Agriculture monitoring at higher spatial and temporal resolutions using open-source satellite imagery

Detailed Final Research Report

Soham Shah
IDEAWORKS, Mohawk College

Contents

Acronyms

GIS	Geographic Information System
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red Edge
Lot/Con	Lot/Concession boundary, typically measuring 100-200 acres in area
R^2	Co-efficient of Determination

1 Introduction

1.1 Background

Assessment of the health of a crop, as well as early detection of crop infestations, is critical in ensuring good agricultural productivity. Stress associated with issues like moisture deficiencies, insects, fungal and weed infestations, must be detected early enough to provide an opportunity for the farmer to mitigate. Remote sensing imagery must be provided on a frequent basis, weekly at a minimum and be delivered to the farmer quickly, usually within 2 days (Natural Resources Canada). Also, crops do not generally grow evenly across the field and consequently crop yield can vary greatly from one spot in the field to another. These growth differences may be a result of soil nutrient deficiencies or other forms of stress. Remote sensing allows the farmer to identify areas within a field which are experiencing difficulties, so that he/she can apply the correct type and amount of fertilizer, pesticide or herbicide. Using this approach, the farmer not only improves the productivity from the land, but also reduces the farm input costs and minimizes environmental impacts (Natural Resources Canada). Currently, the government of Canada publishes a web application of weekly NDVI crop health metric calculated using MODIS satellite imagery that has a spatial resolution of only 250m (Agriculture and Agri-Food Canada). This spatial resolution is not sufficiently accurate to monitor crop health at the farm level as stated above.

Also, when monitoring crops using remote sensing at the farm level and at weekly durations throughout the growing season, imagery acquisition costs can become high. High spatial resolution imagery at a scale of <30m can be acquired by various methods such as private satellites, contract flights or UAVs, but this would have a high cost associated with it, especially when the need is to acquire the imagery on a weekly basis. The figures range from $0.5 to $1 per acre for private satellites and $2 to $5 per acre for contract flights, while using imagery from UAVs is still at an early stage and the cost is highly variable (Darr). Based on the 2011 agricultural census of Canada, the average size of a Canadian farm is 778 acres. Therefore, the cost of high-resolution satellite imagery is a significant limiting factor to more farmers using remote sensing to monitor crop health.

Moreover, high resolution remote sensing imagery is already used by the United States Department of Agriculture's (USDA) Risk Management Agency (RMA), which manages the Federal Crop Insurance Corporation (FCIC). The USDA uses a combination of private and public domain satellite imagery to reconstruct the growing season and to perform forensic remote sensing. Imagery is used to examine the growing conditions, crop health, and vigour and to conduct instant crop risk assessment rather than manual assessment which takes longer as it requires sending people in the field (ArcNews). Although, the USDA already uses satellite imagery to improve efficiencies in its crop insurance programs, all the satellite imagery sources they use are not in the public domain and the temporal resolution or revisit frequency of the public domain Landsat 8 satellite they use the most is only 16 days, which is not suitable for weekly crop health monitoring. However, the recent availability of open-source optical image time series from the Sentinel-2 mission satellites may offer an opportunity to monitor crop health with even higher spatial and temporal resolutions without any cost of imagery acquisition. Therefore, this research project aims to use open-source imagery from the Sentinel-2 A/B satellites to determine if the accuracy and frequency of crop health monitoring can be further improved to allow weekly crop health assessments at the field level.

1.2 Objectives

Timely and accurate information on crop yield and production is critical to many applications in agriculture monitoring. Medium and coarse spatial resolution (> 30 m) satellite imagery has always been used in crop yield forecasting at national and regional scales. However, monitoring crops throughout the growing season at the farm level requires imagery at higher spatial and temporal resolutions, which has a cost associated with it. Recent public domain remote sensing satellites are capable of acquiring imagery at a much higher spatial resolution of 10m - 30m along with a high temporal resolution of every 3-5 days without any cost of imagery acquisition. The overall objective of this applied research project is to determine if open-source multi-spectral satellite imagery from satellites in the public domain can be used to accurately monitor crops at higher spatial and temporal resolutions, meaning at the farm level and frequently throughout the growing season. The specific objectives of this research are to:

