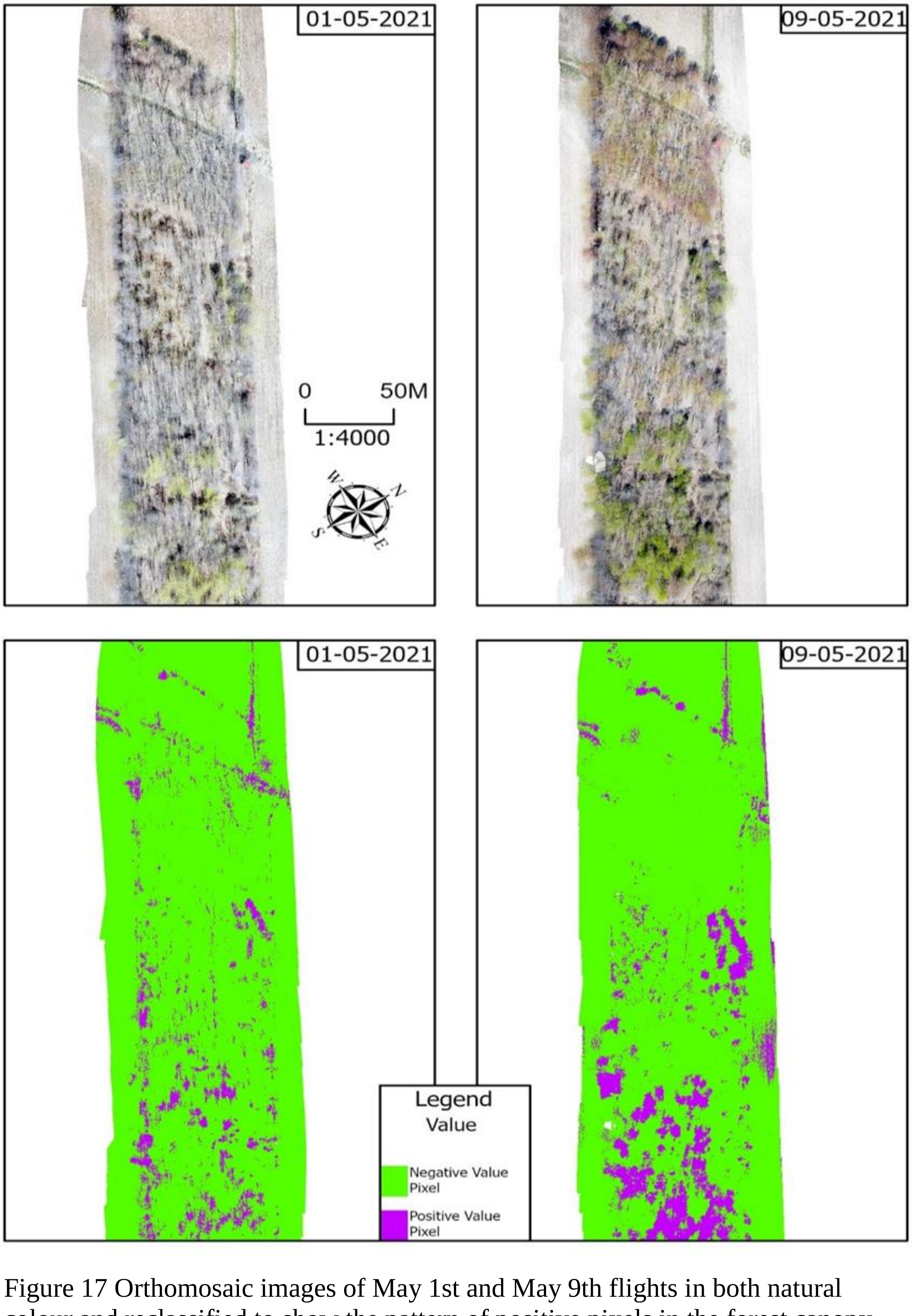

Figure 17 Orthomosaic images of May 1st and May 9th flights in both natural colour and reclassified to show the pattern of positive pixels in the forest canopy.

