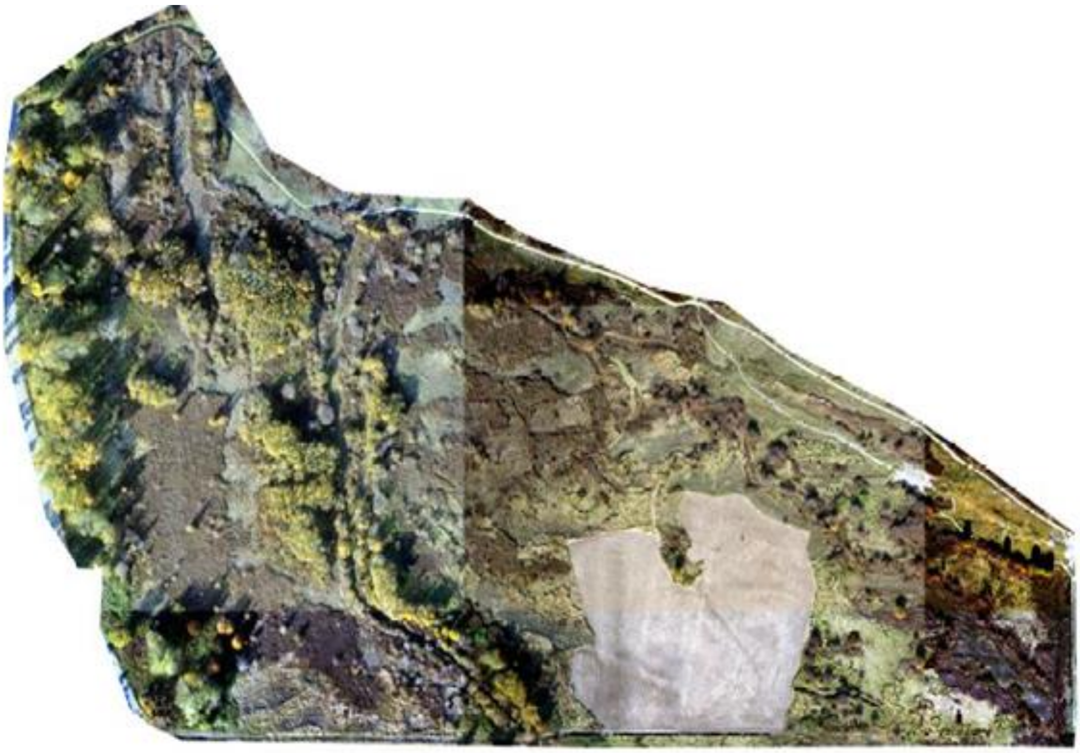
Spectabilis Solutions

Field Verification of Invasive Vegetation Identification Through Remote Sensing and UAV Technology

Ali Bryant

Torin Kelly

Gwynifyre Taylor



Executive Summary

To determine the feasibility of replacing time-consuming large area ground surveys of invasive plant species populations with more time and cost-effective methods, we investigated the use of remote sensing technologies such as satellite imagery and drone imagery. To identify the invasive species quickly and accurately, we trained a computer classification system to locate and classify the species of interest. Our research was conducted in Boundary Bay Regional Park, in South Delta, BC. The park is an important Bird Area in BC with a diverse population of birds and mammals.

Our approach was to focus on the two most prolific invasive species in the park, those being *Rubus armeniacus,* and *Phalaris arundinacea.* With financial support from BCIT and Metro Vancouver we hired Nathan Vadeboncoeur of Smart Shores to fly his DJI Phantom 4 Pro drone over 30 hectares of the 140 hectare park. This flown area became our training and validation site for the study. Nathan Vadeboncoeur created orthophotos from the drone imagery that we used for manual interpretation of the site.

We created the training data for the supervised classification software using a targeted survey approach of Boundary Bay Park. We made 455 10m^2 plots using a Geoexplorer 6000. Each plot had only one species present, either Himalayan blackberry or reed canary grass, to satisfy the 100% homogeneity requirement for training purposes. We collected 240 training sites for Himalayan blackberry and 215 sites for reed canary grass.

The supervised classification program we used was maximum likelihood within the Esri ArcMap application. To run the supervised classification program, we used the 455 training sites to train the program. We used the 2015 WorldView-2 satellite captured imagery. The satellite imagery is global high-resolution imagery with a 50cm pixel size.

We tested the accuracy of the supervised classification program in a variety of ways to capture the variable performance of the program operating within different parameters. We had two different ways to perform ground surveys and four different ways to run the supervised classification, so we had eight ways to analyze the results. We found that the accuracy of the identification of blackberry cover class was higher with first and second classification types and the accuracy of the identification of reed canary grass was higher with the third and fourth classification types. This trend is seen for both ground survey types.

The highest accuracy was achieved for both species simultaneously by using the sub-set of training sites for the ground survey types and the second type of supervised classification. The accuracy was 90% for both blackberry and reed canary grass. This was because the training sites captured the variation in spectral signatures of the plants and more classes were supplied. When enough categories for classes are supplied for the supervised classification, the accuracy of classifier increases. An accuracy varied between 33% and 47% for the randomly generated verification points. This is fairly low due to the high number of other vegetation types that were not given training data. The computer was able to achieve a higher accuracy with more classes of ground types. To increase accuracy, we recommend thorough reconnaissance of the training area to create multiple ground cover classes for the supervised classification system to analyze.

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Introduction

Managing invasive plant populations is a significant concern for Metro Vancouver Parks (Page, 2006). Exotic invasive plant species disrupt the biodiversity and structure of our native ecosystems and can be found in nearly every park in the Metro Vancouver area. The spread of invasive plants is an issue being given priorities by Metro Vancouver. As the spread of these population increase, so does the cost of managing our parks and greenways. The need for comprehensive inventories is increasing. To be able to keep up with the rate of invasive plant spread as urbanization expansion continues, these inventories require efficient means of mapping the location and extent of the invasions.

The large areas covered and dispersed nature of invasive species make ground-based surveys too labour intensive and unviable as a long term effective management strategy for municipalities (Blumenthal et al. 2007). Progress in remote sensing technology paired with computer algorithm classifications have made it possible to test the abilities of these new technologies and assess their accuracy for species identification (Husson et al. 2014). Images from remote sensing technologies such as satellites, small aircraft, and Unmanned Aerial Vehicles (UAV) are the newest tools to accomplish invasive species identification across large areas and specific ecological areas, such as riparian and lacustrine areas (Cuneo et al. 2009; Miches et al. 2015).

Using supervised classification systems, the resources it takes to analyze aerial images is decreasing, and with the increased availability of satellite images this approach to invasive species management is a viable method for municipalities (Schmedmann et al. 2015).

Supervised classification is a computer algorithm that will group the pixels of an image into a category created by the user. The types of categories, for example, plant species or cover type, are defined by the scope of the project and the research question. Conventionally, aerial images were classified by the human eye and people labeled maps with areas of presence/not-detected, percent vegetation cover class, or species composition (Hung et al. 2014). With this conventional method data can be inconsistent, as it relies upon the ability of each researcher to correctly identify 100% of the extent of the plant communities from aerial imagery. The conventional method is also time consuming, whereas supervised classification programs, once trained, can efficiently locate the extents of the communities.

There are several types of supervised classification systems and the objective of the study usually informs which system is used. The table below discusses the most frequently used classification systems.

Table 1. Common Supervised Classification Systems and Their Applications.

Classification Type	**Description**	**Application**
Maximum Likelihood	Used when the spectral signature of each desired classification group can maximize the statistically significant means between groups and minimize the variation within the group.	Used when the subjects in the image are varied, for instance, between leaves of different plant species or between urban and rural areas. (Cuneo et al. 2009)
Parcel-Based	Uses nearest neighbour to take an average of the reflectance value of a group of pixels and assigns a class to an area, making a parcel.	Used in agriculture to classify crop species and monitor crop health and yields. Best used when the desired output is maps of like areas grouped together. (Schmedmann et al. 2015)
Feature-Based	Identifies plant species by using a series of image filters placed over each other to reveal the pixels that have similar values to each other, and those pixels are place into a feature class.	Desired application is when the objects being classified have a distinct shape or texture such as roofs and driveways of residential neighbourhoods. (Hung et al. 2014)
Rule-Based	Takes the value of each pixel and, using the rules defined by the user in a manner similar to a flow chart or a decision tree, runs it through the rule process and outputs the class of that pixel.	Best used when the spectral signatures of the images are close to one another and small details can be brought out through the rulemaking process. An example is classifying canopy types of similar conifer stands. (Miches et al. 2015)

One type of supervised classification uses maximum likelihood, where each pixel is given a probability of belonging to a class based on the reflectance value of the pixel (Cuneo et al. 2009). Parcel-based classification uses nearest neighbour to take an average of the reflectance value of a group of pixels and assigns a class to an area, making a parcel (Schmedmann et al. 2015). Feature-based classification identifies plant species by using a series of image filters placed over each other to reveal the pixels that have similar values to each other, and those pixels are place into a feature class (Hung et al. 2014). Rule-based classification takes the value of each pixel and, using the rules defined by the user in a manner similar to a flow chart or a decision tree, runs it through the rule process and outputs the class of that pixel (Miches et al. 2015). This type of supervised classification is similar to decision tree data processing and the random forest statistical classifier (Cutler et al. 2007). Random forest has been proven useful at statistical classification in other fields, and it is starting to be used in ecology with success.

As technology advances, the accuracy of classification systems is becoming more refined and the cost is becoming reasonable for municipalities to utilize (Husson et al. 2014). Satellite imagery is now readily available but requires verification of the classification process. Traditionally, verification was carried out by ground surveys, however, there is a recent push for UAV flights to replace groundtruthing activities to save time, risk, and labour costs (Metro Van 2017). The use of UAV is especially advantageous when attempting to map areas of limited accessibility. It is important to know if the quality of the UAV imagery from low altitude UAV images are reliable enough to function as a viable ground survey replacement. Used in conjunction with classified satellite imagery we believe time on the ground can be reduced, and the utilization of remote sensing can be expanded. This is the main focus of our project.

Vegetation inventories have been conducted at Boundary Bay Regional Park in the past. A BCIT student group of the Fish, Wildlife, and Recreation (FWR) program completed a project titled "*Invasive Plant Mapping at Boundary Bay Regional Park*" (Hoffman et al. 2016). This project examined the extent of four invasive species, Himalayan blackberry (*Rubus armeniacus*), reed canary grass (*Phalaris arundinacea*), spurge-laurel (*Daphne laureola*), and Scotch broom (*Cytisus scoparius*). The team added their findings to a previous inventory collected by Diamond Head Consulting for Metro Vancouver, to note the changes in total area covered by invasive species within the park.

The FWR team surveyed the park using a Global Navigation Satellite System (GNSS) for stripline ground surveys that covered 100% of the park area. All data collected was processed and configured as shapefiles and georeferenced PDF maps of the infested areas were produced. To conduct ground surveys of the area in its entirety took the three FWR students 14 field days, and a cumulative 269 person-hours to complete 113 hectares (Hoffman et. al 2016). One of the outcomes of our study is to determine whether using the UAV technology will provide a more cost-effective, accessible, and repeatable approach for inventories over large areas.

We are interested in taking the experience of the three FWR students and making the process of collecting a plant community inventory of an area more streamlined. The time that it took the students to do a strip line survey that covered the entire area of the park was too laborious for most companies of municipalities. Doing a quick flight with a UAV at low altitude and recording high-resolution images to capture the plant communities present in the park to replace ground surveys is a pertinent research question worth exploring. It would be beneficial for municipalities to be able to perform less detailed examinations of large areas without time-consuming ground surveys to assist in their high-level planning and budgeting. For these reasons, we are exploring how to use satellite and UAV imagery to reduce to person-hours it takes to perform ground surveys.

Goal and Objectives

Our goal is to examine the feasibility and accuracy of replacing ground surveys of invasive species with aerial images captured by multispectral satellites and unmanned aircraft vehicles (UAV) at Boundary Bay Regional Park.

Our objectives are to:

1. Identify and map location of communities of two invasive plants (*Rubus armeniacus and Phalaris arundinacea*) within our 30ha study area in Boundary Bay Regional Park using WorldView-2 satellite imagery and a Phantom 4 Pro UAV imagery.

2. Assist Nathan Vadeboncoeur of Smart Shores in identifying training sites of the two invasive plants from the high-resolution UAV imagery collected by Nathan within the study area.
3. Run a supervised classification in ArcMap applications of the satellite images using the training sites to identify the species.
4. Assess the accuracy of UAV vs. satellite image classification of *Rubus armeniacus and Phalaris arundinacea* using a series of ground-truthed points.
5. Develop a workflow and guidelines for mapping invasive plants using remote sensing technology in Metro Vancouver Regional Parks.

Study Area

Boundary Bay Regional Park (BBRP) is located on Tsawwassen First Nation (Səwaθn Məsteyəxʷ) land in the Tsawwassen community of south Delta, within the Lower Mainland of British Columbia. The park is situated on the western side of Boundary Bay near the border of the United States. The total area of the park measures approximately 140 hectares in total.

The area is recognized as an Important Bird Area for the Pacific Flyway migration route, with 1.5 million birds of over 225 species using the area each year (Metro Van. 2017). The park is a popular recreational destination with walking trails, boardwalks, beach access, and plenty of bird watching.

The park is within the Moist Maritime Coastal Douglas-fir (CDFmm) Biogeoclimatic Ecosystem Classification (BEC) subzone. This subzone typically experiences dry and sunny summers and mild rainy winters. This subzone is located only on the south coast of B.C. The park has little elevation change, ranging between 2 to 6 meters above sea level.

An inventory of the park's native and invasive species was compiled by Diamond Head Consulting in 2008. Their inventory found the dominant native vegetation to be composed of the following:

red alder (*Alnus rubra*);
black cottonwood (*Populus balsamifera ssp. trichocarpa*);
paper birch (*Betula papyrifera*);
Pacific crab apple (*Malus fusca*);
hardhack (*Spiraea douglasii ssp. Douglasii*);
indian-plum *(Oemleria cerasiformis*);
common rush (*Juncus effusus*);
seashore saltgrass (*Distichlis spicata var. spicata*);
common cattail (*Typha latifolia*).

The dominant invasive vegetation recorded in the inventory were:

Himalayan blackberry *(Rubus armeniacus*);
reed canarygrass (*Phalaris arundinacea*);
purple loosestrife (*Lythrum salicaria*);
spurge-laurel (*Daphne laureola*);
Scotch broom (*Cytisus scoparius*);

cordgrass (*Spartina sp.*);
English holly (*Ilex aquifolium*)

The area flown by Nathan Vadeboncoeur that will be used for the training sites encompasses 30 hectares of BBRP (Figure 1). The study area includes training and validation points.

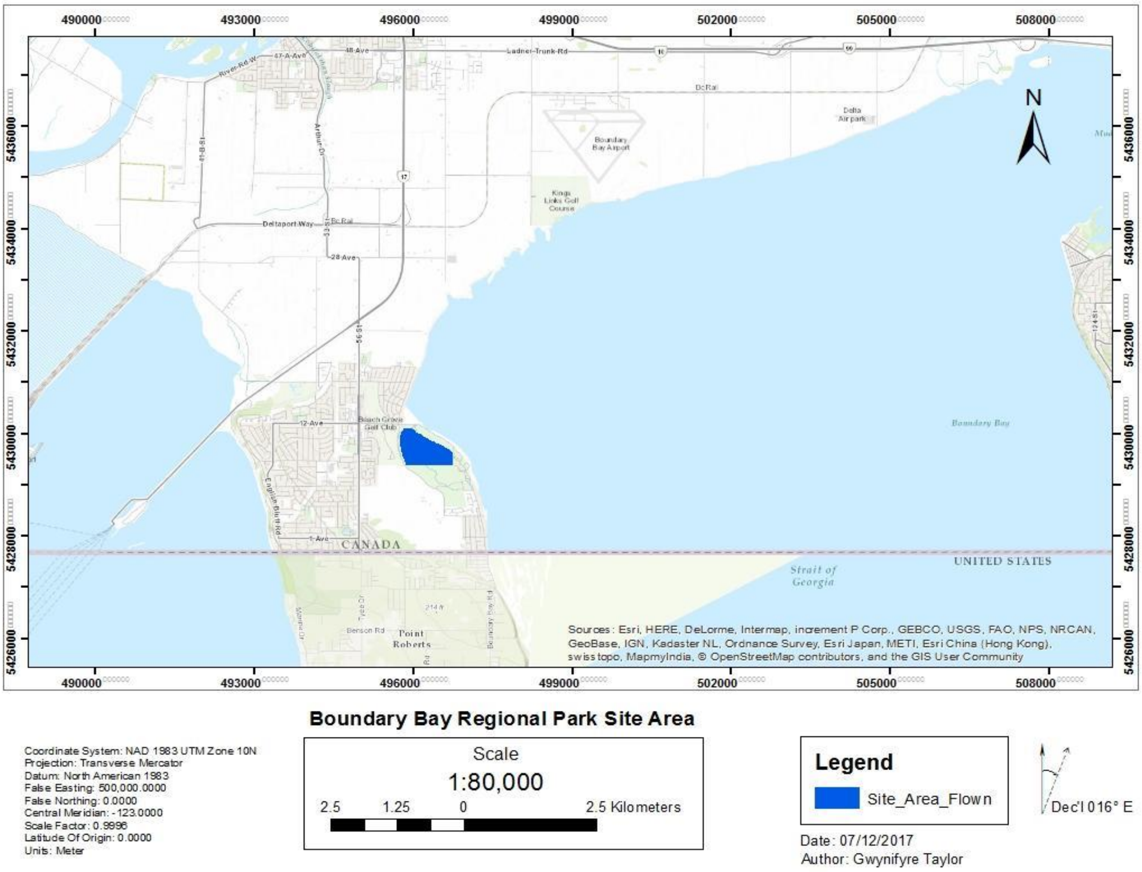

Figure 1. Location of study area within Boundary Bay Regional Park.

BBRP trails are highlighted in green, and the area flown by Nathan in red (Figure 2). The flown area encompasses trail segments, training sites were not taken on the trails. The 30 hectares outlined in red is the location of our species identification training and validation sites.