- Find statistical correlation or trends between the weather and NDVI data calculated using open source satellite images at high temporal resolutions (bi-weekly)
- Find statistical correlation or trends in the NDVI data calculated using open source satellite images at high spatial resolutions (farm level)

2 Methodology

2.1 Research Design

In order to meet the objectives of this research outlined previously we needed to first determine which types of crops we will use in the research and what will be the study area of the research. This research project could have focused on many different parts of the world due to the nature of the global data available. However, we chose to conduct the research in Ontario due to our familiarity with the local agriculture practices and the previous knowledge we have of the available open data sources in Ontario which can be used in the research, such as the annual yield per acre maps provided by the Ontario government or the weather data published by Environment Canada.

The Ontario government through its crown agency called Agricorp provides annual yield per acre maps for some of the most common crops grown in Ontario such as corn, soybean and winter wheat crops. These maps would be used to determine which study areas we should pick for our research, since having some idea of how the yield for the area we were studying would have been helpful in analysing our research results. Therefore, using these yield/acre maps for the year 2019 we chose to study farms in the Counties of Grey, Lambton and Oxford. The reason why we chose these counties is because we wanted to pick study areas with low, medium and high crop yields and the yield/acre maps showed these 3 Counties had the varying degrees of yields we wanted in the year 2019 (See Appendix 7.1 for the yield/acre maps). Oxford County was the one with the highest yields, Lambton County had yields in the mid-range and Grey County has low yields. Also, we only studied Corn and Soybean crops and excluded Winter Wheat crops from our research as the growing season for it is different and it would increase the effort needed to study it as well.

As stated in the objectives of our research, the main part of our research focuses on calculating vegetation indexes from the Sentinel 2 satellite imagery and then analyzing these to reach our objectives. We chose to use 2 of the most commonly used vegetation indexes in the field of agricultural remote sensing, i.e. NDVI and NDRE for our research. We chose these 2 indexes as they are proven to be effective in monitoring crop health. NDVI is calculated using the Red and Near Infrared spectrum bands, both of which are available from the Sentinel 2 satellite images at a spatial resolution of 10m x 10m. NDVI correlates with chlorophyll content in the plant and therefore is a good measure of plant health, especially those plants which have green leaf cover like Corn and Soybean (Soukup). Also, we decided to collect NDRE index as well, because it can be helpful in measuring crop health in later stage of crop growth when more layers of leaves are present on a plant like Corn. The lower level laves in the plant canopy cannot contribute much to an NDVI measurement, which can be solved by substituting

NDVI's red band with NDRE's red edge band, which provides a measurement that is not as strongly absorbed by just the topmost layers of leaves (Soukup). Therefore, NDRE can give better insight into permanent or later stage crops like Corn, because it's able to measure further down into the canopy (Soukup). This is why we decided to include it in our research in case our NDVI values are not giving us accurate results.

We also used statistics such as mean, range and standard deviation to find trends in these indexes and correlation statistical values such as the R^2 co-efficient of determination to look at relationships between these index values and the weather data to meet our research objectives. To summarize, in order to prove our hypotheses that public domain satellite images can be used to monitor crop health and high spatial and temporal resolution, we would use only the quantitative methods outlined above. We only used qualitative methods to determine our study areas by looking at the yield/acre maps.

2.2 Data Collection

The datasets which we had to collect for the research were the Sentinel 2 satellite imagery, the weather data and the crop inventory data for our study area in the Counties of Grey, Lambton and Oxford as stated before. At first we tried to acquire Sentinel 2 satellite imagery from the Sentinel 2 Toolbox and the Sentinels Application platform software (SNAP), provided by the European Space Agency (ESA). However, this was a slow process and required downloading and installing the cumbersome software and then downloading a huge amount of raw satellite imagery data as well as a lot of data processing to filter out the clouds and calculate the NDVI and NDRE values. We were able to find a much quicker easier solution by using a Sentinel Explorer GIS Web Application, which allowed us to zoom to the spatial resolution we wanted the imagery at and download small chunks of the satellite imagery which was already processed for us. This application has been developed by ESRI, which is the leading company in the field of Geographic Information Systems (GIS) and the full functionality of the app is openly available to the public as long as you create a free account on their online platform called ArcGIS Online. This app allowed us to filter the images in our study areas by cloud cover and therefore we were only able to quickly see which days had low cloud cover and only download imagery for those days. Also, we were able to download imagery which was already calculated for both NDVI and NDRE indexes that we wanted to use in our research. For our research we downloaded available data with low or no cloud cover in all 3 Counties throughout the growing season starting from March, and ending in November. We were not able to collect imagery at a weekly frequency due to the cloud cover and most of the time we managed to get bi-weekly imagery with some cases where we could only get imagery once a month.