The pattern changes in the positive value pixels in the forest canopy show that the VARI detects growth over a long period, but it was found to be inconsistent when looked at slight changes in a short period because it requires almost identical conditions at the moment of the data capture. When looking at the pixel numbers, the index has identified vegetation, but the distribution of the positive pixels makes it challenging to draw any conclusions. When the number of positive pixels should steadily increase due to growth in the forest canopy, the VARI does not detect that increase in a similar fashion. It does detect larger-scale changes in the canopy, but this paper seeks to answer a question about the ability of the VARI to detect finer changes in the forest canopy. The variance that the VARI shows on a small temporal and spatial scale inhibits its ability to do so. For fine change detection using the VARI, the flight conditions should always stay the same, including the time of flight and the weather conditions, which is not a realistic expectation to have over a period of three months.

4.4 High-value pixels distribution analysis

Finally, this last method is designed to observe the VARI's abilities to detect subtle changes. Instead of separating the pixels into two groups based on their value being either positive or negative, Figure 18 demonstrates the high-value pixels of a segment of the study area. Initially, this method was to be employed similarly to the one in the research paper of Rokhmatuloh & Hernina (2020). They used the average pixel value of a polygon to estimate the health of oil palm trees using the VARI over time. It was used as a more accurate way to classify the health of the trees (Rokhmatuloh & Hernina, 2020). However, the drone flights were found to have slightly different coordinates from each other. Each flight had a difference of a few metres, making using a polygon in the exact location difficult. While orthorectifying the flights could have fixed this issue, it was decided to use the method differently. Instead of using the average pixel value of a segment of the canopy, a visual analysis of the high-value pixels of a small section of the study area will be equally able to answer whether the VARI can detect more nuanced changes in forest canopy growth. Figure 19 displays a quick overview of the segment chosen for this methodology.

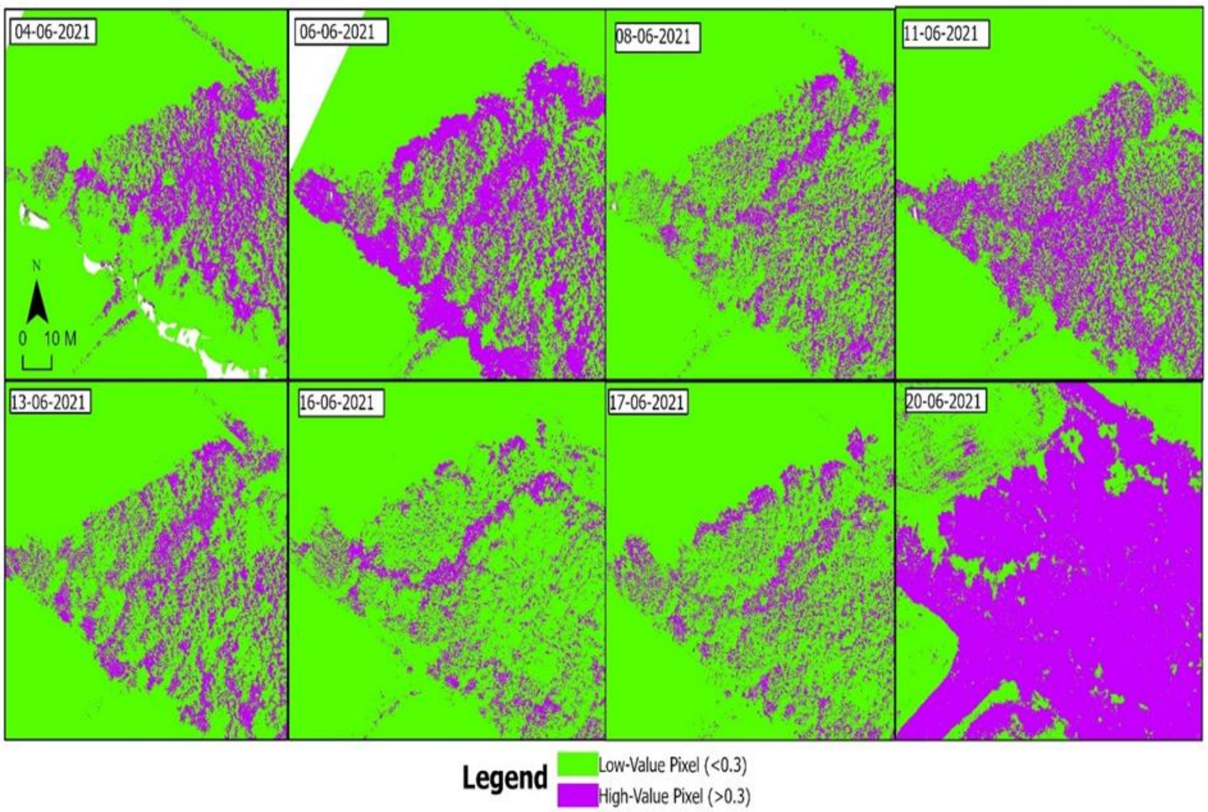

Figure 18: Images of the segment with reclassification showing the high-value pixels.