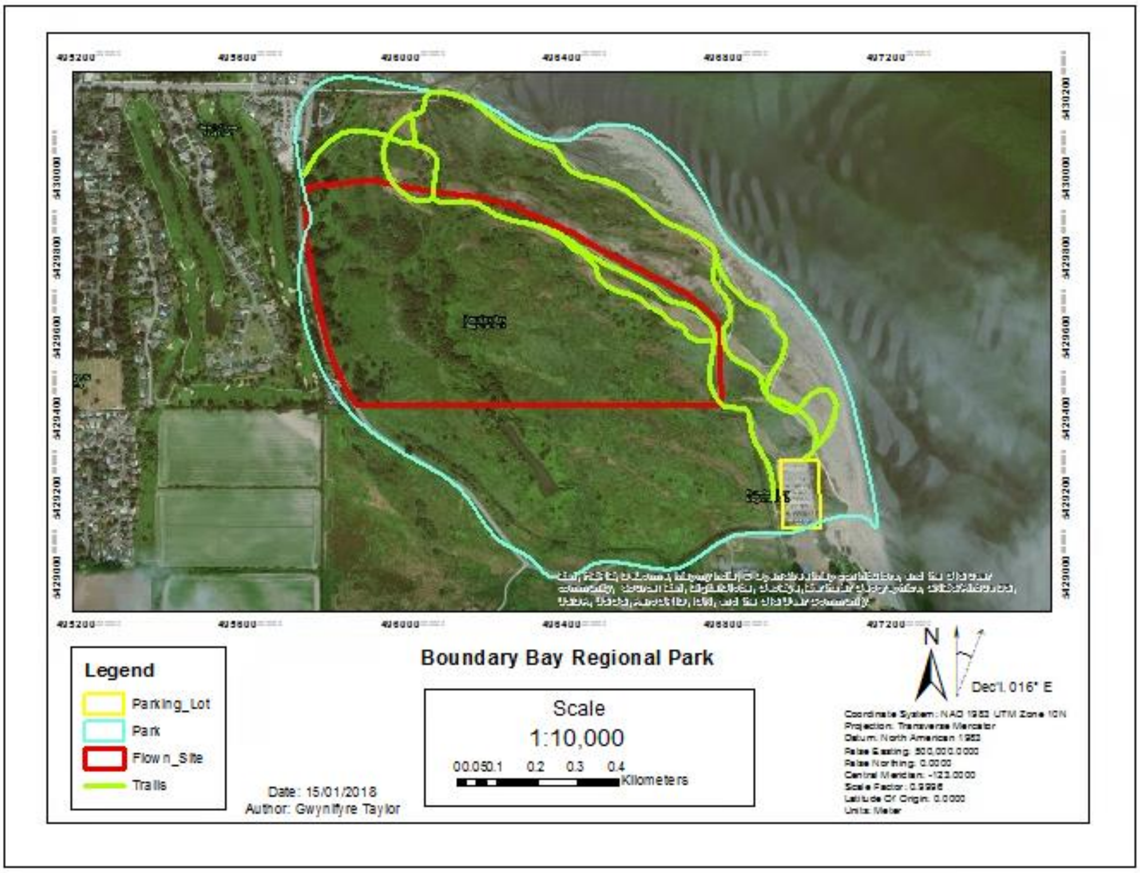

Figure 2. Location of trails, flown site, and park boundary.

Methods

Our method for performing supervised classification in this project had four phases. Phase one was to perform a reconnaissance or information gathering of the site. Phase two was to design and collect information from the site that we used to train the classification program. Phase three was running the classification program, and phase four was to analyze the results. We created a work-flow diagram to summarize our process and so that others could replicate our work. This diagram can be found in appendix D.

In phase one we performed a recce and gathered information about the site. We read the previous report done by the FWR students and the report published by Diamondhead Consulting. We noted where each of these documents reported Himalayan blackberry and reed canary grass to be growing in the past. We viewed the satellite images from Google Earth (https://earth.google.com/web/) and compared them to what we found in the reports. An interesting feature on this software is that you can view older images of the same area in quick succession. We used this feature to track how the blackberry and reed canary grass has spread over time to anticipate where we would find it on site. We performed a site visit on our first field day to confirm our findings from the previous reports, to assess how accurate the Google Earth images were, and to collect information about the plant ecology on site. We recorded the types of plants growing next our target species, how open the tree canopies were, and instances where blackberry and reed canary grass could be confirmed to be growing. We brought our GPS equipment with us to test how many satellites we were receiving and the positional accuracy we could achieve on site. The GPS unit we used was the GeoExplorer 6000. The GNSS setting we used to gather our data can be found in table 2 below.

Table 2. GeoExplorer 6000 GNSS settings.

Setting	Value
Datum	NAD 1983
Projected Coordinate System	UTM Zone 10 N
PDOP	3
HDOP	3
SNR	41/42
Elevation Mask	15

In Phase two, we collected the training data to use for the supervised classification program. This is where we divided the process into two streams; one using more conventional methods of data gathering by going to the field with the GPS unit, and the other using manual interpretation of the high-resolution UAV images. For the on-site ground collection of GPS points, hereto forth called training sites, we determined that we were going to sample 1% of our site because that is the convention generally accepted by other professionals working with supervised classification (Husson et al. 2014). Our study site area was approximately 30ha so 1% of that area is 3,000m^2. We determined that circular plots of 10m^2 would be sufficient to train the program based on Schmedmann et al. (2015) and that this could be easily performed within the ESRI ArcMap program. We needed a minimum of 300 training sites. Each site had to have and area of 10m^2 where the entire area was only comprised of one of our target species. Before heading to the field, we used the information gathered in our research and our recce to direct us to the areas that is would be likely that we would find instances of blackberry and reed canary grass that met the 10m^2 of one species criteria.

Once on the ground, we found a point, used a plot cord with a radius of 1.78m to check that the point fell completely within a patch of blackberry or reed canary grass. If the point met the specifications, we recorded it in the GPS unit along with which species that point represented. We collected 240 points for blackberry and 215 points for reed canary grass for a total of 455 training sites over two field days. We collected more than the minimum required amount of points because we wanted to make sure that we had enough points should it be discovered back in the lab that some points were not accurate enough to train the classifier. We disregarded a few points because they fell in the shade of a tree or a shrub. In order to ensure the positional accuracy of our training points, we post processed the GPS data once we left the field. All of the data that was collected on the GeoExplorer 6000 was processed using TerraSync software and had to be transferred through a software portal called “Windows Mobile Device Center”. See appendix A for a full breakdown of the process of transferring the data. All our data was post-processed in pathfinder office using the closest base station available, which was Metro Vancouver’s Lulu Island Base station. The Lulu Island Base station was located approximately 22km north of our site.

To create training sites from the UAV images we used manual interpretation. While viewing the high-resolution images on the computer screen, we used our knowledge of the site, the maps generated by previous projects, and the satellite images to identify our target species. We used the same criteria that each point had to only contain one species of interest. Instead of creating $10m^2$ circles, we drew polygons that appeared to encompass the entire patch of either blackberry or reed canary grass. Again, we recorded the species of each polygon in order to use them to train the supervised classification program. The fantastic high-resolution and spatial accuracy of the UAV images allowed us to easily see the patches of our target species on site and the margins of each instance were clearly visible even though the patches were of different size, shapes, and textures in the image. We used this interpretation of the UAV images to replicate these patches with the polygons on the satellite imagery. Once we had our two sets of training sites, the $10m^2$ circular GPS points and the manually interpreted polygons, we were able to move on to Phase three; performing the supervised classification.

In phase three, we uploaded both sets of training sites into ArcMap to perform the maximum likelihood supervised classification on the 2015 WorldView-2 satellite captured imagery. To increase the accuracy of the results and to confirm what we found in the literature (Schmedmann et al. 2015), we decided to vary the number of classes to give the supervised classification program. First, we assigned it only two classes: blackberry and reed canary grass. Second, we assigned it five classes: blackberry, reed canary grass, trees, ground, and water. Given that we had two sets of training sites and two sets of classes, we ran four types of supervised classification. For clarity, we named them: Training Sites Only, Training Sites + Land Cover, Polygons, and Polygons + Land Cover. A summary of the four classification types can be found in table 3 below.

Table 3. The four types of supervised classification with classes.

	Supervised Classification Type	Process
No Manual Interpretation	Training Sites Only	$10m^2$ Circular plots Blackberry + reed canary grass
	Training Sites + Land Cover	Training sites + additional classes for trees, water, and ground
Manual Interpretation	Polygons	Polygons with 100% species composition
	Polygons + Land Cover	Polygons + additional classes for trees, water, and ground

When the supervised classification was finished, it produced an image where every pixel in the image was classified. This type of image can be used to make maps by adding grids, coordinates, a north arrow, etc. and issued to municipality staff for use. Figure 4 is an image of the four classifications in ArcMap.

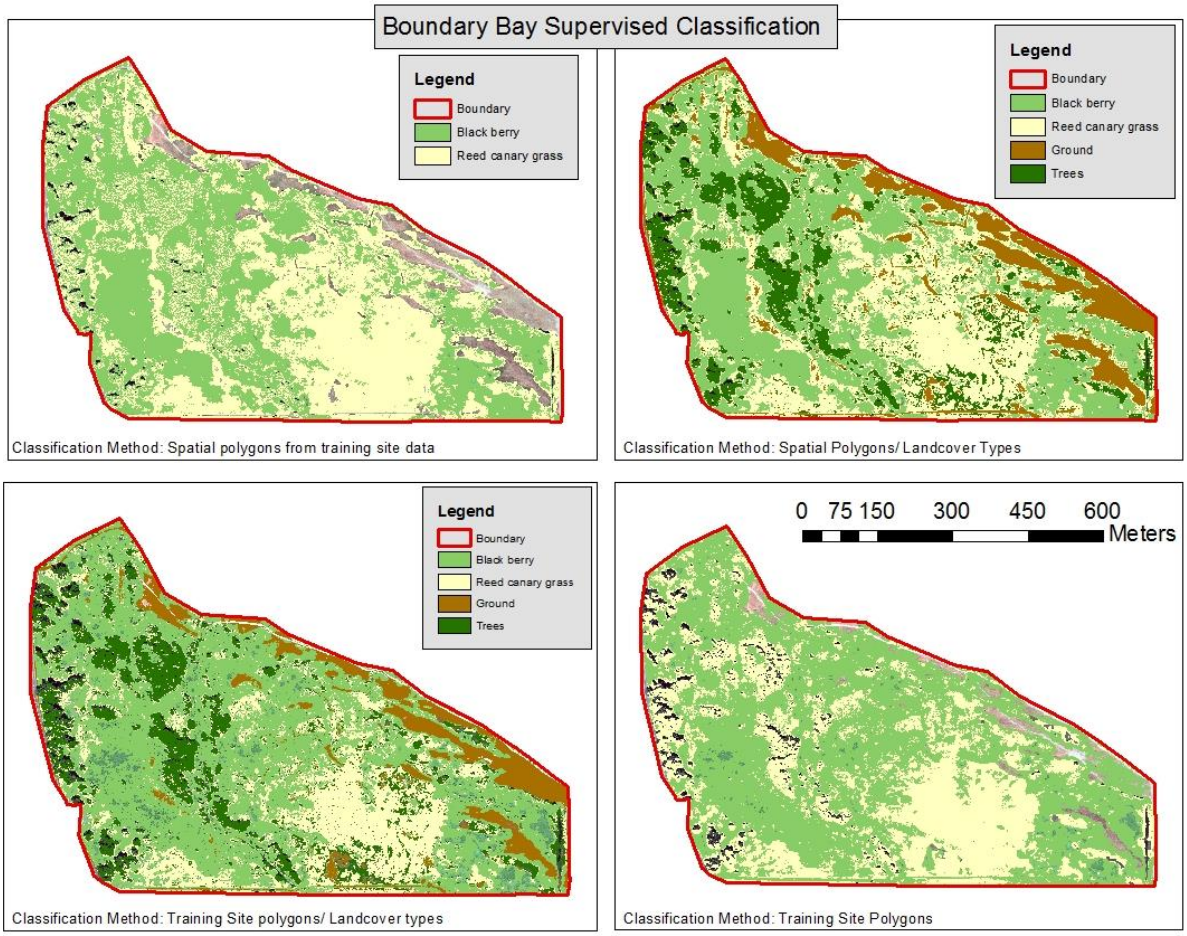

Figure 3. Four classification method outputs

In phase four, we determined the accuracy of the four types of supervised classification. We used two types of surveys to assess the accuracy. The first survey was to randomly select a sub-set of the $10m^2$ circular plots that were used as training points. We randomly selected 30 out of the 240 blackberry points and 30 out of the 215 reed canary grass points. To do this unbiased, we assigned the numbers 1 through 455 to all the training sites and used a random number generator to select the 30 from each species. Once we had the points, we located it on the classified image, and recorded what class it was put in, recording if it was classified correctly or not. We recorded the results in a table.

The second type of survey we performed was to randomly generate points within our study site. We used ArcMap to randomly generate 100 points. Splitting the study area into three, we designed a route on each third for each of us to navigate to our points on the ground. These images were uploaded to Avenza PDF maps on our smart phones, with which we navigated to each accessible point on the map and recorded what class it was present on the ground. We ended up collecting data for 76 points because some points were inaccessible due to thick vegetation or water ways. In the lab we overlaid the randomly generated points on the classified image and recorded what the supervised classification had classified each point as. We compared this to what we found on the ground on site and recorded the results in a table. With two complete data tables for the two survey types, we could analyze the accuracy of the supervised classification program.

We used confusion matrices to calculate the percentage of accuracy for each of the four types of classification and for both survey types. Given that we had four classification types and two ground survey types, we produced eight confusion matrices. They can be found in table 4. Each plot was classified by the ground survey and the imagery classification and placed on the matrix under the species it was identified as. The number in each cell was the number of plots that fall into that category. When there was agreement between the two classification systems it formed a diagonal line from which we calculated the percent accuracy of the classification system.

Results

The general results of our confusion matrices were that the sub-set of training sites had a higher accuracy than the randomly generated points. It is evident from the results that the randomly generated points type of accuracy survey did not lead to very high accuracies. The over-all accuracy ranged from 33% to 47%. But if you isolate the accuracy of each of the target species on each classifier, the results improve and can be as high as 73% for blackberry using the Training Sites and Training Sites + Land Cover classifiers and 75% for reed canary grass using the Polygons and Polygons + Land Cover classifiers.

Table 4. Confusion matrices results for randomly generated points and sub-set of training sites surveys for each classification type.

Randomly Generated Points

Training Only					Accuracy
	BB	RCG	O	Total	
BB	11	4	28	43	73%
RGC	4	6	8	18	50%
O	0	2	13	15	27%
Total	15	12	49	76	39%

Land Cover Types					Accuracy
	BB	RCG	O	Total	
BB	11	4	27	42	73%
RCG	3	6	3	12	50%
O	1	2	19	22	39%
Total	15	12	49	76	47%

Spatial Polygons					Accuracy
	BB	RCG	O	Total	
BB	8	2	32	42	53%
RCG	6	9	9	24	75%
O	1	1	8	10	16%
Total	15	12	49	76	33%

Spatial Polygons + Land Cover					Accuracy
	BB	RCG	O	Total	
BB	8	2	27	37	53%
RCG	3	9	5	17	75%
O	4	1	17	22	35%
Total	15	12	49	76	45%

Sub-set of Training Sites

Training only				Accuracy
	BB	RCG	Total	
BB	27	4	31	90%
RCG	3	26	29	87%
Total	30	30	60	88%

Land Cover Types				Accuracy
	BB	RCG	Total	
BB	27	3	30	90%
RCG	3	27	30	90%
Total	30	30	60	90%

Spatial Polygons				Accuracy
	BB	RCG	Total	
BB	24	3	27	80%
RCG	6	27	33	90%
Total	30	30	60	85%

Spatial Polygons + Land Cover				Accuracy
	BB	RCG	Total	
BB	25	4	29	83%
RCG	5	26	31	87%
Total	30	30	60	85%

The same results from the confusion matrices can be seen in the bar graphs below, figure 4 and figure 5. In these graphs it can be seen that to get the best results for both blackberry and reed canary grass, you want to use the Land Cover Types classifier with the sub-set of training sites used as the accuracy survey type. Both blackberry and reed canary grass were identified with a 90% accuracy when this combination of classifies and accuracy survey type was used.

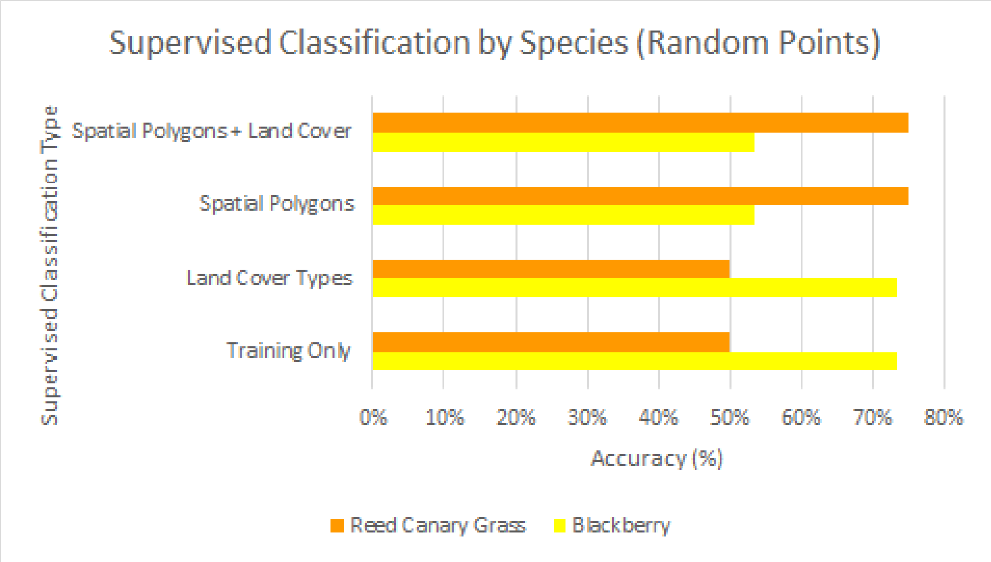

Figure 4. Accuracy of the supervised classification from random generated points.

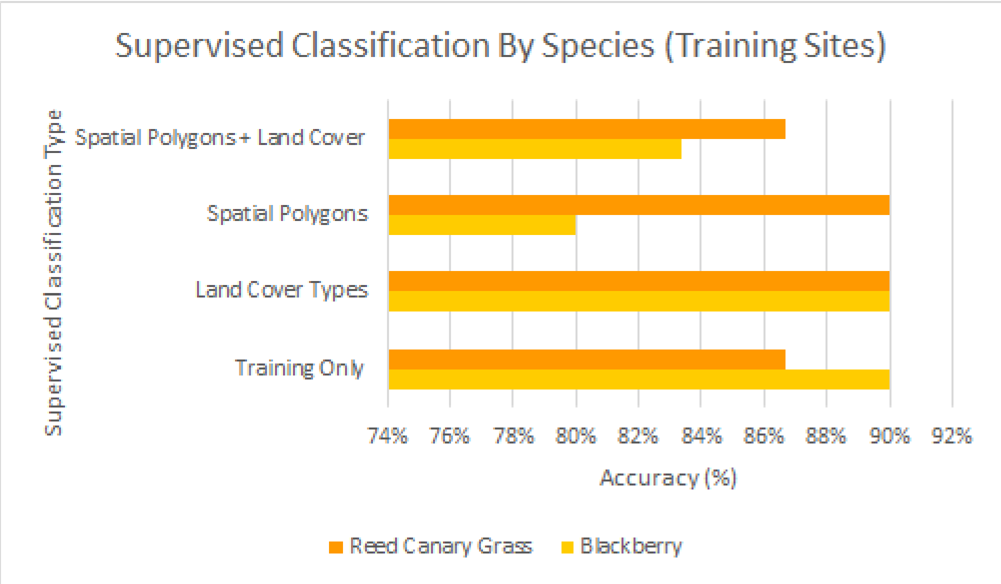

Figure 5. Accuracy of the supervised classification from subset of training sites.