The other big step in our research was the need to classify our satellite imagery and only extract those areas from our satellite imagery which were Corn and Soybean crops. At first we tried to do this using image classification methods, which were not as accurate and easy to implement as they took a lot of time. However, we found a solution to this by using the Annual Crop Inventory dataset provided by Agriculture and Agri-Food Canada (AAFC) at the Open data website of the Government of Canada. This data was not going to be available for the year 2019 growing season on the website till March 31, 2020, but we were able to get it in December 2019 by contacting AAFC directly and asking for the dataset before it is published on the government's website. This dataset was key to our entire research as it meant we could extract areas in our imagery where Corn and soybean crops were planted in 2019 more easily and accurately.

In order to analyze at the farm level we decided to use lot/concession boundaries as they are similar in area to farms. We acquired this dataset from the Ontario GeoHub open data portal. Property boundaries could have been used instead of these as they would cover even smaller areas, however there was not an open dataset for property boundaries.

Finally, we had to download the weather data for 2019 to find a relationship between the vegetation index values and the weather at a weekly frequency to prove our objective of monitoring crop health at a high temporal resolution. Therefore, we were able to download weekly and monthly weather summaries from different rain station near our study areas from the Government of Canada's environmental and natural resources portal for historical weather data. We would only use the monthly climate summaries in our research however, because some of the daily and weekly climate data had gaps in it.

2.3 Data Analysis

Throughout the research the main software program which we used to process and analyze the data was ArcGIS Pro, which is a GIS and remote sensing software created by the company ESRI. The first step of the analysis we did using this software was using the Annual crop Inventory dataset along with the satellite imagery. After downloading the satellite imagery from the sentinel explorer web application we loaded it into ArcGIS Pro and then intersected it with the annual crop inventory data to only extract crop areas that were corn and soybean. The next step was to intersect these crop areas with the lot/concession boundaries and only use lot/concession blocks which were covered in majority by either of the 2 crops we were studying. This ensured that we only included valid areas in our research and reduced the noise in our research results from other crops and land cover types skewing our vegetation index results.

The next step was to summarize the pixel values of NDVI and NDRE vegetation indexes from the satellite images for each lot/concession area (lot/con). This was done by using statistically summary tools in ArcGIS Pro, which gave us the min, max, mean, range, standard deviation and pixel count in each lot/con. We also calculated the pixel count/acre density next. We looked for a high pixel/acre density combined with variations in the NDVI/NDRE data by looking at the range and the standard deviation statistics for each lot/con to prove our objective of monitoring at high pixel resolutions to find variations at the farm level was possible. The step which followed next was to add the weather dataset to this dataset and find significant correlation between the two datasets so that we could prove our objective of monitoring crop health frequently throughout the growing season. To do this, first, we took the average of the mean monthly temperature and the total monthly precipitation of the rainfall stations which were nearest to our research study areas. Then we joined these two values with the NDVI/NDRE summaries. In situations where we had bi-weekly NDVI/NDRE values we used the same monthly average for all values in that month. In order to find correlation between the weather data and the NDVI/NDRE data we created scatter plots using ArcGIS Pro and Microsoft Excel to find the R^2 co-efficient value.

2.4 Limitations

There were some limitations based on the research design and the availability of the data we used in this research project. First of all, we encountered a limitation related to our research design. Although we downloaded NDVI and NDRE satellite imagery for all 3 Counties, we only analyzed NDRE satellite imagery for Oxford County. This was done to reduce effort and save time and meant that we could not include the NDVI vs. NDRE comparison in our research results for Lambton and Grey Counties. This had a limited impact on our research results, since this was not the main objective of our research project.