It is the north-western end of the study area. The main reason why this location was chosen as the segment used in this method is because of the three natural features surrounding it. Three ditches delimit the area, as detailed in Figure 19. Those natural features were captured in every flight, which makes it simple to remediate the coordinates of the orthomosaic image being different. For this methodology, the high-value pixels were given a value of 0.3 as a lower limit. In Figure 18, the distributions of the high-value pixels within the chosen segment of the canopy of all the flights in June were compiled. The goal here is to determine if the VARI can detect very fine changes and demonstrate the variance in the results of the VARI due to external factors when the canopy is almost fully grown. As there should be very little change in between flights, the VARI should stay relatively consistent in its identification of vigorous vegetation. However, Figure 18 shows that it is not the case, further demonstrating how the VARI is unreliable and inconsistent. In the June 4th flight, there is still some data corruption from the drone issue observed as the canopy grew, which explains why, in the next flight, there are so many more high-value pixels. However, that same explanation does not apply to the difference between the flights of the 6th of June and the 8th of June. The VARI detects fewer high-value pixels with only two days in-between even though the canopy should be the same. Then, the number of high-value pixels goes back up on the 11th of June to go back down again for the flight on the 13th of June. As it even further decreases in the flights of June 16th and 17th, it suddenly jumps up in the 20th of June images. Those changes in the high-value pixels of the canopy are caused by external factors as the canopy is nearly fully grown, and all flights were completed at a similar time (between 10 AM and 12 PM) and with similar light conditions. The one exception was the last one where the flight occurred at 1PM due to unfavourable morning weather. Such external factors are most likely the quantity and density of the shadows caused by the multi-level canopy and by the wind. When there is wind, the canopy is in constant movement, so it is always

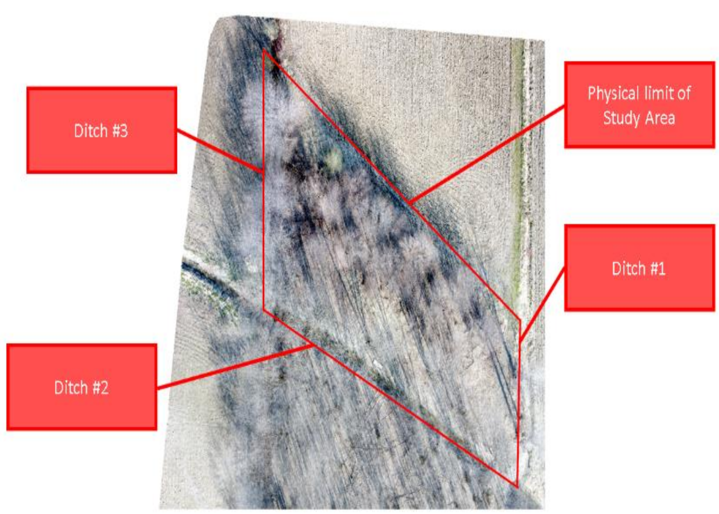

Figure 19: Overview of the segment created using the natural features of the study area.

slightly different when the drone captures it. That could explain why there is variance, but it is doubtful that it would cause such a significant variance between flights. To summarize the results on the VARI, the vegetation index has shown a poor ability to detect changes in the forest canopy over short periods. Only when the weather conditions and the sun's brightness are similar could the index detect subtle growth changes in the forest canopy. However, expecting similar conditions over a long period is unrealistic. The VARI was found to be inconsistent in its identification of vegetation in the short term, but it could identify changes in the canopy over a more extended period. The VARI is unreliable to identify vegetation when used because it is influenced by external factors such as snow, shadows, and wind. Using the VARI in combination with another vegetation index, which was also found to be the case in Jay et al. (2019) research would likely result in more accurate results.