Statistical Analysis

Research Question: χ^2 Test of Homogeneity

Our research question was to find out what percent of the plots were correctly identified by the supervised classification when compared to the ground survey. We claim that there is no difference between the ground survey classification and the supervised classification. The null and alternative hypotheses are:

H_0: The percentage of plots that are correctly identified is the same for both species.

H_A: The percentage of plots that are correctly identified is not the same for both species.

Data Collection: χ^2 Test of Homogeneity

The predictor variable was the species and the response variable was the correct identification of plant species. We collected the data in the field in a table similar to below:

Plot Number	Ground Survey	Satellite Image
1	Blackberry	Blackberry
2	Blackberry	Blackberry
3	Other	Blackberry
4	Reed canary grass	Reed canary grass
5	Reed canary grass	Reed canary grass

Figure 6. Field data collection table.

In this table, we recorded the plot number and the species of each plot during the ground survey. We added what species each plot was classified as into the table. We checked that the expected frequency was at least 5. We used RStudio to calculate the p-value. We used the industry standard of $\alpha = 0.05$. The RStudio output can be seen below in figure 7.

```
       classification
ground BB  O RCG
   BB  25  3   2
   RCG  1  3  26
> xchisq.test(x)

        Pearson's Chi-squared test

data:  x
X-squared = 42.725, df = 2, p-value = 5.276e-10

   25         3        2
(13.00)  ( 3.00)  (14.00)
[11.08]  [ 0.00]  [10.29]
< 3.33>  < 0.00>  <-3.21>

    1         3       26
(13.00)  ( 3.00)  (14.00)
[11.08]  [ 0.00]  [10.29]
<-3.33>  < 0.00>  < 3.21>

key:
        observed
        (expected)
        [contribution to X-squared]
        <Pearson residual>
```

Figure 7. RStudio output.

Results: χ^2 Test of Homogeneity

Since the p-value < α, we reject the null hypothesis. At of α = 0.05, the evidence is not strong enough to support the claim that the percentage of plots that are correctly identified was the same for both species.

Discussion

As noted above, the lower accuracy of the randomly generated points can be seen in the confusion matrices and the bar graphs. We believe that the supervised classification program did not perform well because 63% of the randomly generated points fell onto ground that was neither blackberry nor reed canary grass. Since the classifiers were trained using training sites of only blackberry and reed canary grass, it seems unlikely that it would be able to classify anything other than the content of the training sites with any accuracy. There were no training sites that covered the other vegetation communities that were present on the site so it stands to reason that the classifier would not be able to recognize them.

Himalayan blackberry received the highest accuracy at identification when using the Training Sites and Training Sites + Land Cover classifiers. This is most likely due to the fact that the 10m2 circular plots captured the variability of the spectral signature of the blackberry plant. The way that blackberry grows lends itself to be quite consistent in its composition within a small area. Also, the way we gathered the training points for blackberry may have led to a high accuracy of classification when using only the training points. Large blackberry patches can be very dense and proved to be difficult to penetrate very far into. As a result, the training sites for blackberry were around the perimeter of large patches. When taken as one group, the training sites formed an outline of the patches and we created large areas where it would be easy for the classifier to fill in the missing points in between the training sites.

The accuracy for reed canary grass was highest when using the Polygon and Polygon + Land Cover classifiers. This has to do with the way that reed canary grass grows. It grows in large patches that out-compete most every other plant. The 10m2 training sites were not large enough to capture the amount of variation within a patch of reed canary grass. It also tends to have very clean margins and stops growing abruptly. This attribute allowed us to accurately outline the polygons of reed canary grass on the high-resolution UAV images leading to a better training site and more consistent species composition within the training site. The opposite if true for blackberry. It tends to grow by sending out tendrils and has indistinct margins thus making drawing polygons around the edges difficult and introducing extra plants into the training site that should not be there.

The quality of the training sites that you feed into the classification program has a significant influence on the accuracy of the classifier. If your training sites are not purely of one species, or if they overlap with tree canopies, the accuracy of the classifier will be reduced. If you spend the time to collect training sites that are homogeneous in composition and do not have any interference with over-head obstacles, the quality of your results will show it. A supervised classifier is only as good as the person training the program. The program does not think for itself and will only classify objects in the ways that you give it to classify them.

To increase the accuracy of our randomly generated point ground survey, we could supply the classifier with additional cover classes. We only collected training sites for blackberry and reed canary grass. There were many other plants on site but the classifier only had those two classes to put them into, so it did a poor job at classifying anything other than blackberry or reed canary grass. For instance, a large portion of the site was covered with hardhack (*Spiraea douglasii*), and the classifier could not distinguish it from blackberry, so it was all labeled blackberry. To improve on this, next time we should collect training sites to reflect the complete plant community present on site and collect extra training sites for species that are close in their spectral signatures, such as hardhack and blackberry. It would also be beneficial to collect training sites for all the cover types, including abiotic types such as roads and buildings found on site, in addition to the types of vegetation communities.

It will be advantageous to use this type of technology in the future as satellite images and the use of UAV use become more prevalent. Satellite images can cover large areas of parks and municipal land. The price of satellite imagery is becoming more affordable, making it well within the means of a management board to purchase a few images to cover their area. Given the fact that we collected our training sites in two days, the potential for someone to analyze their satellite images quickly and accurately is high. When compared to the amount of time and effort the FWR students dedicated to their project, the advantages of using remote sensing and supervised classification systems seems evident. When combined with UAV high-resolution imagery, there is positive potential for this type of remote sensing survey for municipalities to save time and money in invasive species management.

Conclusion

In conclusion, we achieved our goal of examining the feasibility of using supervised classification of satellite images in conjunction with UAV aerial photos to analyze the plant species composition of Boundary Bay Regional Park. We achieved all five objectives to locate reed canary grass and Himalayan blackberry, utilize UAV imagery to manually interpret reed canary grass and blackberry, run the supervised classification program on the satellite images, analyze the accuracy, and develop a work flow. We found that the best classifier result was the one with the most classes, and the highest accuracy was achieved using ground survey verification based on a sub-set of training sites. We learned that we need to have classes that reflect the variety of objects on the ground and enough training sites to capture the variety in the plant communities.

Recommendations

1. **Collect data for all cover classes found on-site**

   A supervised classification program can only put data into the types of classes that it is given. For the best results when using the program, it is best to include training data to every surface that will be present in the image that is being classifies. Include classes for objects such as gravel trails, dirt paths, gravel roads, paved roads, buildings, and other infrastructure. Garbage cans, park benches, cars and other machinery, light and utility poles, and other such objects should also be given a class. Examine the site closely to discover how many cover classes you might need to classify your area accurately.

2. **Record data for the variety of vegetation communities**

   To the human eye, plants vary in size, shape, texture, and colour which make identifying them possible. To a supervised classification program, the variation between different plants is much harder to detect. For an accurate analysis of your satellite images, a classifier needs training sites that capture the variation within a single plant species as well as the difference between species. It is important to capture a complete picture of the plant community on your site in order to have the classification program work well.

3. **Use the type of training site appropriate for that plant**

   The way a plant grows and changes over its life cycle can have an effect on how successfully it can be identified by the supervised classification program. For example, reed canary grass tends to grow in large swaths of dense grass with few other plants mixing together. An appropriate training site for this should cover a large area and have discrete edges. A polygon or several polygons would work for this application and a point cloud or smaller area plot would not. Spend time looking at aerial photos of your area to determine the best method to capture the variation of the plants given the way they grow. Quality training sites produce quality results.

4. **Use the optimum number of cover classes**

   The number of training classes given to the classifier has a great effect on how accurate it is. We found that two classes were not enough to give accurate results and five class was a way to improve the accuracy of the classifier. It seems that the more classes you give the classifier, the better results you will get. We suspect that is true up to a point. If you give the classifier too many classes, we suspect that the image will be split up too much and your accuracy will drop again. It warrants further investigation into how many classes is optimal and how that number may change with the complexity of the site.

5. **Collect a library of training sites over time**

   As this type of technology becomes available to more people, it will be used for more applications. It would be pertinent for some users to build up a database of training sites along a multitude of variables. It would be beneficial to have a variety of plant communities captured in different seasons and at different times of their life cycle. Once a database is established, you would only have to load the training sites for the season and time of day for the satellite image that your have, and the classification program would do the rest for you. This would also help to track how invasive species are moving and spreading over time.

6. **Use professionals**

   We were lucky to utilize Nathan Vadeboncoeur of Smart Shores to fly the UAV and collect the phenomenal aerial images. The quality work of a professional made this project achievable. The amount of time one of our team would have required to learn how to fly a UAV and take high-resolutions photographs would have exceeded the time and resources available. The skill and knowledge needed to perform manual interpretation of aerial photos can be greatly valued by using a professional. However, with a little training and practice this skill can be learned.

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Appendices

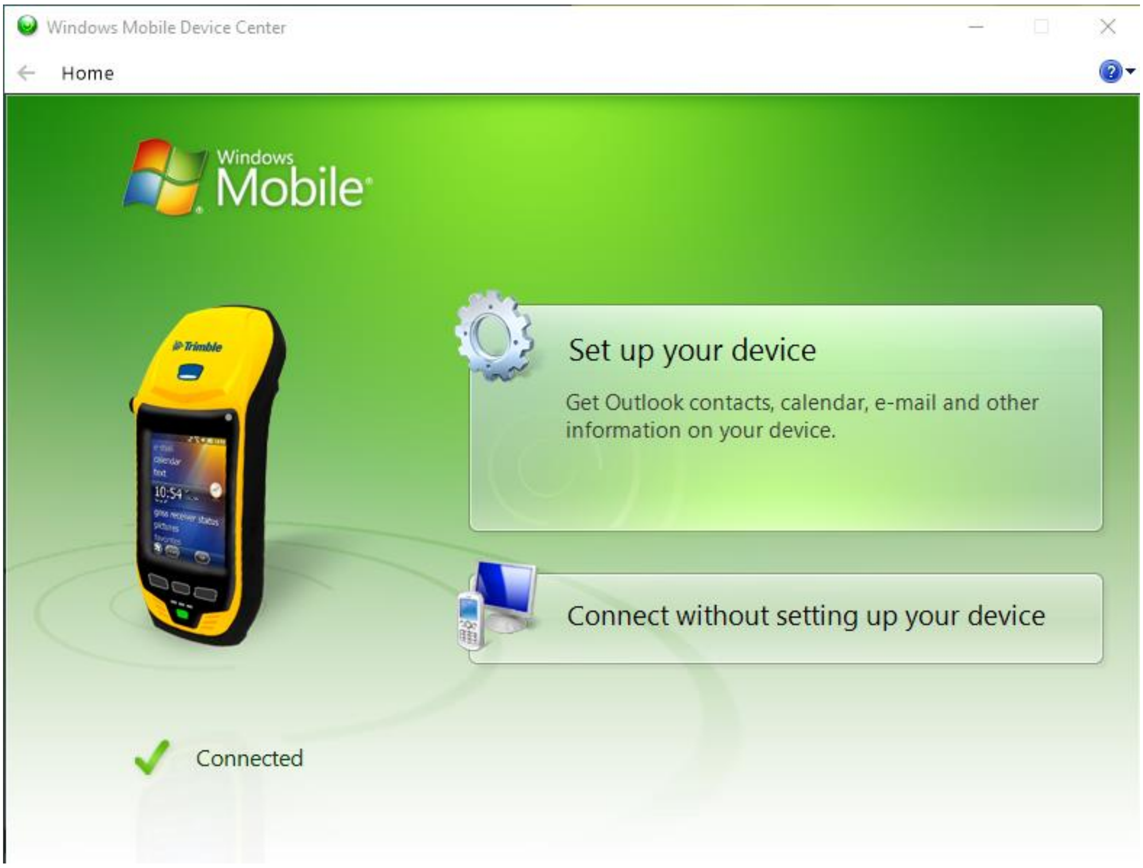
Appendix A

Extracting Data off of GeoExplorer 6000:

1. Download latest version of Windows Mobile Device center

2. Plug GeoExplorer 6000 into computer with USB cable

3. Press "Press connect without setting up device" to access file directory on the unit

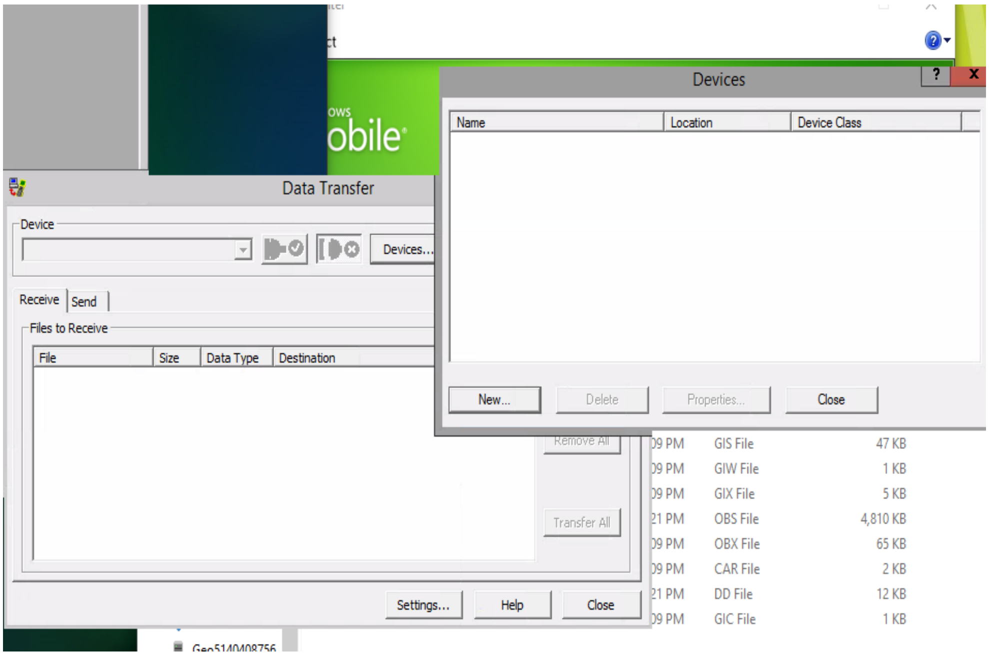


4. Find "My Documents", "TerraSync", and extract 9 files that we will be turning into the .ssf, they should all have the name you gave your ddf in TerraSync.

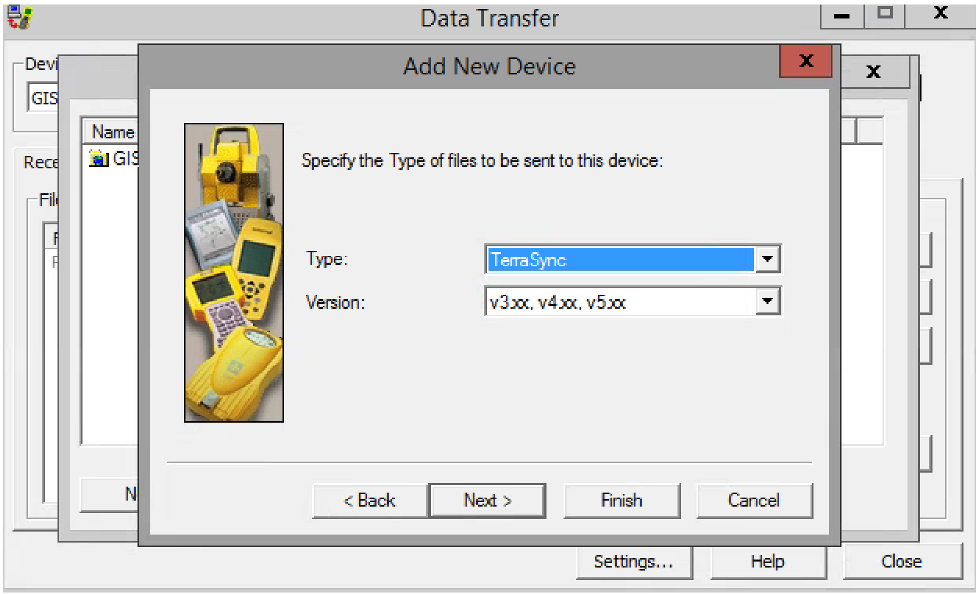
5. Now that you are have the files we are going to open "Pathfinder Office and begin the transfer process into an .ssf

6. Once Pathfinder Office opens, open the utilities tab and click data transfer.

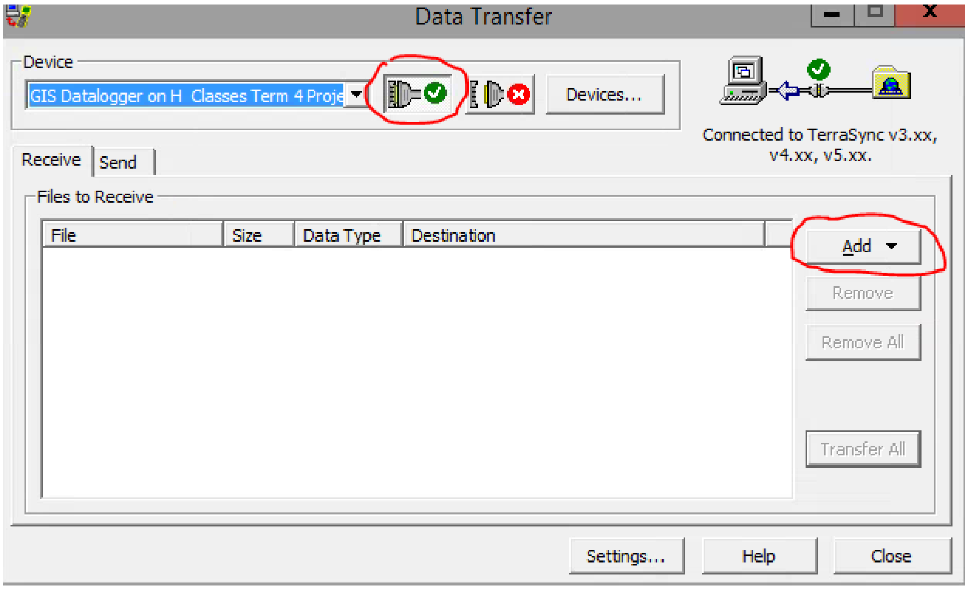
7. We are going to make a connection to the folder you have stored the 9 files in by pressing devices and selecting GIS Folder and picking the folder with the files in it.