Another limitation of our research we encountered during data collection was due to the accuracy and frequency of satellite imagery. Due to cloud cover we encountered some months with limited usable satellite imagery, only 1 or 2 clear days in the entire month, or even some months with no imagery available at all. We also encountered limitations about the accuracy and frequency of weather data with some months and even weeks not having daily weather data for our rain stations. We used monthly averages to overcome this issue, but the lack of data could have skewed the averages.

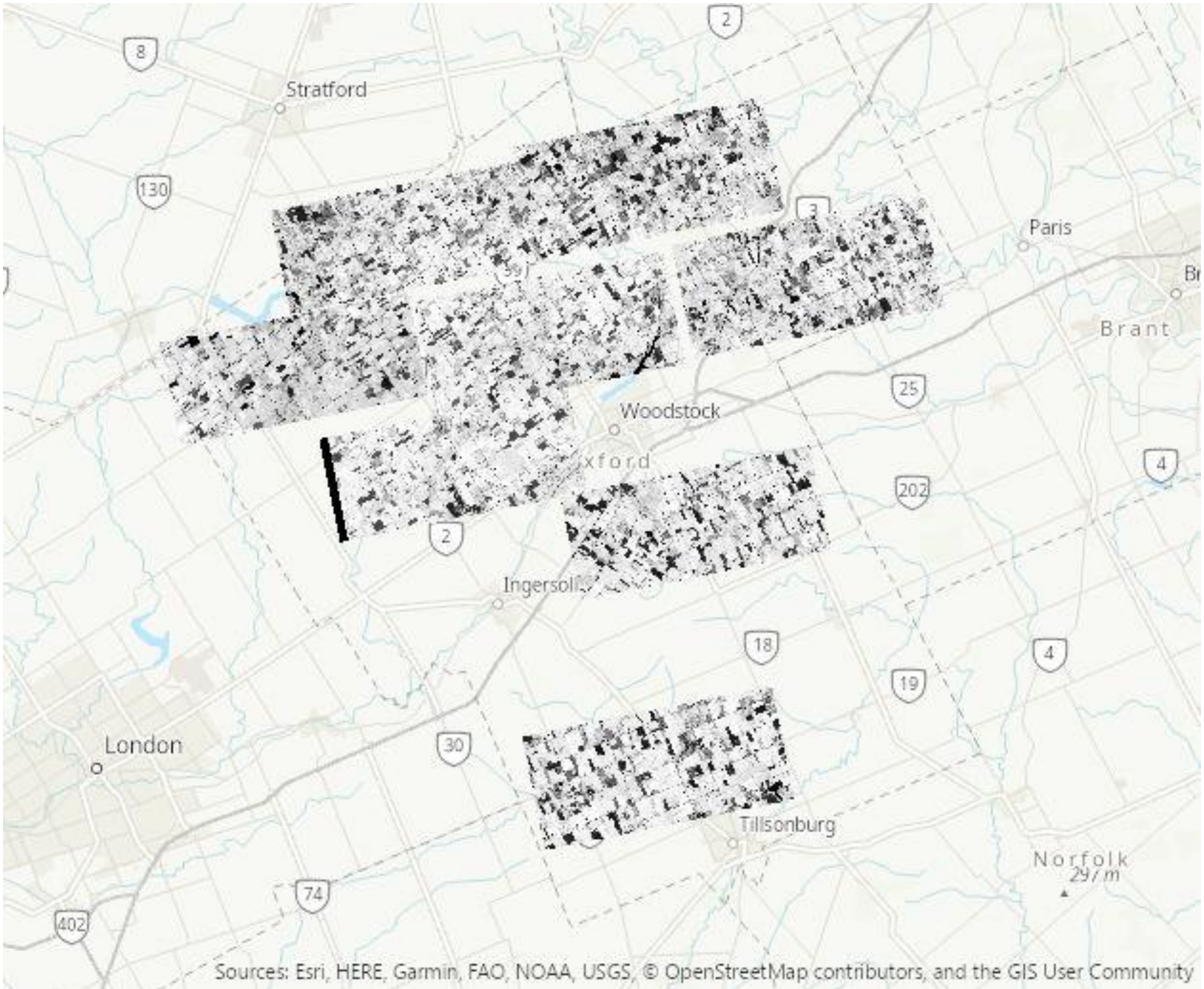
Finally, the last limitation we encountered during data collection was the availability of property boundaries. Since our research was aimed at analyzing crop health at high spatial resolution at the farm level we would have ideally liked to have acquired property boundaries, however these are not openly available and have a high cost of acquisition. We were able to overcome this to a large extent by using the centroid of a lot/concession area which ranges from 100 to

200 acres throughout Ontario. This was acceptable because based on the 2011 agricultural census of Canada, the average size of a Canadian farm is 778 acres, which is actually much bigger than the lot/concession boundary area. Therefore, analyzing at the farm level would still be possible if we analyzed our data at the lot/con level.