Chapter 5: Conclusion

Combining a low-cost drone and a vegetation index limited to the visible light spectrum can be an excellent way to reduce research costs and perhaps increase efficiency. However, it would heavily depend on the size of the study area, the focus of the research, the time of data collection, and how they are utilized. Both have great benefits, but also have downsides in their usage.

5.1 Discussion and limitations of a low-cost drone

The DJI Mavic Mini, as a lightweight drone that costs less than a $1000 CAD and that is equipped with a simple high-definition camera without any additional lenses or sensors, was found to be an excellent tool for remote-sensing focused research. While its battery life might be a bit short and limited to flying in warm temperatures, it is easy to use and reliable. It captures images of superb quality with relative ease. However, depending on the study area, the GPS connection can fluctuate slightly, limiting the distance and altitude the drone can be from the pilot. Most of the problems experienced with this drone can be explained by the pilot's inexperience with flying drones and the fact that the flights were done manually. The drone's altitude had to increase as the canopy grew; otherwise, the orthomosaic images would experience data corruption, which was an unforeseen issue that drones of a higher caliber would likely not encounter. If possible, automatically flying the DJI Mavic Mini would perhaps solve these issues, but the software enabling automatic flying is an additional purchase and not from DJI themselves. Another issue encountered was that the GPS coordinates of each flight were different over time. While they were only slightly different, it was enough to alter the methodology of the MRP. This issue is not unfixable but needs to be considered, nonetheless. To answer the question asked at the start of this paper on whether a lightweight and low-cost drone is an adequate tool for monitoring canopy growth over a few months. This paper found that it is. However, multiple factors would affect the drone's ability to complete the task effectively, such as weather and temperature. In addition, the effectiveness of a lightweight drone can be reduced depending on the size and location of the study area, as those drones often have shorter battery life. Therefore, consumer-grade drones are effective for academic research in smaller study areas where calm, warm, and sunny weather prevails.

5.2 Discussion and limitations of the Visible Atmospherically Resistant Index

When it comes to the Visible Atmospherically Resistant Index, the question asked by this research pertained to its ability to detect subtle changes in forest canopy growth. The results found by this project are mixed, and this paper determined that the VARI is not an adequate vegetation index to use for fine observations of canopy growth. That said, the VARI showed good results at detecting large-scale changes over a long period, but not on small spatial and temporal scales. The only time the VARI adequately captured subtle changes in the canopy was when the weather and lighting conditions were near-identical at the moment of the flight. In other words, for the VARI to show good results at detecting more delicate changes on a small scale, the flights would have to be at the same hour of the day and in identical weather, which is unrealistic as the weather is constantly changing. The index showed significant variance in its results, in the range of its pixels' values and their averages. It does not return consistent results that could be used for a more nuanced examination of canopy growth. It was also easily affected by several external factors that could not be controlled, such as the density of clouds and shadows, the wind constantly moving the canopy, and snow in the images. Its reliance on the visible light spectrum was initially why it was chosen, but it was ultimately why it faced so many problems at recording fine changes in the forest canopy. For better results, the combination of the VARI with another vegetation index, such as the NDVI is recommended.

5.3 Future Research

The continuation of this research would allow for modifications of the methodologies and techniques employed in this paper. The three months of data collection was a learning experience that allowed for reflection on how the research could be improved, how the results could be possibly changed by altering the methods and what can be done to control for external factors that affected the results of this paper. First, automatically flying the drone instead of manually flying it would allow for a more consistent and accurate data collection of the canopy. Also, maintaining an altitude of 120 metres for all flights would avoid the issue of the growing canopy being inaccurately captured as it grows. Second, the orthomosaic images could be clipped to focus on the forest canopy prior to applying the VARI's calculations in order to eliminate the impacts of the surrounding fields. This could potentially make the results of the VARI more accurate at detecting the subtle changes in the canopy as it would be focused solely on it. The orthomosaic images could have been orthorectified as well to fix the slight difference in-between every flight. Third, the inclusion of another similar vegetation index such as the GLI or the addition of satellite data such as Sentinel-2 could be very interesting. The inclusion of other methods to the paper would allow for a validation method and would make for an effective comparison to the VARI's performance at capturing forest canopy growth. Satellite images could also assist in determining whether drone images are the better alternative. Finally, the inclusion of other indices would also allow for the optimal combination that would have the best results at detecting canopy changes while reducing research costs.