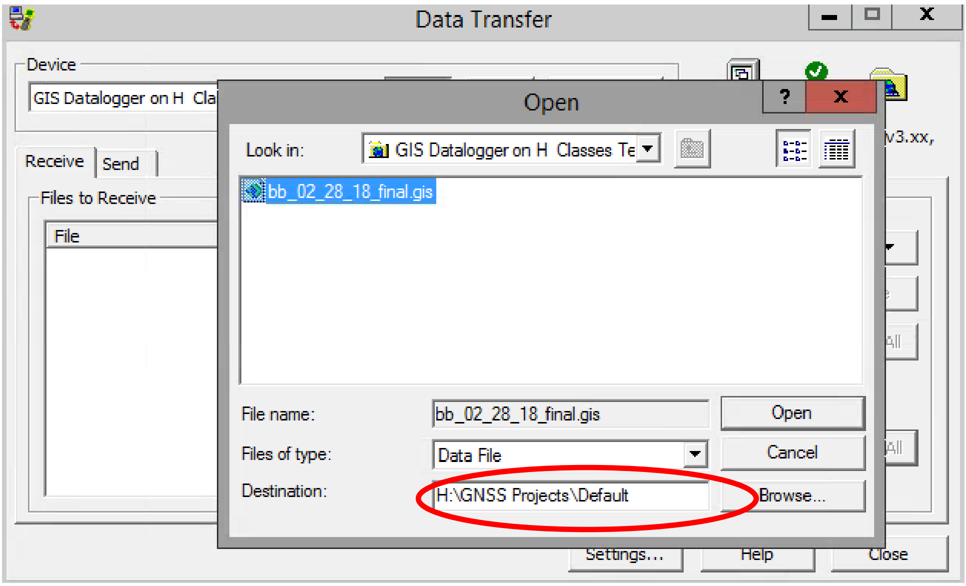


8. Make sure the type of device is set to TerraSync Version (see picture below)



9. Once we have created the folder connection we will press the green connection button, and then "Add" button, select the .gis file and then press transfer all.



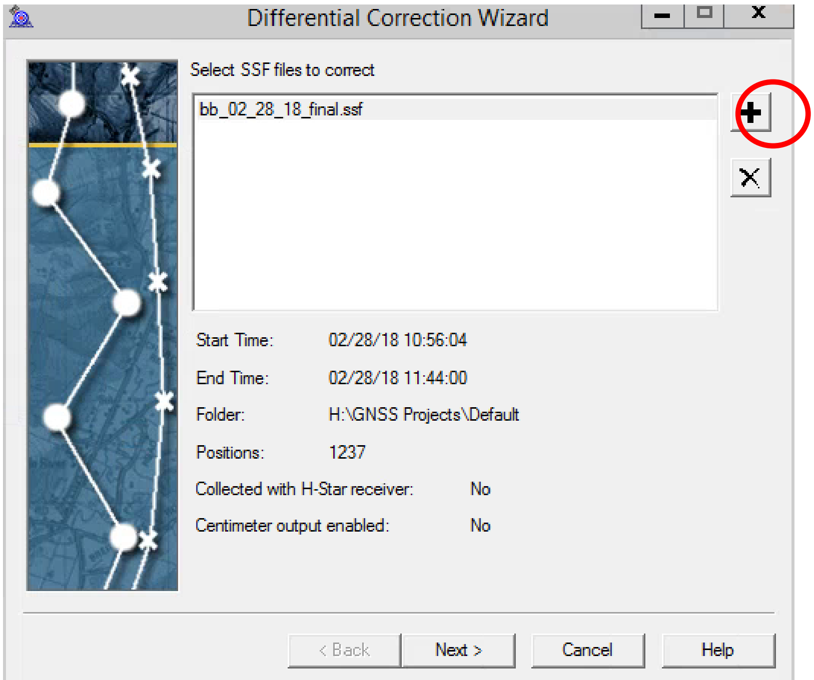


10. Once this process is complete, we will find the destination folder you selected previously and there we will find the .ssf file

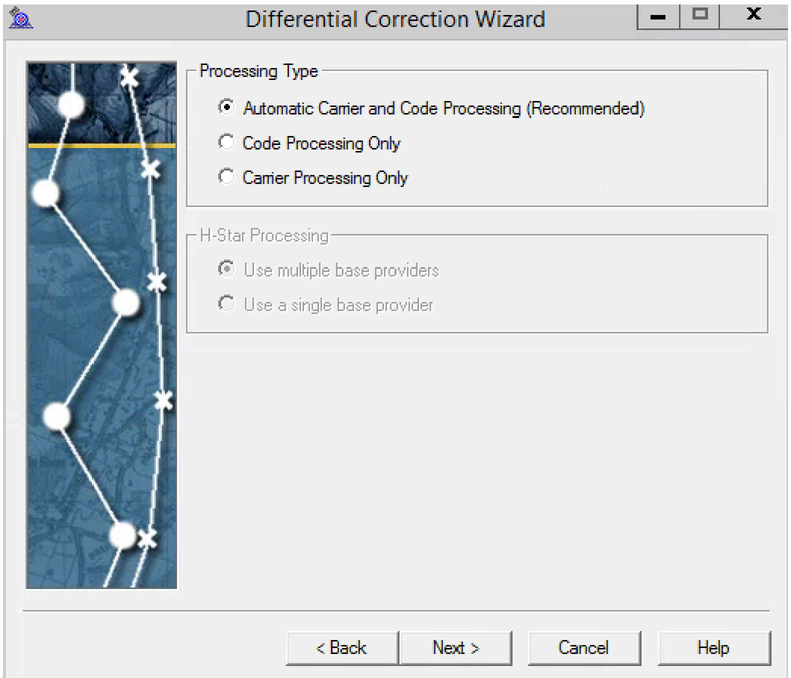
11. Now that we have the uncorrected GNSS data we are going to correct it, the data can **only be corrected 24 Hours after the data of collection**.

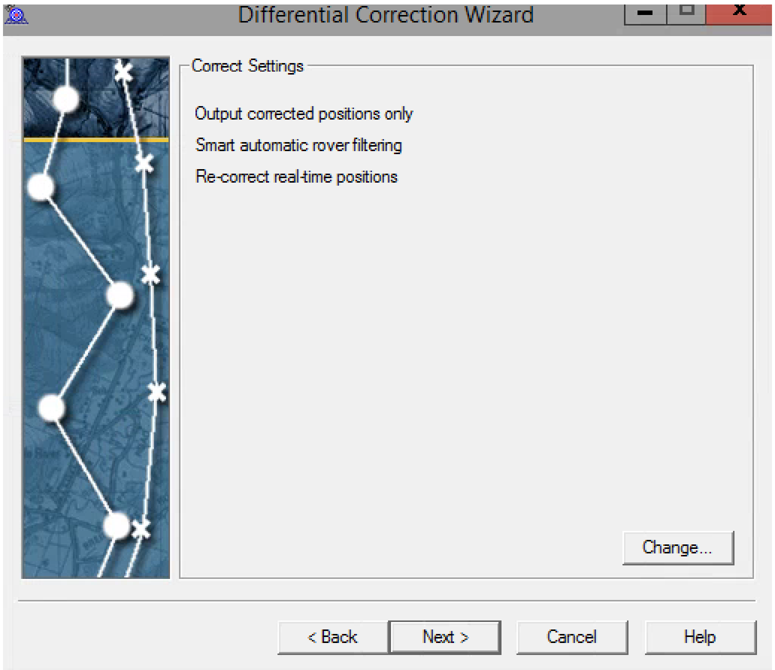
Data Correction:

1. Open The "Utilites" tab and select "Differential Correction", if your .ssf does not show up, select the plus button and find your .ssf



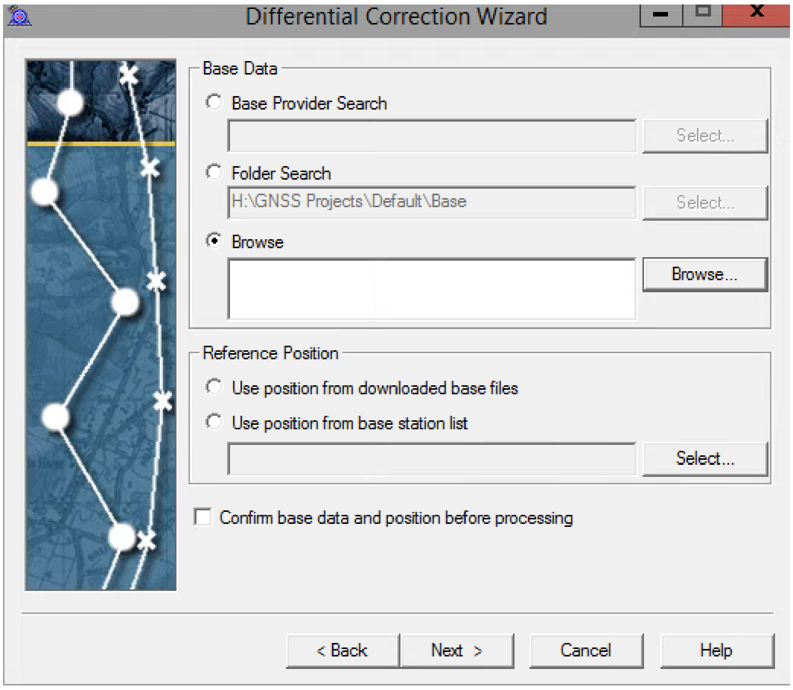
2. Select the settings seen below and press next, next



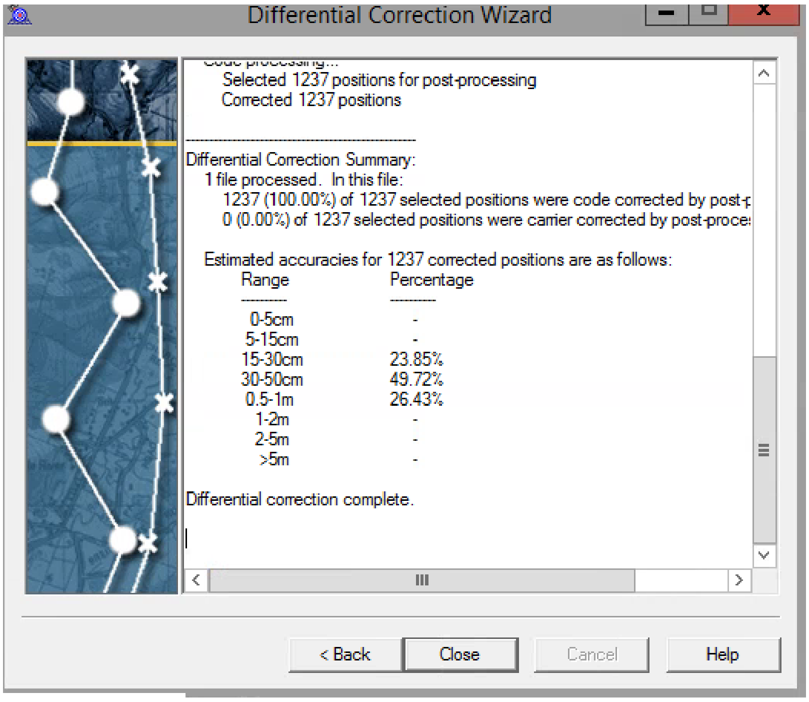


3. Now we will choose a base station, for our project we used base stations provided by Metro Vancouver. I will show you how to acquire those in a different method labelled “Acquiring Metro Vancouver Base Station Data”

4. Once we have found the base station we will use and put it into a folder, we will press the “Browse” button and select the folder with the base station we would like to use.

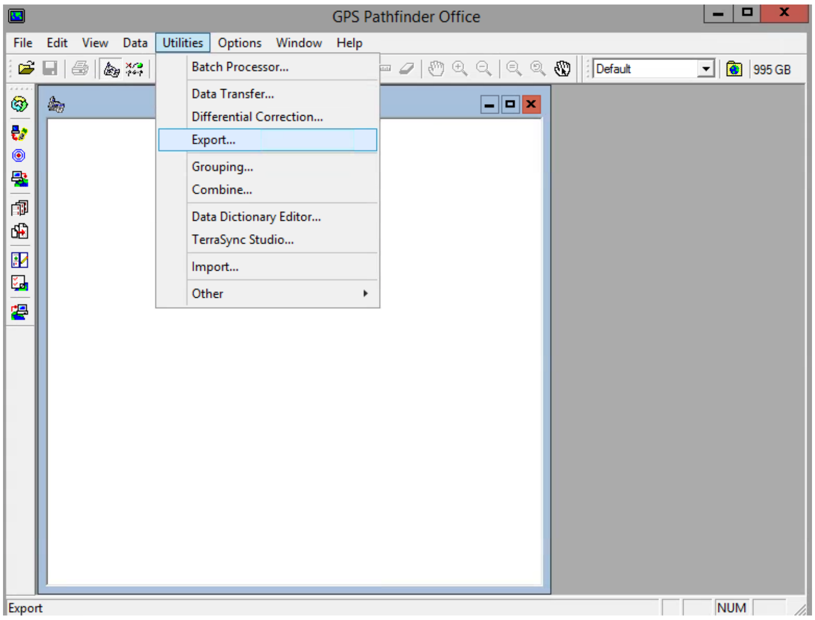


5. Now that the .ssf has been corrected into a .cor file, we will now convert the s

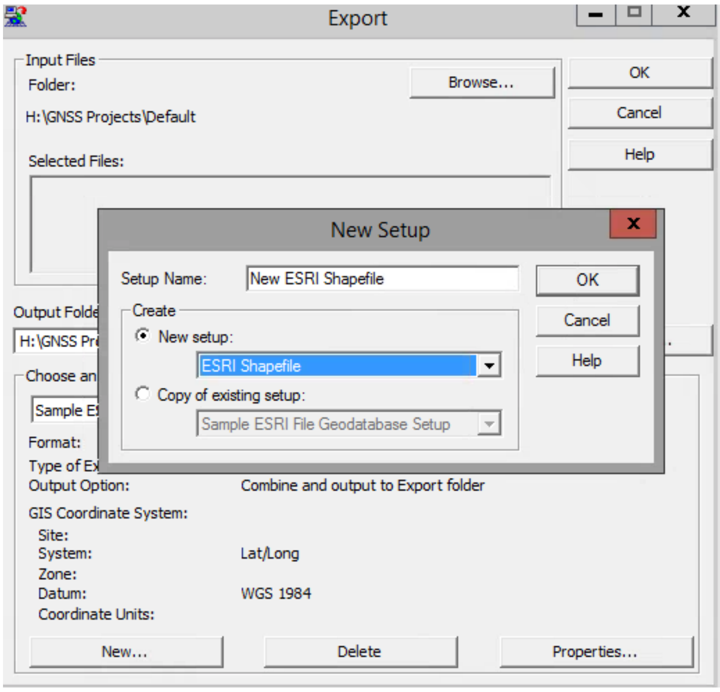


Converting .cor into Shapefiles for ArcMap:

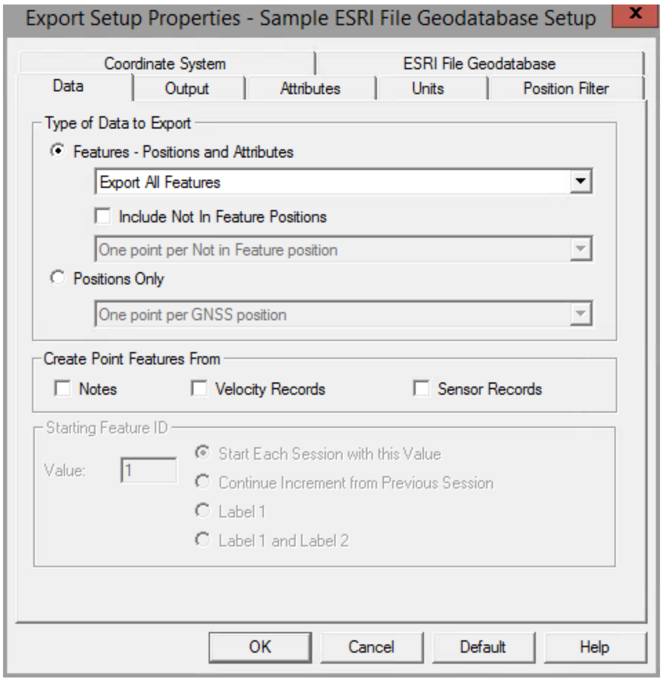
1. With Pathfinder Office open, click the “Utilities” tab and select “Export”



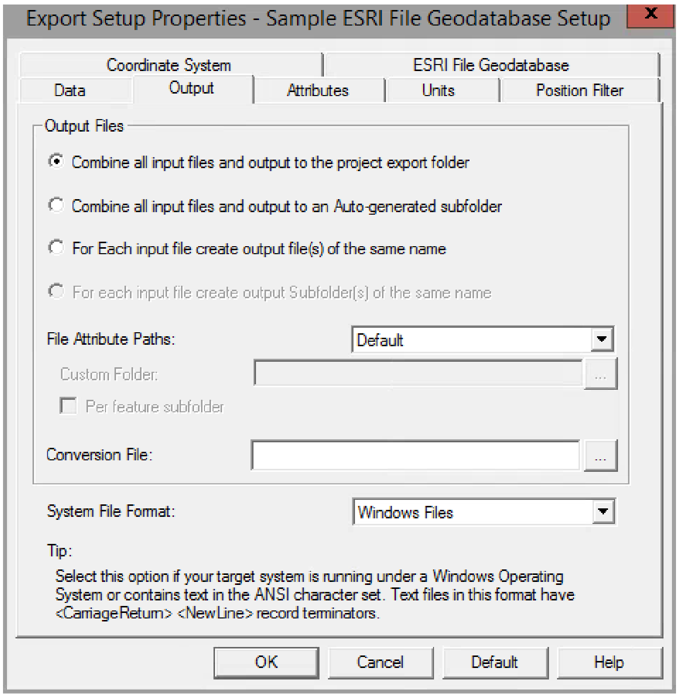
2. Now that the export menu is open, we are going to change some of the options for export. Begin by clicking on the “New” button, and select “ESRI Shapefile” for type, then hit ok.