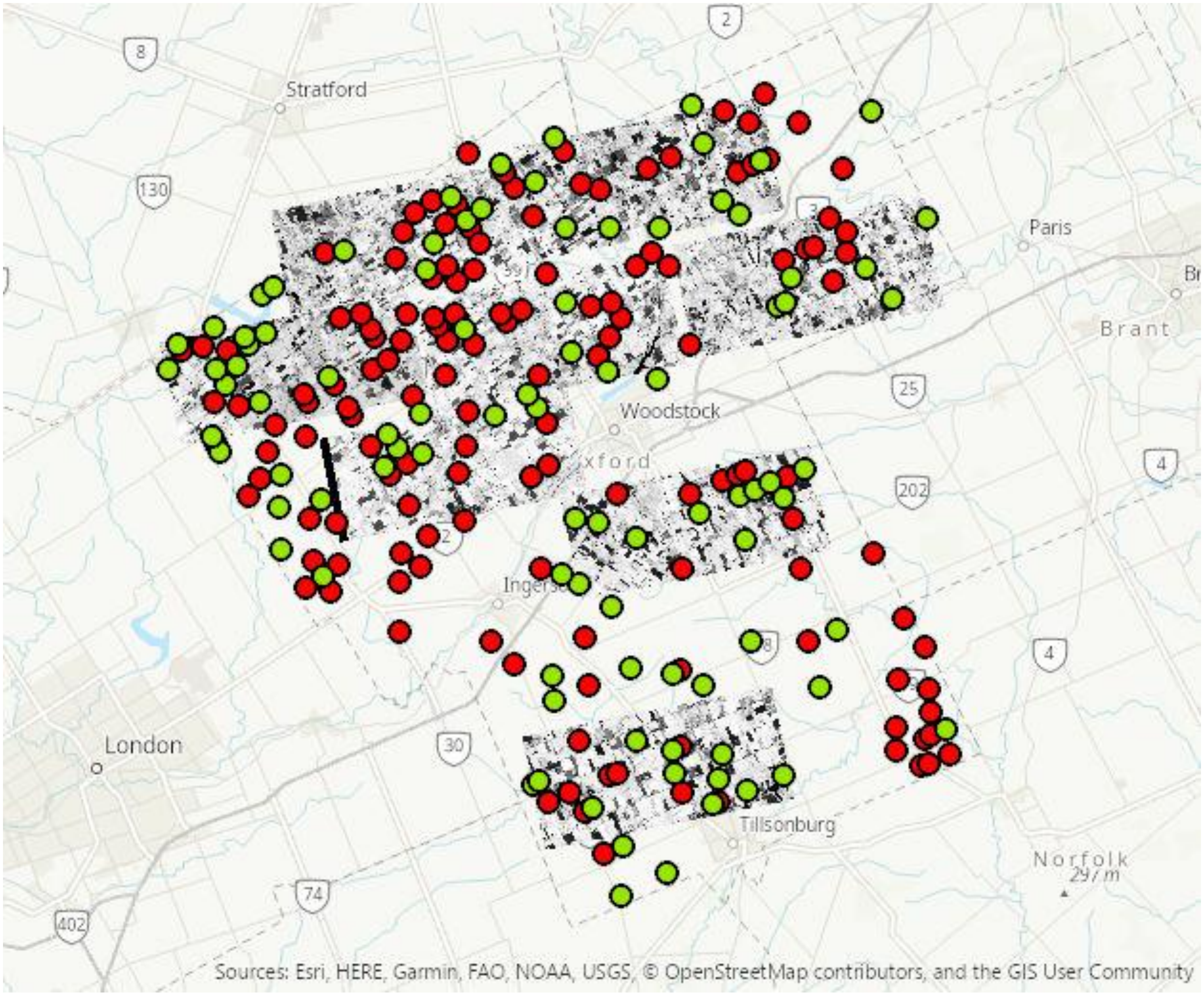
3 Results

3.1 Study Area Maps

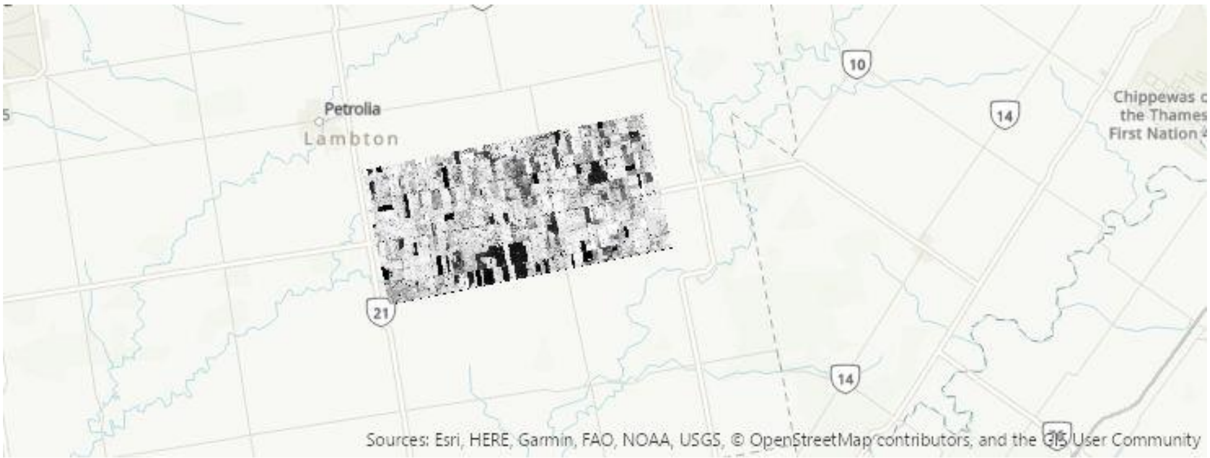
The following images below show the satellite imagery along with the lot/concession centroids