5.4 Concluding remarks

Combining the lightweight drone with the Visible Atmospherically Resistant Index as a potential research tool for forest canopy growth monitoring showed mixed results. The drone was efficient but limited to specific weather conditions. The VARI failed to detect fine changes in forest canopy and was often influenced by shadows, which requires all the data to be captured in similar weather at similar times to reduce shadow impacts on the overall analyses. The usage of drones weighing less than 250 grams and costing less than $1000 CAD is a good tool that could reduce research costs while maintaining the efficiency of research, while the VARI needs to be used in combination with another index to show satisfactory results.

References

DJI (2019). DJI Mavic Mini Specs. Retrieved 07-08-2021 from https://www.dji.com/ca/mavic-mini

Dronefly (2021). Dronefly NDVI/NDRE Cameras. Retrieved 12-08-2021 from https://www.dronefly.com/ndvi-ndve.html

Duffy, J. P., Pratt, L., Anderson, K., Land, P. E., & Shutler, J. D. (2018). Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone. *Estuarine, Coastal and Shelf Science*, *200*(Complete), 169–180. https://doi.org/10.1016/j.ecss.2017.11.001

Esri (2021). Core GIS Software pricing. Retrieved 29-08-2021 from https://www.esri.ca/en-ca/store/overview

Government of Quebec (2019). Open Forest. Retrieved 12-08-2021 from https://www.foretouverte.gouv.qc.ca/

Jay, S., Baret, F., Dutartre, D., Malatesta, G., Héno, S., Comar, A., Weiss, M., & Maupas, F. (2019). Exploiting the centimeter resolution of UAV multispectral imagery to improve remote-sensing estimates of canopy structure and biochemistry in sugar beet crops. *Remote Sensing of Environment, 231,* 110898. https://doi.org/10.1016/j.rse.2018.09.011

Kellaris, A., Gil, A., Faria, J., Amaral, R., Moreu-Badia, I., Neto, A., & Yesson, C. (2019). Using low-cost drones to monitor heterogeneous submerged seaweed habitats: A case study in the Azores. *Aquatic Conservation: Marine and Freshwater Ecosystems, 29*(11), 1909–1922. https://doi.org/10.1002/aqc.3189

Rokhmatuloh, M.N.A. & Hernina, R. (2020). UAV application to estimate oil palm trees health using visible atmospherically resistant index (VARI) (case study of Cikabayan research farm, Bogor City). *E3S Web of Conferences, 211,* 05001. https://doi.org/10.1051/e3sconf/202021105001

Sakamoto, T., Shibayama, M., Kimura, A., & Takada, E. (2011). Assessment of digital camera-derived vegetation indices in quantitative monitoring of seasonal rice growth. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*(6), 872-882. https://doi.org/10.1016/j.isprsjprs.2011.08.005

Soon Eng, L., Ismail, R., Hashim, W., Baharum, A.

(2019). The use of VARI, GLI and VIGreen formulas in detecting vegetation in aerial images. *International Journal of Technology* 10(7): 1385-1394. DOI:10.14716/ijtech.v10i7.3275

Stow, D., Niphadkar, M., & Kaiser, J. (2005). MODIS-derived visible atmospherically resistant index for monitoring chaparral moisture content. *International Journal of Remote Sensing, 26*(17), 3867-3873. https://doi.org/10.1080/01431160500185342

Tang, L. & Shao, G. Drone remote sensing for forestry research and practices. *J. For. Res.* 26, 791–797 (2015). https://doi-org.ezproxy.lib.ryerson.ca/10.1007/s11676-015-0088-y

Transport Canada (2020). Flying your drone safely and legally. Retrieved 08-07-2021 from https://tc.canada.ca/en/aviation/drone-safety/learn-rules-you-fly-your-drone/flying-your-drone-safely-legally

Ventura, D., Bruno, M., Lasinio, J., G., Belluscio, A., & Ardizzone, G. (2016). A low-cost drone based application for identifying and mapping of coastal fish nursery grounds. *Estuarine, Coastal and Shelf Science*, *171*(Complete), 85–98. https://doi.org/10.1016/j.ecss.2016.01.030

Zhang, J., Virk, S., Porter, W., Kenworthy, K., Sullivan, D., & Schwartz, B. (2019). Applications of unmanned aerial vehicle based imagery in turfgrass field trials. *Frontiers in Plant Science, 10*, 279.