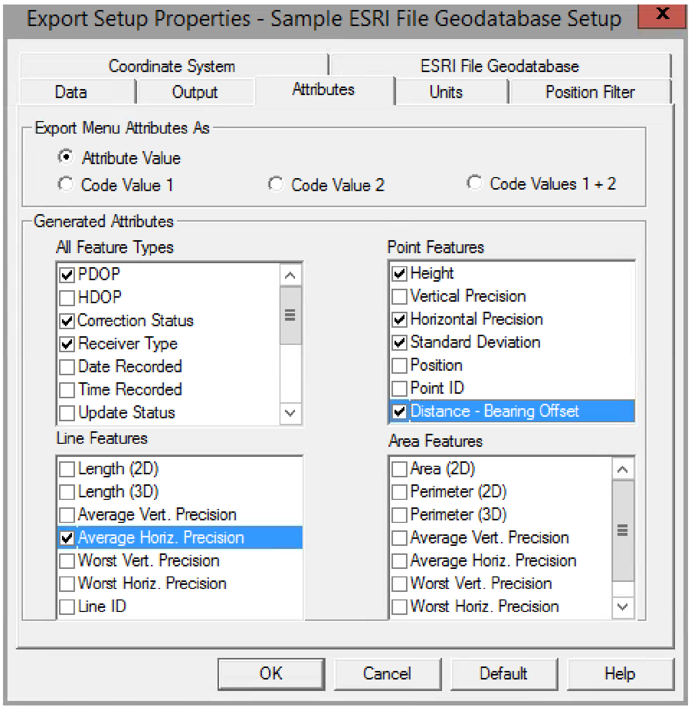
3. Now we are going to go through all the tabs in the Export Properties Menu
   a. Data



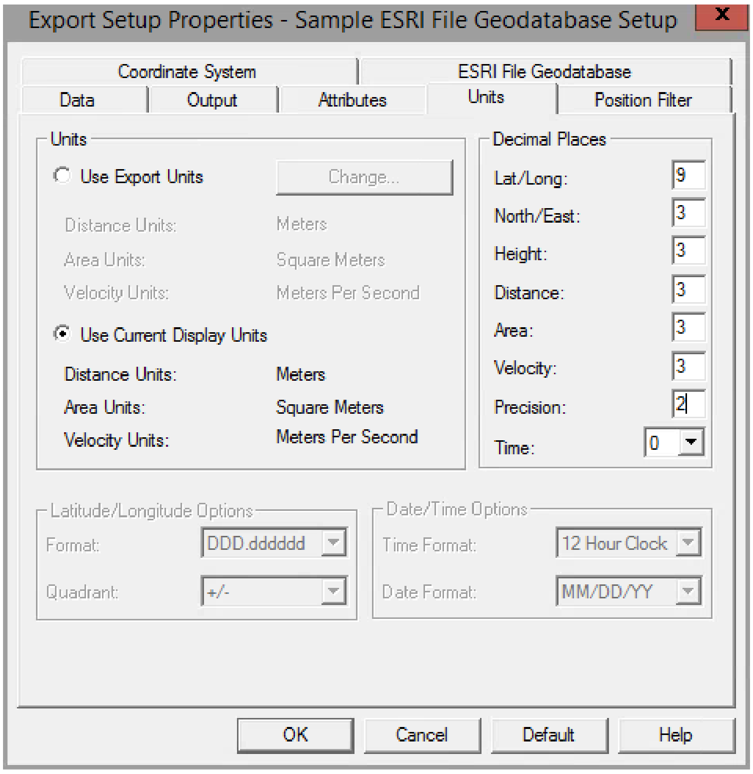
   b. Output



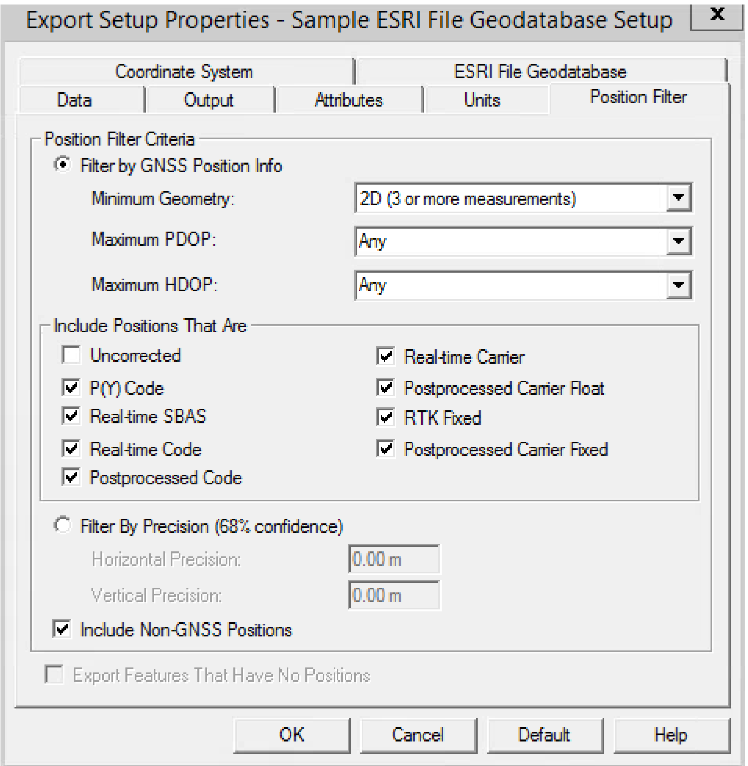
c. Attributes



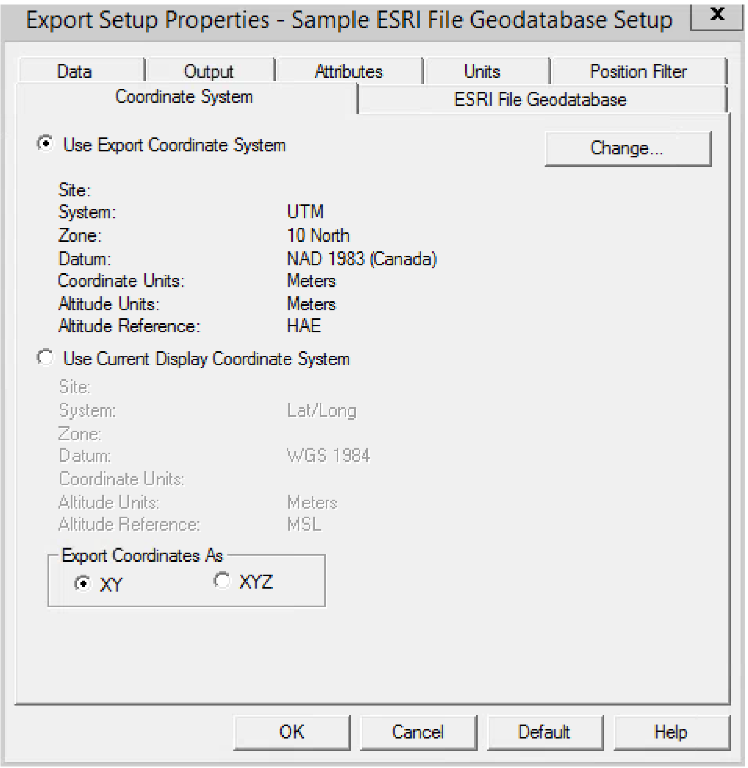
d. Units



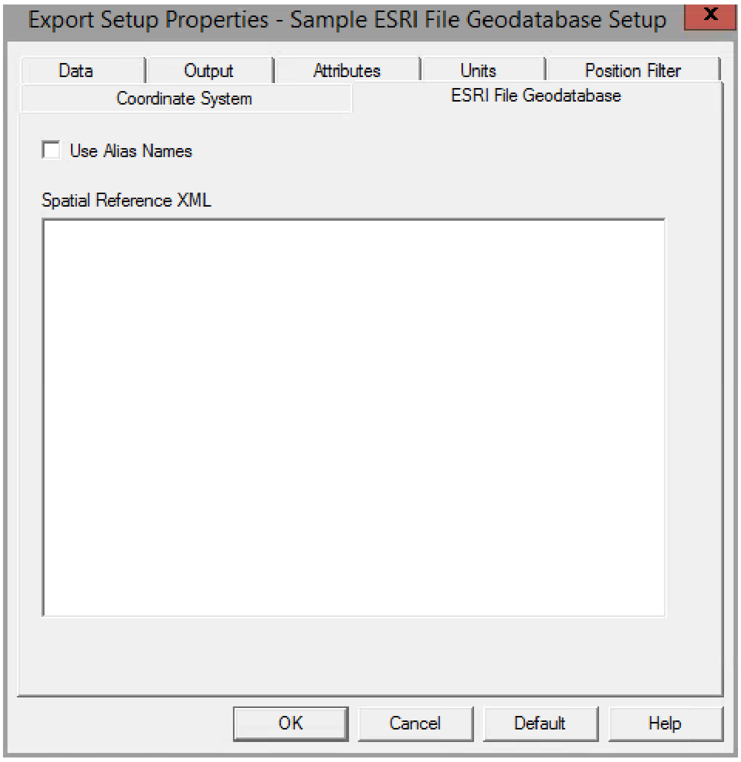
e. Position Filter



f. Coordinate System

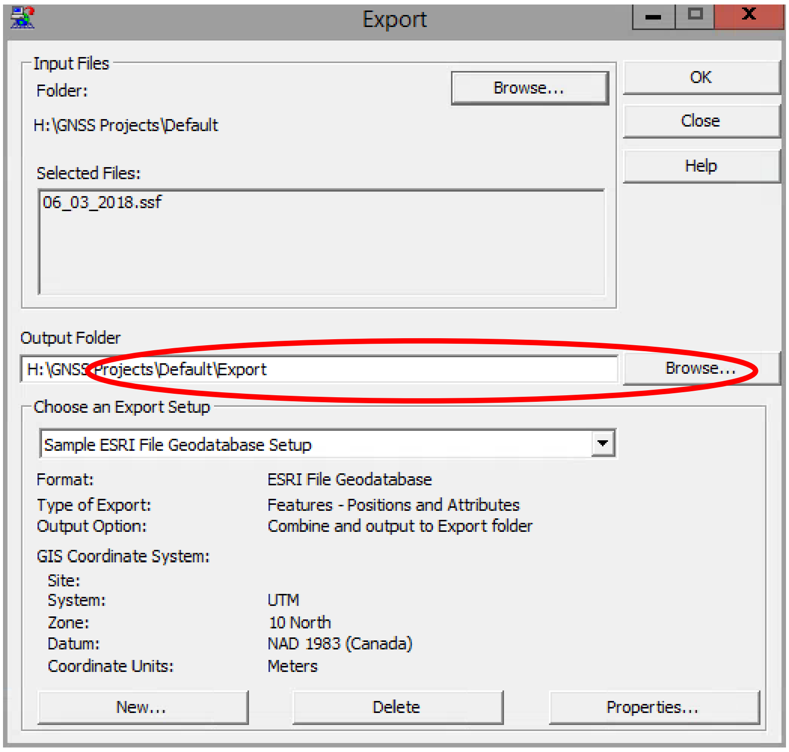


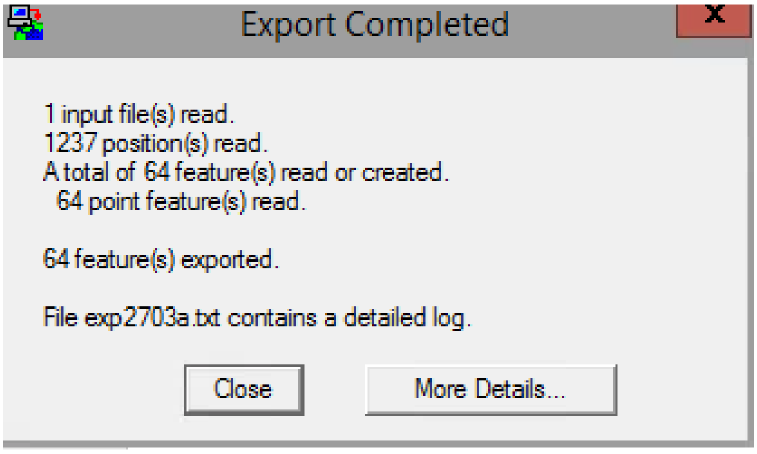
g. ESRI Shapefile



4. Once you've matched all the settings found in the above pictures you can hit "OK"

5. Now select the .cor file you want to convert into shapefiles , make sure you select a location you would like your shapefiles to go to

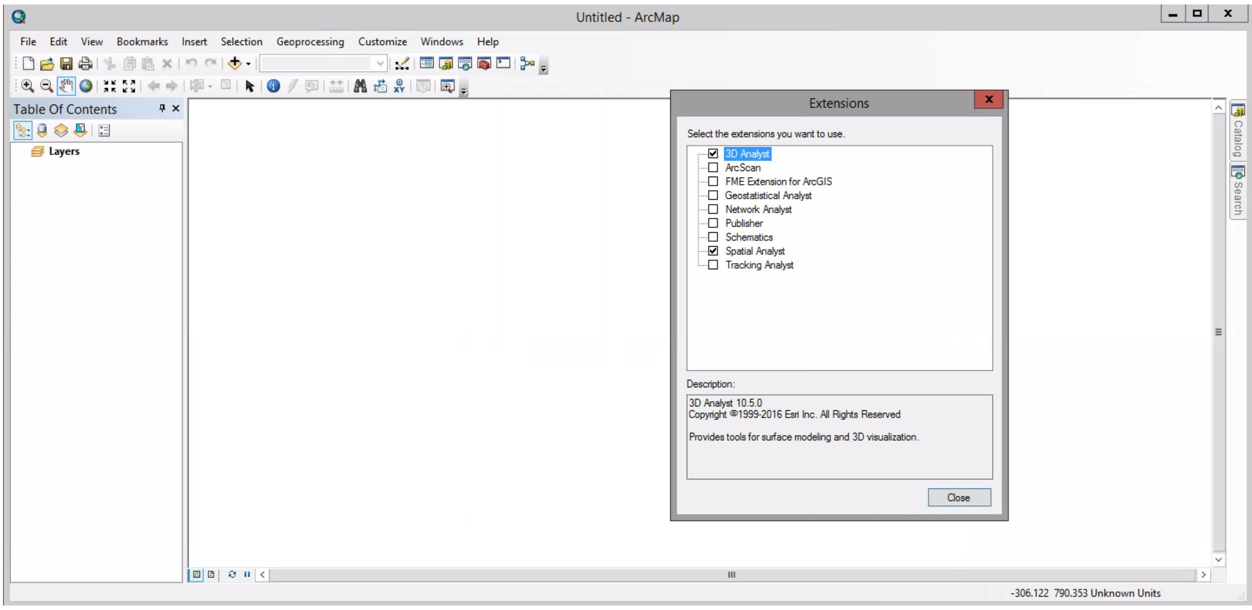

Export
Input Files
Folder:
Browse...
H:\GNSS Projects\Default
Selected Files:
06_03_2018.ssf
OK
Close
Help
Output Folder
H:\GNSS Projects\Default\Export
Browse...
Choose an Export Setup
Sample ESRI File Geodatabase Setup
Format: ESRI File Geodatabase
Type of Export: Features - Positions and Attributes
Output Option: Combine and output to Export folder
GIS Coordinate System:
Site:
System: UTM
Zone: 10 North
Datum: NAD 1983 (Canada)
Coordinate Units: Meters
New...
Delete
Properties...


Export Completed
1 input file(s) read.
1237 position(s) read.
A total of 64 feature(s) read or created.
64 point feature(s) read.
64 feature(s) exported.
File exp2703a.txt contains a detailed log.
Close
More Details...

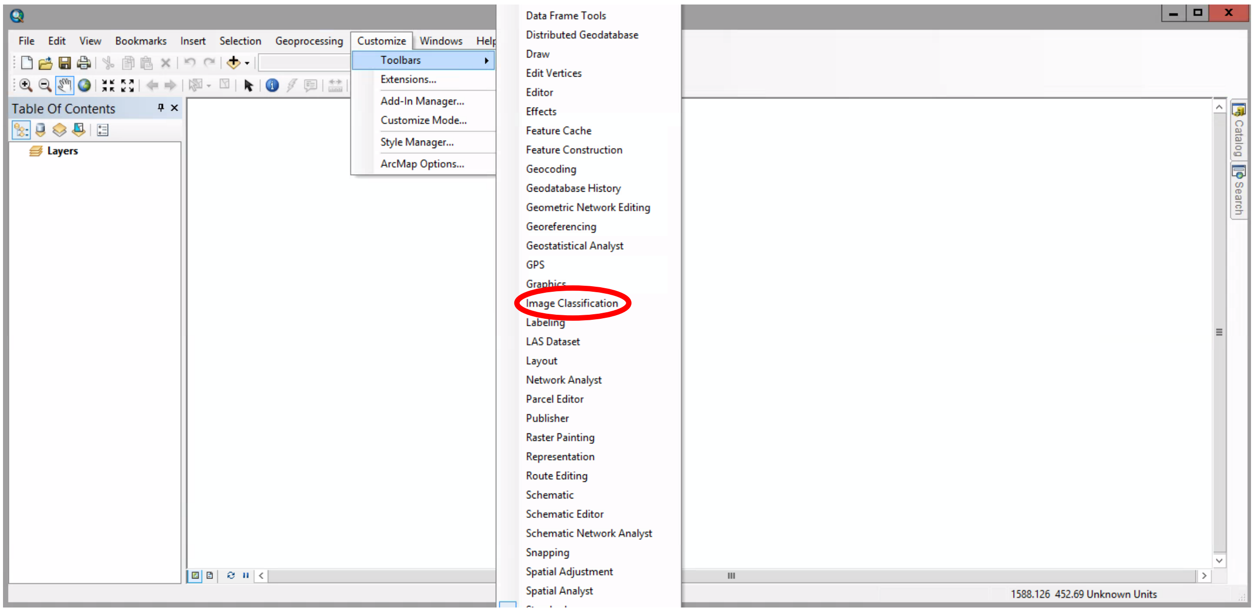
Appendix B

Supervised Classification:

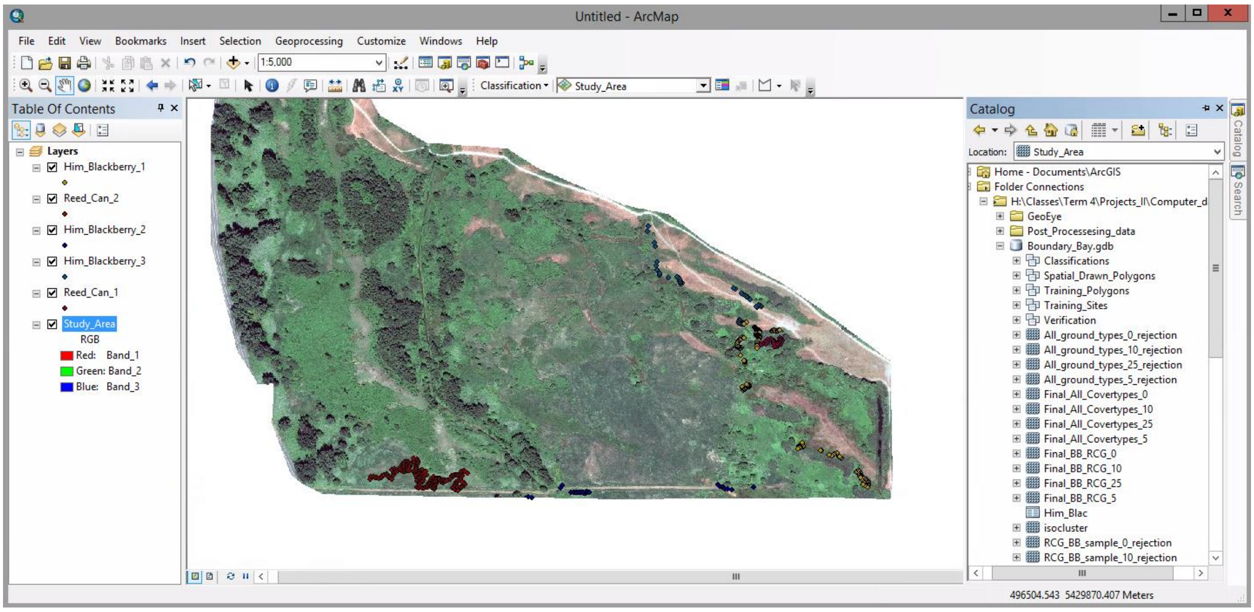
Start by opening ESRI ArcMap and set your data frame to match the data weve collected (NAD 1983 UTM Zone 10N). Select extensions under the customize tab, then check off spatial analyst and 3D Analyst.



Now Select the customize tab, and under toolbar activate the “Image Classification” Tool by clicking on it



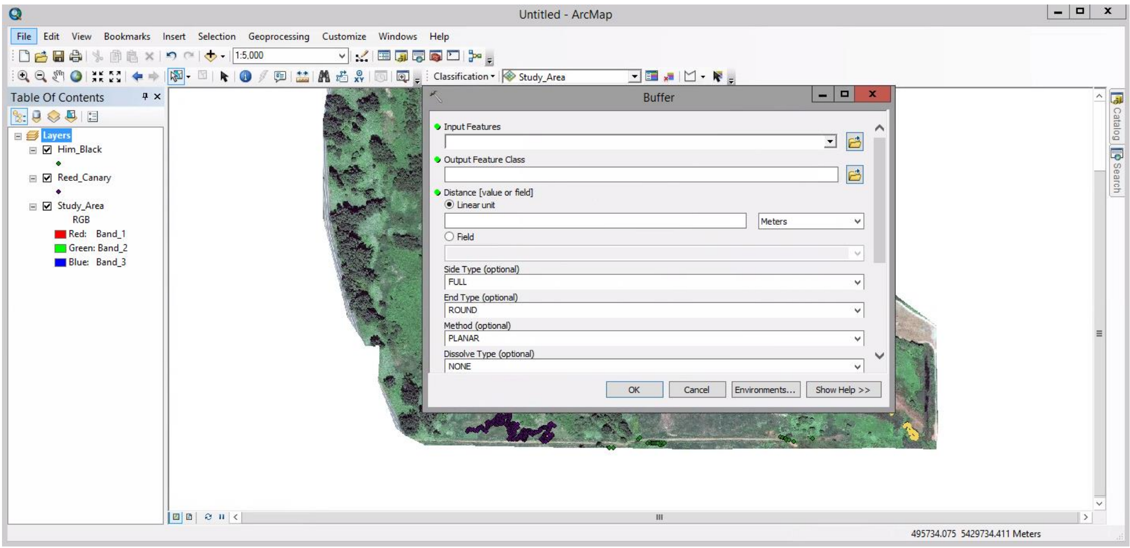
We will now make a folder connection to the shapefiles we exported from pathfinder office, and to give it some contexed we will add a background image of the study area, and over lay the training points.



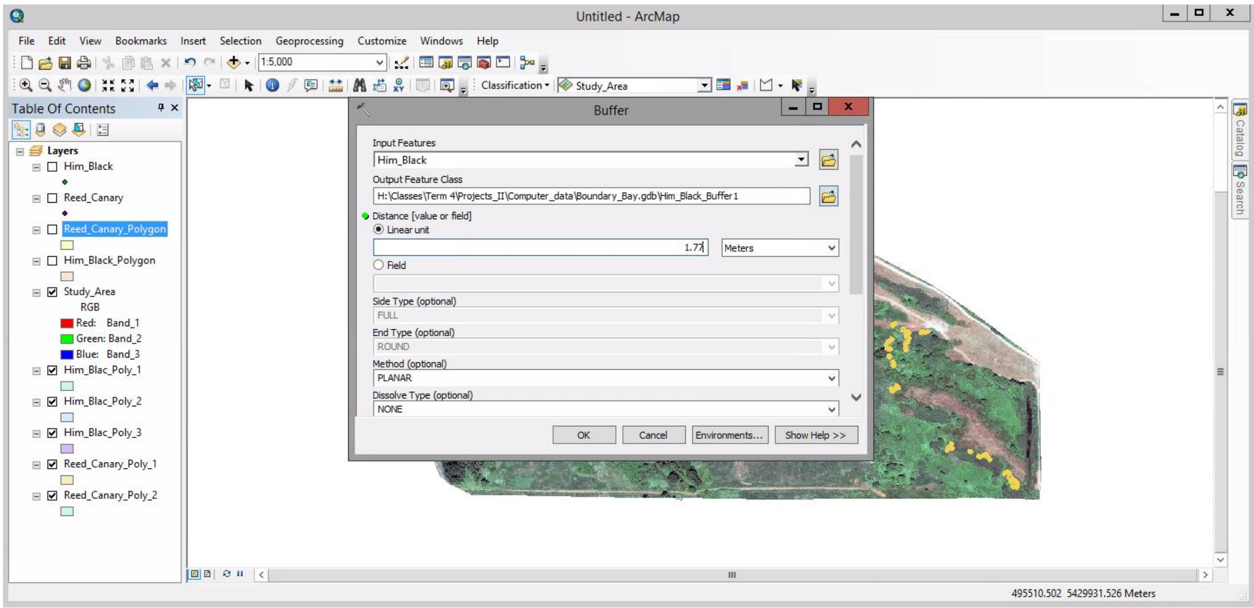
Now that we have the data into ArcMap we will now need to produce a signature file for the classification to work. This is where we used 4 different methods, (**Training site polygons**), (**Training site / land cover types),** (**Spatial polygons**), and (**Spatial polygons / land cover types**). We will show the process of creating all 4 files

Training Site Polygons:

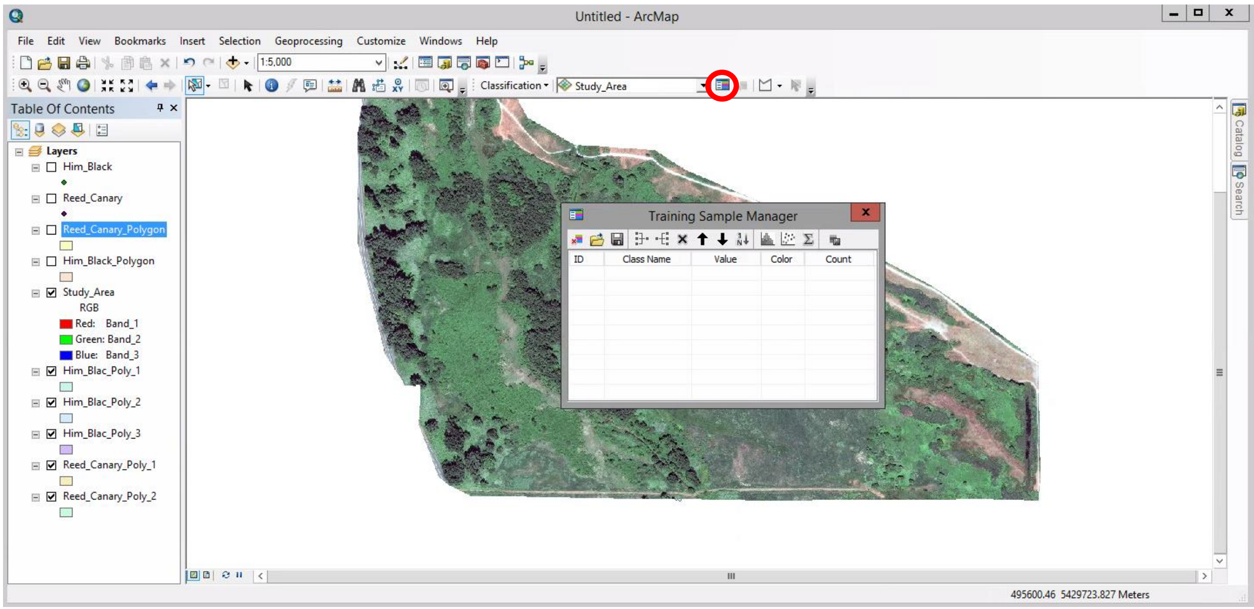
To make a signature file we need to input polygons, and since our shapefiles are point data, we are going to offset all the points by the size of our plot on the ground, which was 10 m^2 (1.77m radius). We can do this by using the buffer tool found under "Geoprocessing" tab.



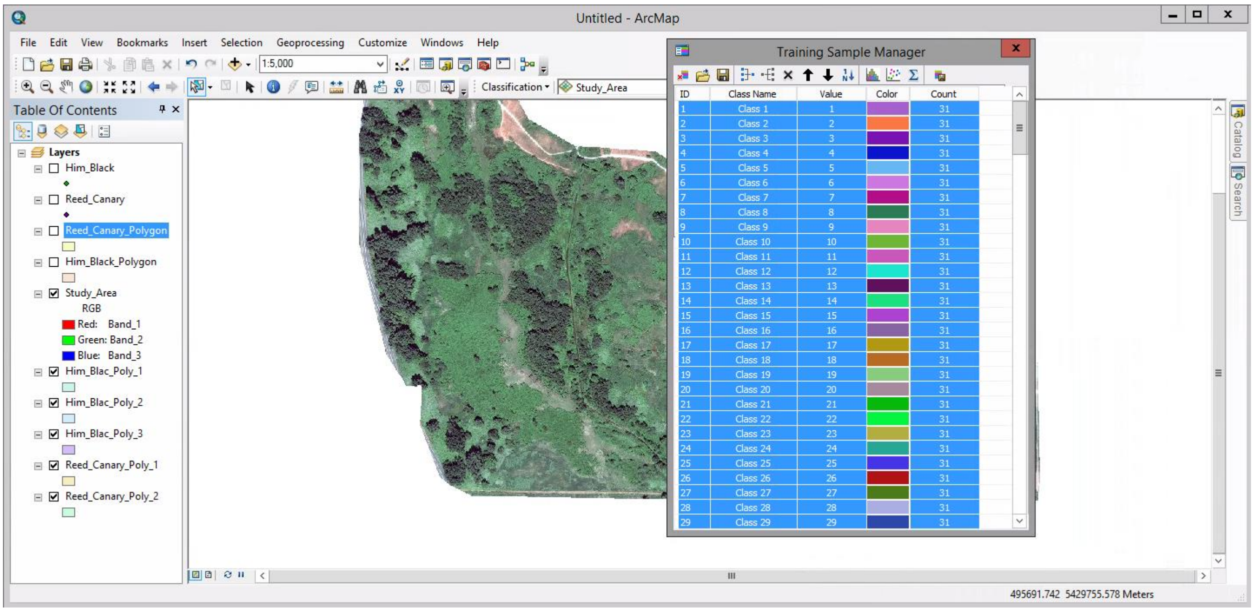
Once the buffer tool is open select one of the species as an input feature and make sure you know where the output feature class is going, as we are using this in the next step. For linear unit put in the 1.77 m length and then press okay.

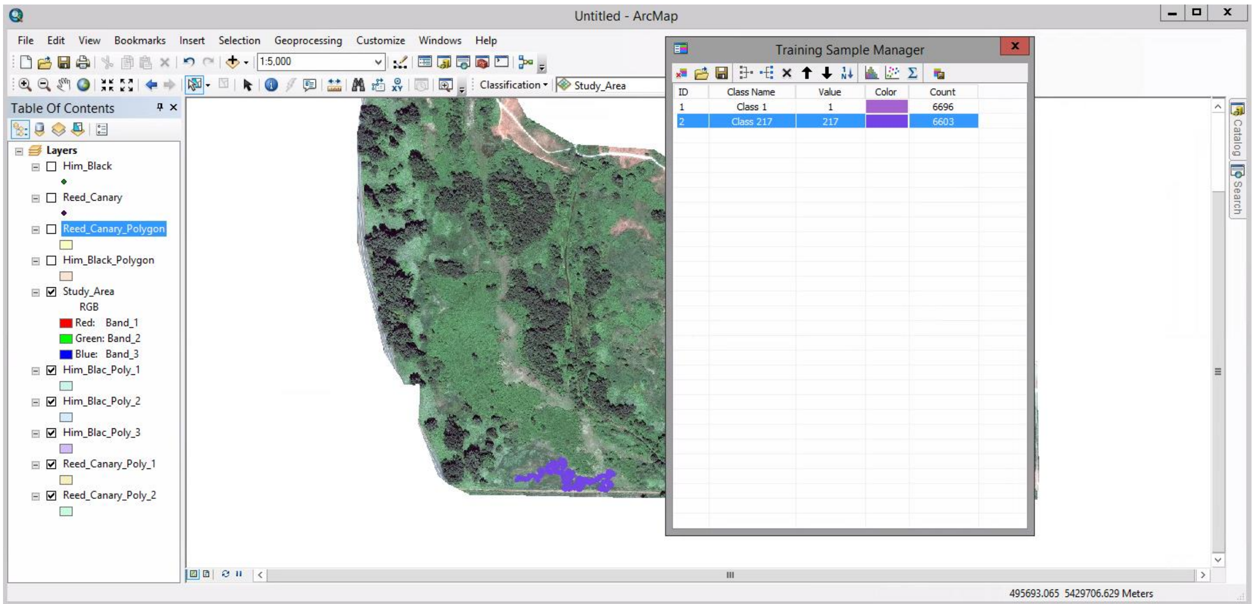


Now that we have the polygons, we can now create the signature file. Press the training sample manager on the image classification tool bar.

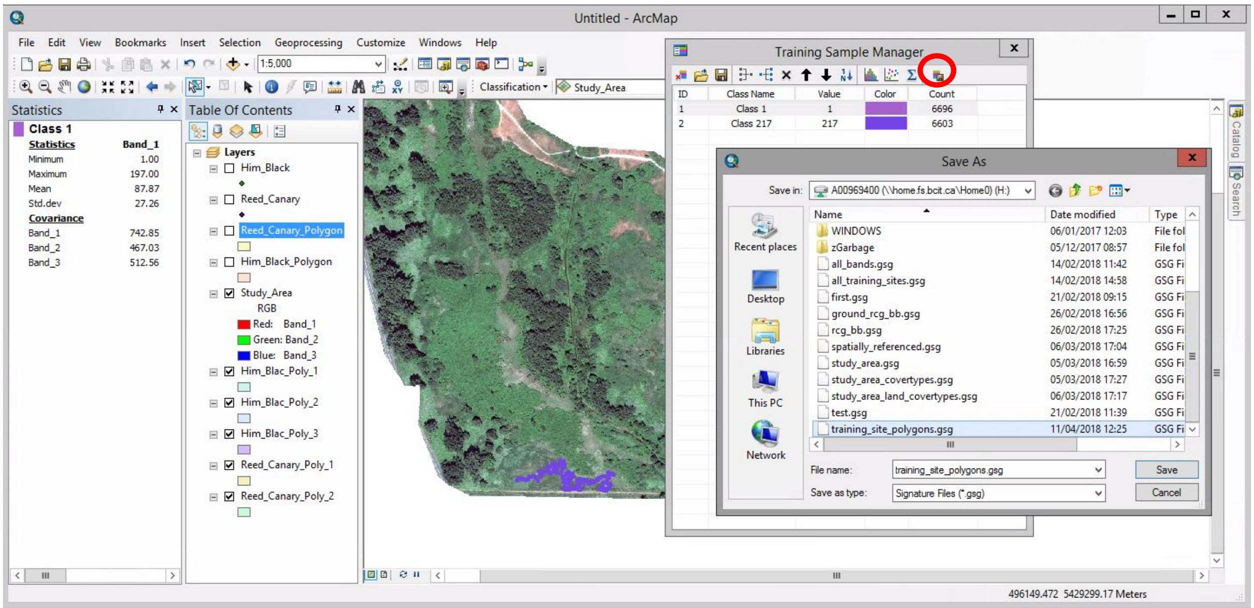


In the training sample manager, we are going to click the folder icon and select the training polygons we just made, make sure to only pick one at a time as we are going to need to group all the individual polygons into one class. Once you have one in, select all the values by clicking the top one and shift clicking to the bottom value. Once selected press the merge training sites button at the top of the training sample window. And repeat this process with the other polygon feature.

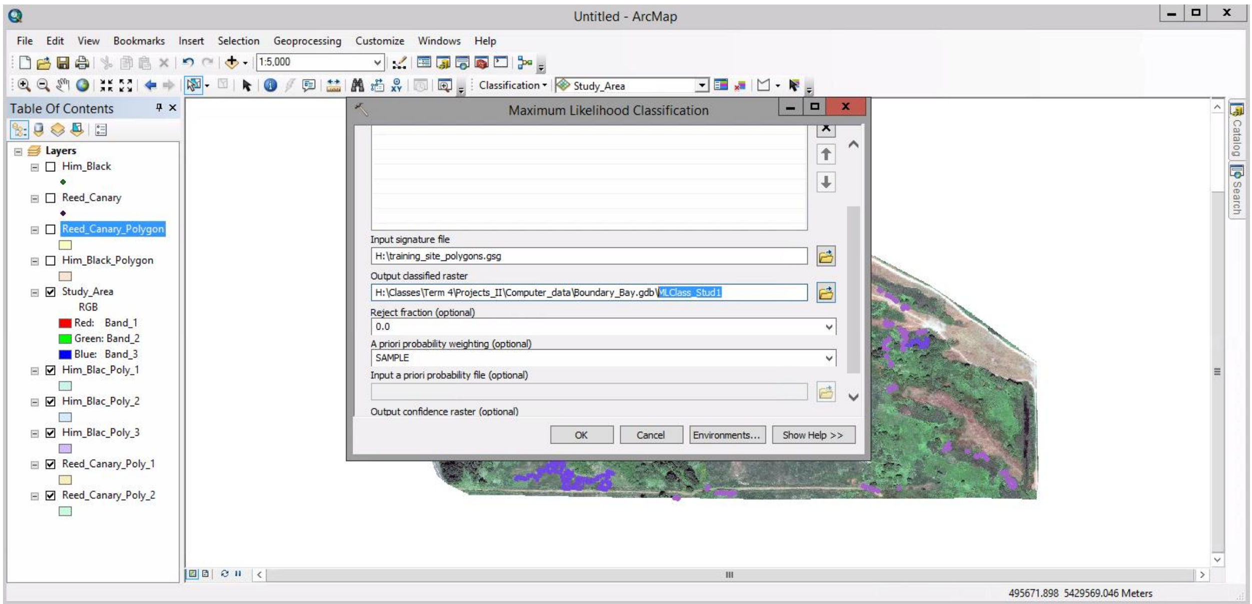




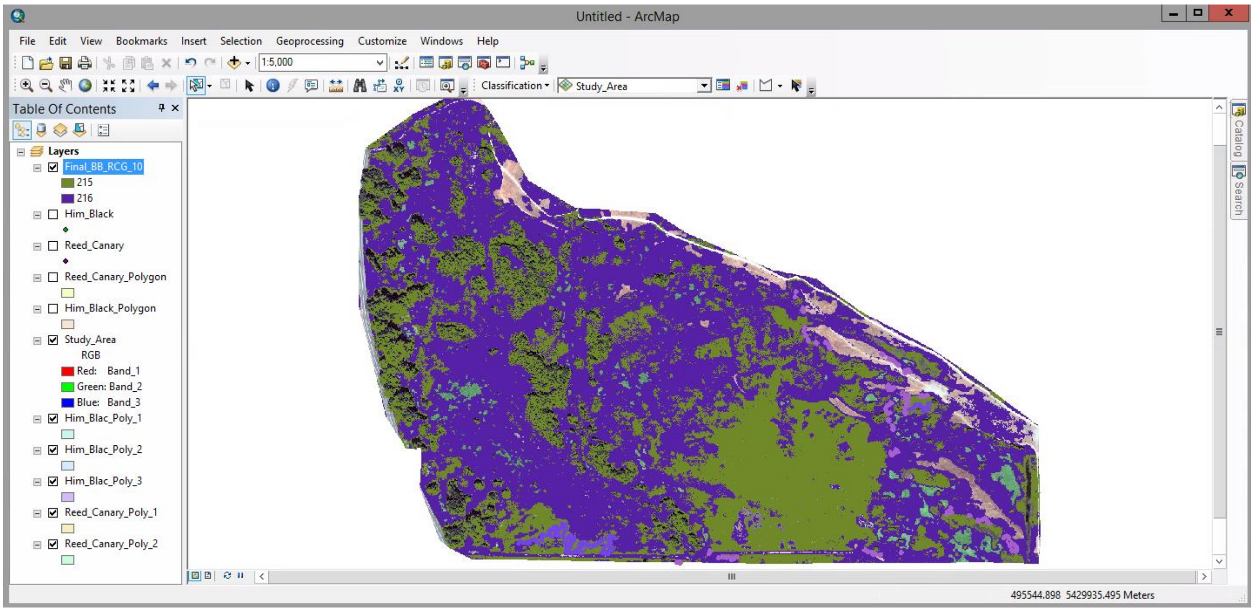
Now that we have the training data in the training sample manager, we just need to save it as a signature file and we can begin running the classification. At the top right of the window click the create signature file.



Now we have the signature file, we can run the classification. On the image classification tool bar, press the classification dropdown menu and select “Maximum Likelihood Classification”. Once the window opens, we will make sure the satellite data of our area is selected for an input raster, and the signature file we just created is selected, for the rejection fraction, we played with 4 different options (0%, 5%, 10% and 25%) but we decided 10% was the most accurate.



Once the software is done running, it should produce a raster file like this.



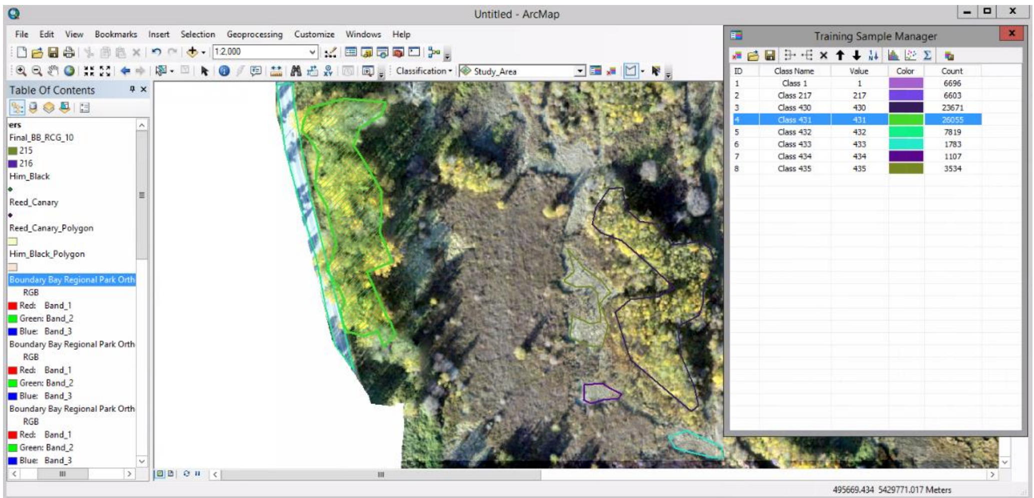
This the two colours correspond with the two-training sample we gave to the computer.

Training site / land cover type polygons:

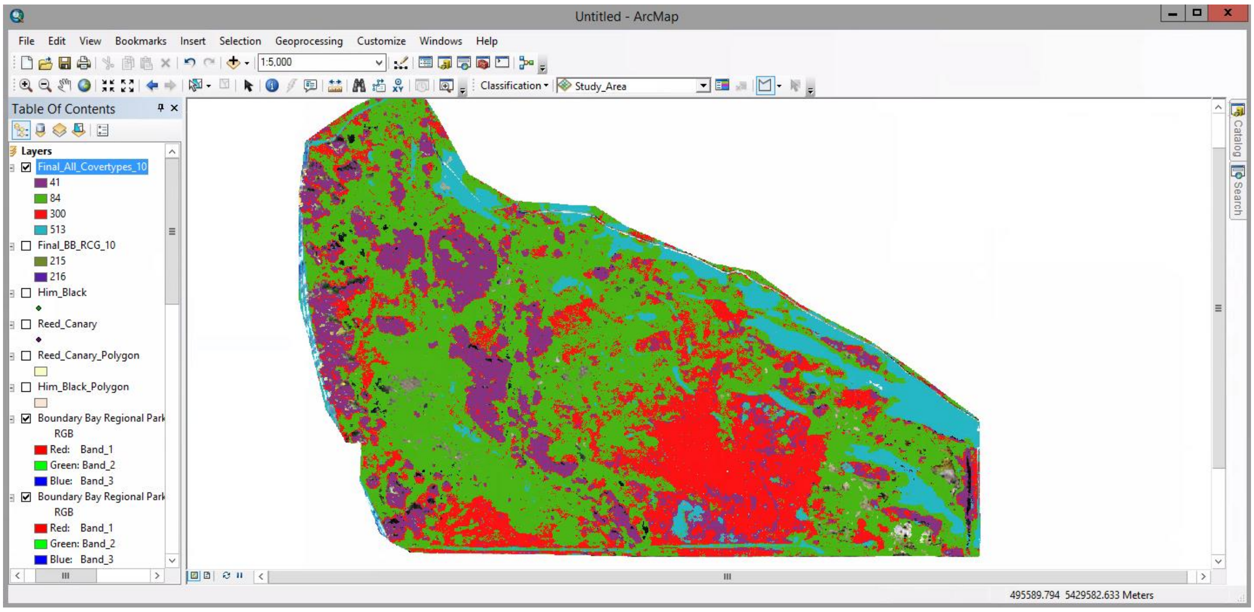
So, for this method it is the same process as the previous training sites but with additional classes added for the classification software.

Going back to the image classification toolbar we can draw in training sites by selecting the select training site button and the polygon tool.

We can use the satellite data to do this, but and even more accurate option would be to use the drone data we have to see to sub centimetre accuracy if the areas we are grouping are homogenies.



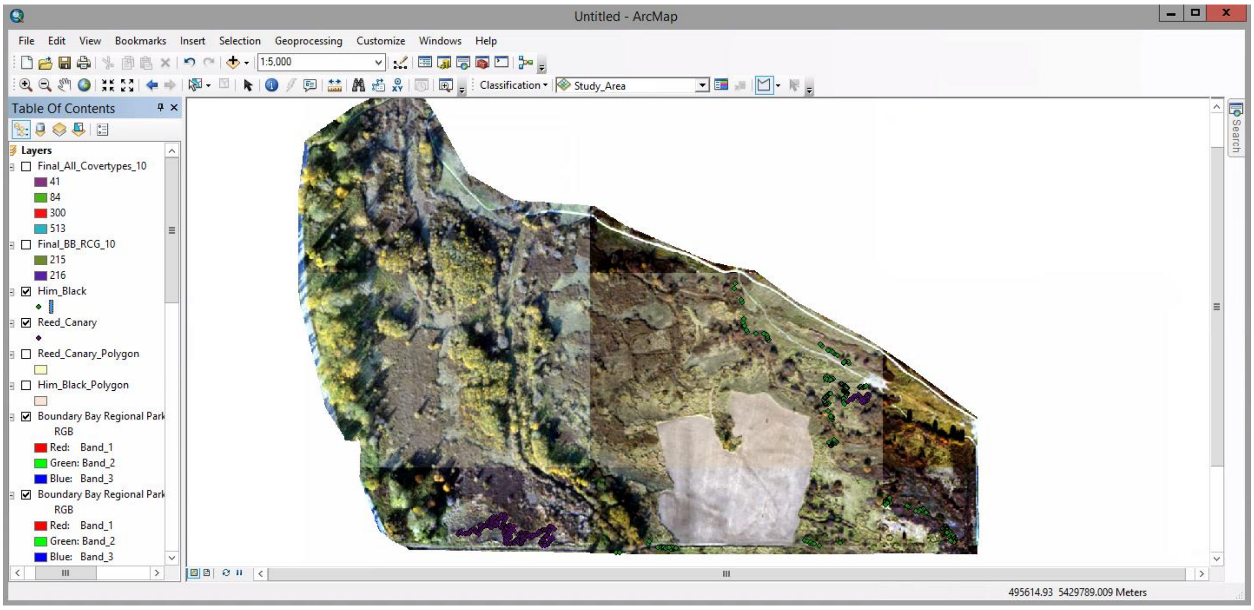
We only picked “Ground”, “Trees”, and “Water” as 3 more classes the computer worked with. Once you have drawn all the polygons you want, group the polygons into there respective classes and save this as a new signature file. Run the Classification and you should get something like this.



Spatial Polygons:

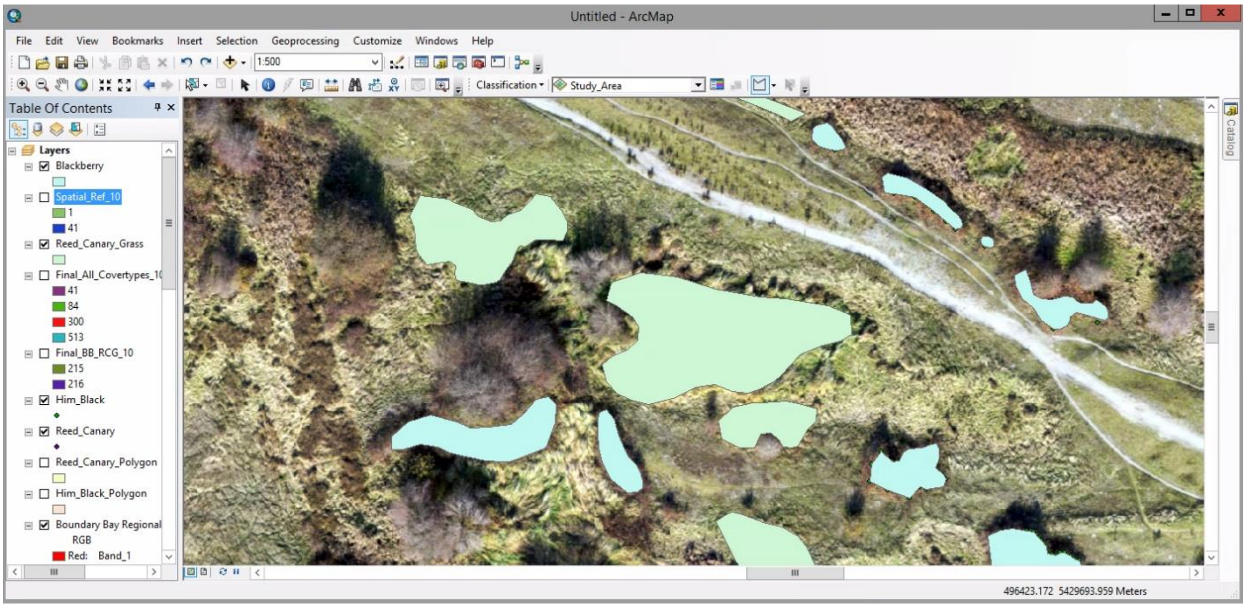
Now using the drone ortho we will produce spatially referenced polygons from the training points.

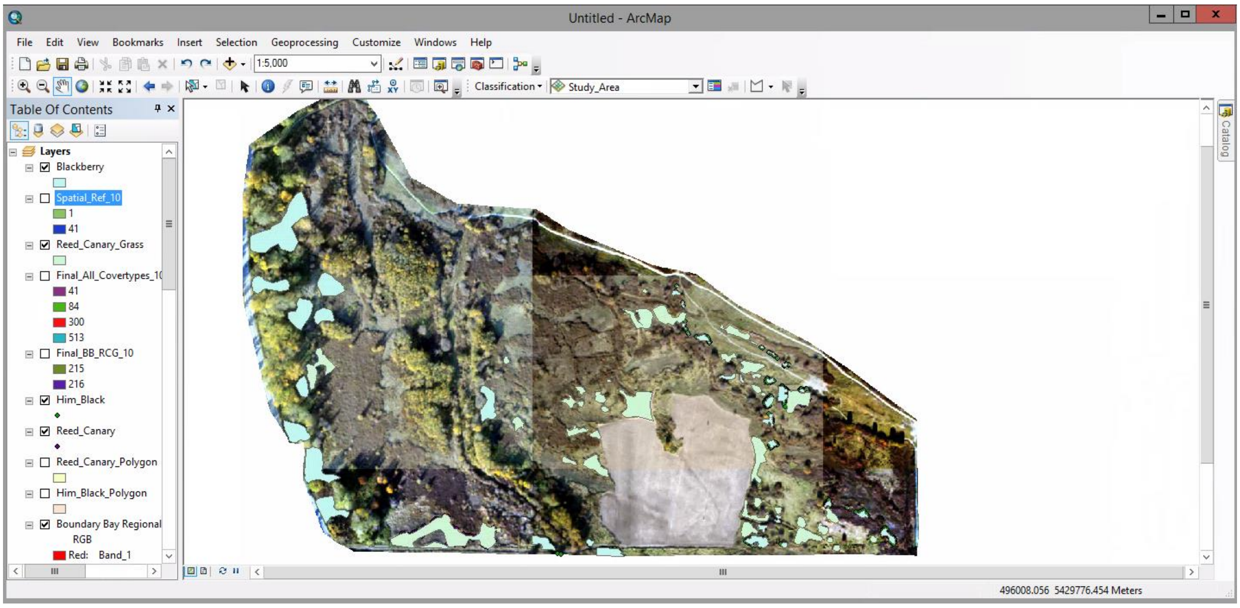
Let’s start by pull up the drone orthophotos and over laying the training point data onto it.



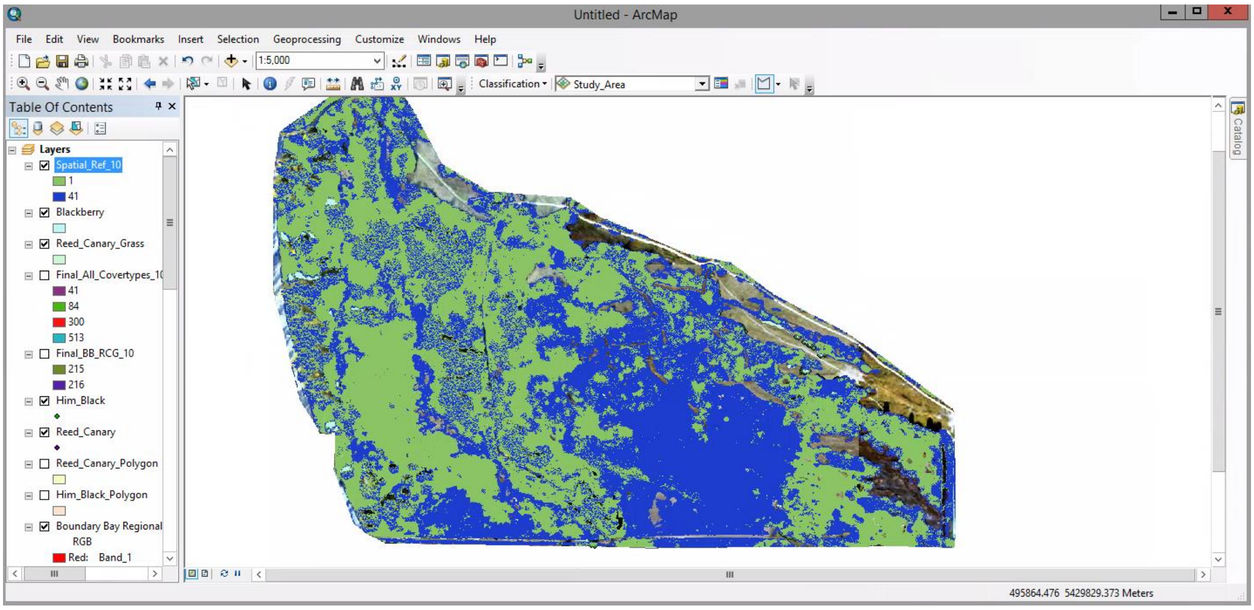
To make it easier for ourselves, lets create polygon feature classes for each species of interest.

Once we have the features made, lets begin drawing the species from the points that have been collected on the ground, easily capturing the full extent of the point data.

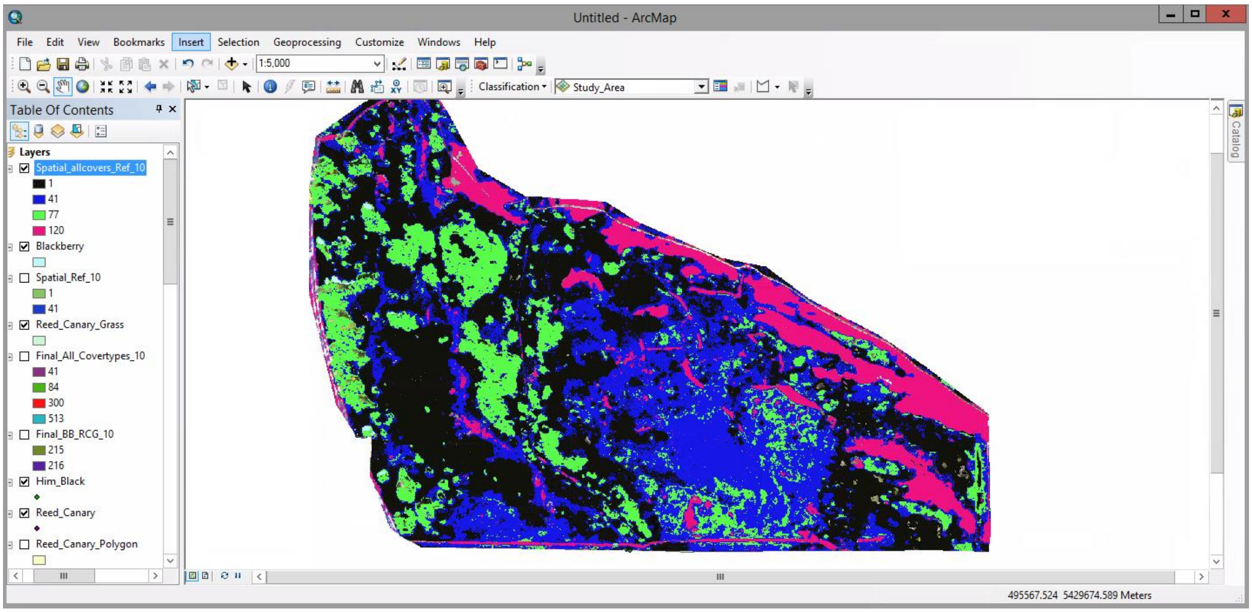




Once we have drawn out all the training site data we want, we can now do the similar method as before for create a signature file. Making sure to use the polygon features we have just been working with and combining each induvial polygon into its respective class. And after you run the classification, it should look like this.



Spatial polygons / land cover types:
Now combining these spatially referenced polygon features, with sample we drew in for the other land cover type method, we allow this classification to have more classes to work with. This again is drawing the 3 classes of land cover, “Ground”, “Trees”, and “Water” and creating a new signature file with the five classes, and than running the classification which should produce a map like this

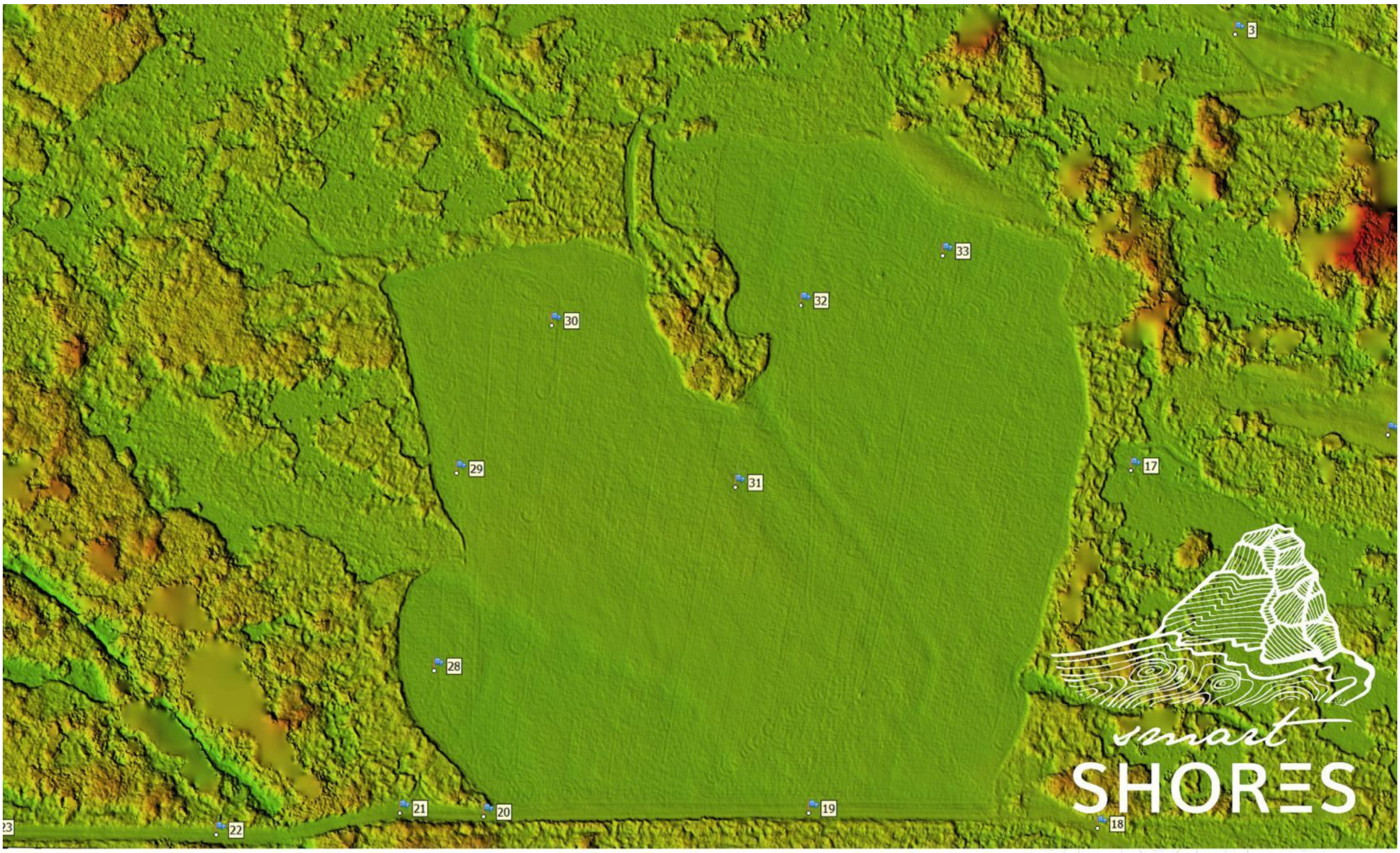


Appendix C

Boundary Bay Regional Park

Invasive Species Mapping Survey

October, 2017



November 15, 2017

Submitted by:

Nathan Vadeboncoeur
President
Vadeboncoeur Consulting Inc.
935 W 23rd Ave
Vancouver, BC V5Z 2B2

Submitted to:

Helene Marcoux
Instructor
School of Construction & Environment
BCIT
3700 Wilingdon Ave
Burnaby, BC V5G 3H2

Dear Ms. Marcoux,

Thank you for the opportunity to collaborate with BCIT to test UAV-based approaches to invasive species mapping. The ground-truthed invasive species surveys conducted by BCIT in Boundary Bay Regional Park provide excellent data to validate the visual ID of plant species using high-resolution aerial imagery. We look forward to working with you, your students and staff/faculty at BCIT to explore strategies for rapid identification of invasive species.

This document outlines the process used for data collection and provides metadata for the GIS deliverables provided to you and your team.

Sincerely,

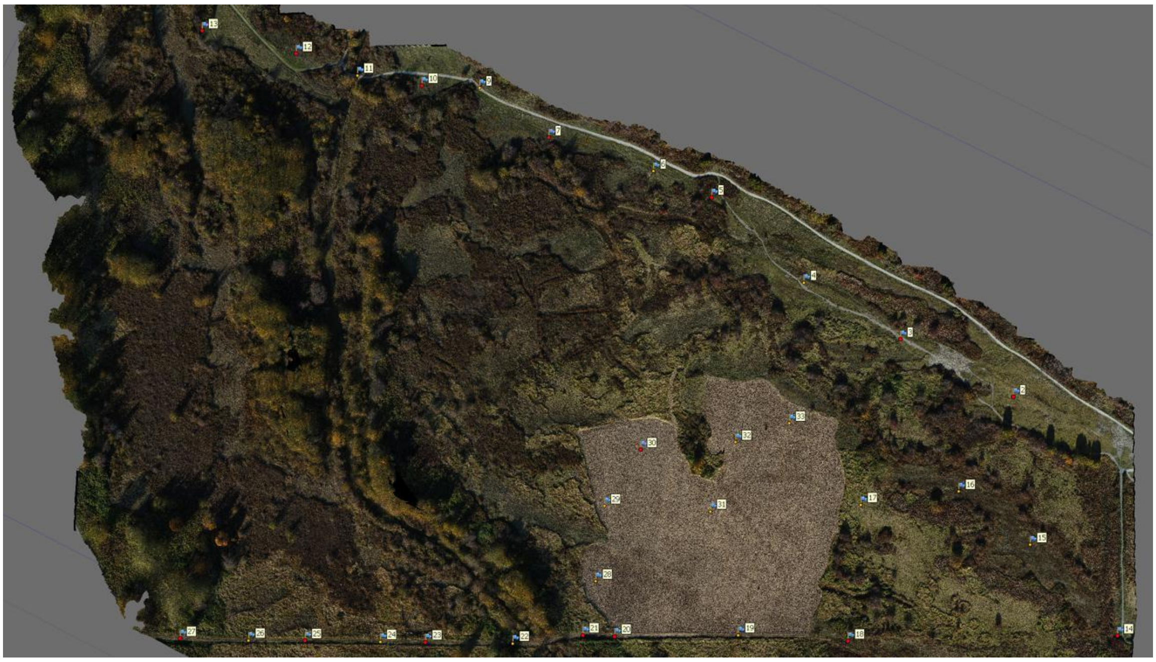
Nathan Vadeboncoeur, PhD

President and Founder – Smart Shores

Approach and Methods

A photogrammetric survey was conducted for a pre-identified section of Boundary Bay Regional Park on October 30, 2017. To begin, targets were distributed around the border of the target area and within an open central area of mulched grass. The targets used for this operation were yellow discs with a hole drilled in the centre. A 25cm spike was used to secure each disc to the ground and provide a stable platform for measuring. The spikes in the centre of each target were measured using a Trimble r10 RTK GPS unit to obtain northing/easting/elevation measurements.

Figure 1 – Distribution of Ground Control Targets



Thirty-three targets were distributed and measured. Two were destroyed by dogs during the survey, leaving thirty-one useable targets. Of these, fifteen were used for model calibration (control points – red) and sixteen were used for validation (check points - yellow). The average horizontal and vertical precision of field measurements was 10.9mm and 15.9mm, respectively.

A Phantom 4 Professional UAV equipped with a 20MP camera and a 24mm sensor was used to collect images of the target area. The UAV was flown over the area at an altitude of 60m Above Ground Level (AGL) in a grid pattern with a target front overlap of 80% and a target side overlap of 75%. The target area was covered in 31 minutes flying at an average speed of 12m/s, yielding 1,200 unique overlapping images. The camera maintained constant setting throughout the flight: 1/800s shutter speed, ISO100, *f*2.8. A shutter speed between 1/600s and 1/1000s would have produced clear images for this flight, given the light conditions on site. We aimed for a target

EV value of -0.3 in order to maintain good colour contrast among the ground vegetation. A shutter speed of 1/600s was selected because it gave us an average EV of -0.3 while maintaining ISO100 and *f*2.8. We selected a manual white balance to further improve image quality and colour consistency.

Images were sorted into overlapping sets using GPS data recorded by the UAV and attached to images as EXIF data. Images were aligned using a Structure from Motion algorithm to obtain a 3D point cloud of the coverage area. We then identified each image containing a ground target and created virtual markers on the measurement points – the heads of the spikes in the centres of the discs. Each marker was given a label matching the naming convention used for collecting GPS ground control points. All the GPS coordinates from the UAV that were contained in EXIF data were then removed and GPS ground point data were imported into Photoscan and automatically paired with the appropriate makers (because the same naming convention was used). Of the 31 markers imported 15 were used to calibrate the model, while the remaining 16 markers served as controls to validate the survey precision. The point could was then recalibrated using the ground control points[1].

Following re-calibration, a dense point cloud was generated using the tie points from the initial point cloud. Points were then classified as "Ground" or "Other." Ground points were defined using a nearest neighbour algorithm that rejected all points at that changed altitude at more than 15 degrees within 1m of horizontal distance.

The point cloud was then processed into two elevation models. First, a Digital Elevation Model (DEM) that included all points was calculated. This shows the height of each surface represented by the point cloud. Next, a Digital Surface Model (DSM) was created using ground points only. The DSM eliminated trees and heavily treed areas by predicting ground surface height relative to surrounding ground level. Estimated ground (surface) height data are not reliable for heavily treed areas because they are generated based on surrounding ground (surface) heights rather than any measurements below the tree canopy.

[1] GPS data collected by Phantom 4 Pro UAV are rated by the manufacturer at 1m horizontal precision and 1.5m vertical precision but in practice this level of precision is not reliable for vertical elevations. This is also insufficient for the purpose of this model. Therefore, we used a Trimble R10 RTK GPS/GNSS unit to collect ground control points. The Trimble R10 is the most advanced civilian RTK GPS unit in the world and is capable of sub-centimetre precision in ideal conditions (many visible satellites, low electromagnetic interference and a connection to the regional base station). The use of this unit allows for a reliable

photogrammetric accuracy of sub-5cm when surveying in a grid (ground control point measurement error is usually doubled for horizontal and tripled for vertical measurements when used to calibrate photogrammetric models). Our GPS error ranged from 9-19mm during this project.

An orthomosaic was then created by projecting a georeferenced image texture onto the DSM. The DSM was selected over the DEM because it’s flatter surface yields flatter, more aesthetically pleasing images than the DEM projection.

Metadata

This section presents information on the data collected and produced.
Data for Tables 2 and 3 have also been provided as .CSV and .TXT files.

Flight date: October 30, 2017
Flight time: 2:40pm
Flight duration: 32 minutes in the air, 5 minute battery change after 22 minutes
Conditions: Mostly sunny, 14 degrees, wind 15kph

Table 1. Model Precision and Accuracy

Segment	Control Point Precision (cm)			Check Point Precision (cm)			DEM / DSM Resolution (cm)	Ortho Resolution (cm)	Control Points (#)	Check Points (#)	Check Points as % of Control	Area (Ha)	Perimiter (m)
	Easting	Northing	Elevation	Easting	Northing	Elevation							
Boundary Bay Regional Park	1.0	1.2	2.1	1.9	2.3	10.1	5.93	1.4	15	16	107	47.68	2982.8

Table 2. Marker Positions

#Label	X/Easting	Y/Northing	Z/Altitude	Error_(m)	X_error	Y_error	Z_error	X_est	Y_est	Z_est
2	496659.687	5429609.95	1.912	0.0319	0.008254	-0.011282	-0.028673	496659.695	5429609.93	1.883327
3	496558.334	5429661.84	1.755	0.022948	-0.009904	-0.011295	0.017348	496558.324	5429661.83	1.772348
4	496471.423	5429712.93	1.689	0.078363	0.0319	0.030104	0.064937	496471.455	5429712.96	1.753937
5	496388.115	5429789.98	1.734	0.027783	0.006136	0.017868	0.020371	496388.121	5429790	1.754371
6	496335.89	5429813.46	1.897	0.070818	0.016468	-0.017579	0.066595	496335.906	5429813.45	1.963595
7	496241.799	5429843.71	1.389	0.010977	-0.008553	0.006013	0.003343	496241.79	5429843.72	1.392343
9	496179.315	5429888.62	1.225	0.065488	-0.017376	0.058078	-0.024775	496179.298	5429888.68	1.200225
10	496127.297	5429890.81	1.132	0.025105	0.014892	-0.020022	0.002759	496127.312	5429890.79	1.134759
11	496069.328	5429899.95	1.072	0.158438	-0.015803	0.018751	-0.156529	496069.312	5429899.96	0.915471
12	496014.145	5429919.72	1.039	0.023175	-0.021051	0.001815	-0.009522	496014.124	5429919.72	1.029478
13	495929.577	5429940.22	1.588	0.014557	0.012176	0.00558	0.005702	495929.589	5429940.22	1.593702
14	496753.323	5429394.38	2.107	0.016721	0.014308	0.002349	-0.008327	496753.337	5429394.38	2.098673
15	496674.85	5429476.53	2.411	0.225743	-0.017147	-0.000526	-0.22509	496674.833	5429476.53	2.18591
16	496610.631	5429524.51	2.21	0.212331	0.007153	-0.029503	-0.21015	496610.638	5429524.48	1.99985
17	496522.732	5429512.37	1.22	0.068749	0.002599	-0.003709	-0.0686	496522.735	5429512.37	1.1514
18	496511.088	5429389.53	1.881	0.033091	-0.013188	0.024024	0.018545	496511.075	5429389.55	1.899545
19	496412.303	5429394.82	1.649	0.130017	0.000409	0.021503	0.128226	496412.303	5429394.84	1.777226
20	496301.024	5429393.68	1.605	0.046805	-0.008873	-0.009373	0.04499	496301.015	5429393.67	1.64999
21	496272.319	5429394.92	1.451	0.02491	0.000747	-0.009789	-0.022894	496272.32	5429394.91	1.428106
22	496209.337	5429387.38	1.451	0.008315	0.004287	0.004883	-0.005188	496209.341	5429387.39	1.445812
23	496130.747	5429388.41	1.521	0.011381	0.001779	0.011163	-0.00132	496130.749	5429388.42	1.51968
24	496090.042	5429389	1.747	0.0361	-0.019121	-0.027009	-0.014427	496090.023	5429388.98	1.732573
25	496022.45	5429389.98	1.84	0.011243	0.001875	-0.008892	-0.006621	496022.452	5429389.97	1.833379
26	495971.506	5429390.21	1.802	0.01118	0.006059	-0.009373	0.000651	495971.512	5429390.2	1.802651
27	495909.857	5429391.95	1.825	0.002894	-0.000374	0.00249	0.001426	495909.857	5429391.95	1.826426
28	496284.074	5429443.52	1.416	0.034958	-0.007134	0.013606	-0.031401	496284.067	5429443.54	1.384599
29	496291.7	5429511.37	1.615	0.086745	0.006535	-0.006425	-0.08626	496291.707	5429511.36	1.52874
30	496324.32	5429562.2	1.564	0.0436	0.005188	-0.00156	-0.043262	496324.325	5429562.2	1.520738
31	496387.014	5429506.45	1.501	0.059049	0.049057	0.03071	0.01171	496387.063	5429506.48	1.51271
32	496409.765	5429569.02	1.511	0.019447	0.000337	0.012021	-0.015283	496409.765	5429569.03	1.495717
33	496458.197	5429586.03	1.293	0.073419	0.022372	0.007525	-0.069521	496458.219	5429586.04	1.223479

Table 3. GPS Readings and Precisions

Point	North	East	Elev (m)	Hz Prec (m)	Vt Prec (m)	PDOP	Sats
NWE2	5449717.85	504250.132	21.148	N/A	N/A	N/A	N/A
1	5429568.62	496742.618	2.195	0.011	0.017	1.1	18
2	5429609.95	496659.687	1.912	0.009	0.014	1.3	17
3	5429661.84	496558.334	1.755	0.008	0.013	1.2	17
4	5429712.93	496471.423	1.689	0.009	0.014	1.4	16
5	5429789.98	496388.115	1.734	0.009	0.014	1.4	17
6	5429813.46	496335.89	1.897	0.009	0.014	1.4	17
7	5429843.71	496241.799	1.389	0.009	0.013	1.3	17
8	5429843.71	496241.798	1.376	0.009	0.013	1.5	17
9	5429888.62	496179.315	1.225	0.01	0.014	1.3	18
10	5429890.81	496127.297	1.132	0.009	0.013	1.3	18
11	5429899.95	496069.328	1.072	0.011	0.016	1.4	17
12	5429919.72	496014.145	1.039	0.01	0.014	1.5	17
13	5429940.22	495929.577	1.588	0.009	0.014	1.5	16
14	5429394.38	496753.323	2.107	0.01	0.014	1.2	17
15	5429476.53	496674.85	2.411	0.012	0.016	1.2	15
16	5429524.51	496610.631	2.21	0.012	0.016	1.2	16
17	5429512.37	496522.732	1.22	0.012	0.016	1.3	15
18	5429389.53	496511.088	1.881	0.012	0.017	1.8	14
19	5429394.82	496412.303	1.649	0.012	0.017	1.7	15
20	5429393.68	496301.024	1.605	0.012	0.017	1.7	15
21	5429394.92	496272.319	1.451	0.012	0.017	1.7	15
22	5429387.38	496209.337	1.451	0.012	0.019	2.1	13
23	5429388.41	496130.747	1.521	0.012	0.017	1.6	15
24	5429389	496090.042	1.747	0.012	0.017	1.6	15

25	5429389.98	496022.45	1.84	0.012	0.017	1.6	15
26	5429390.21	495971.506	1.802	0.012	0.018	2.1	14
27	5429391.95	495909.857	1.825	0.012	0.018	2.2	13
28	5429443.52	496284.074	1.416	0.013	0.019	1.5	14
29	5429511.37	496291.7	1.615	0.012	0.018	1.1	15
30	5429562.2	496324.32	1.564	0.012	0.018	1.2	15
31	5429506.45	496387.014	1.501	0.012	0.016	1.2	15
32	5429569.02	496409.765	1.511	0.012	0.018	1.2	14
33	5429586.03	496458.197	1.293	0.012	0.018	1.4	15

Appendix D

Flow chart of work process