of farms with corn and soybean crops for Grey, Lambton and Oxford counties.



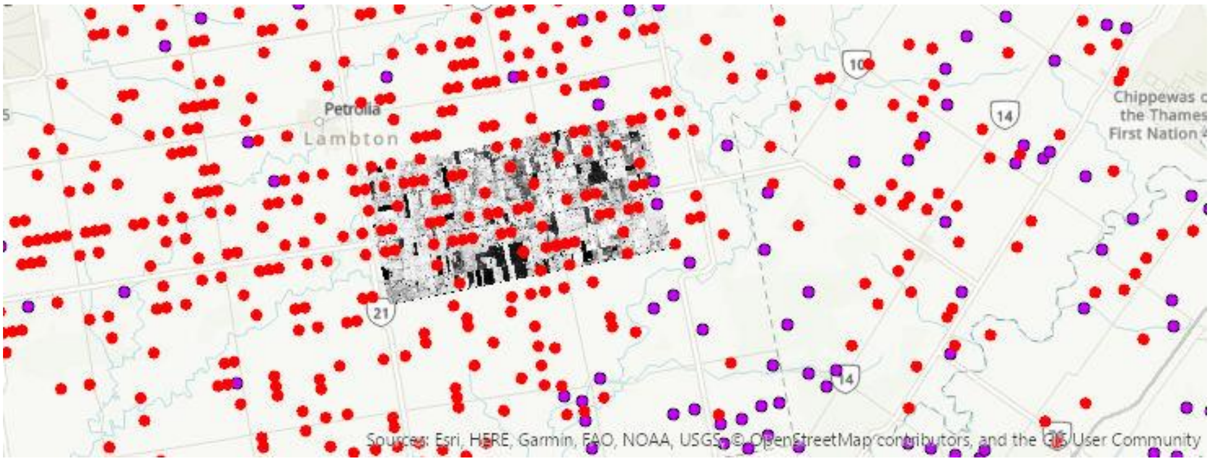
<u>Figure 3.1.1:</u> Oxford County NDVI Satellite Imagery samples on August 3



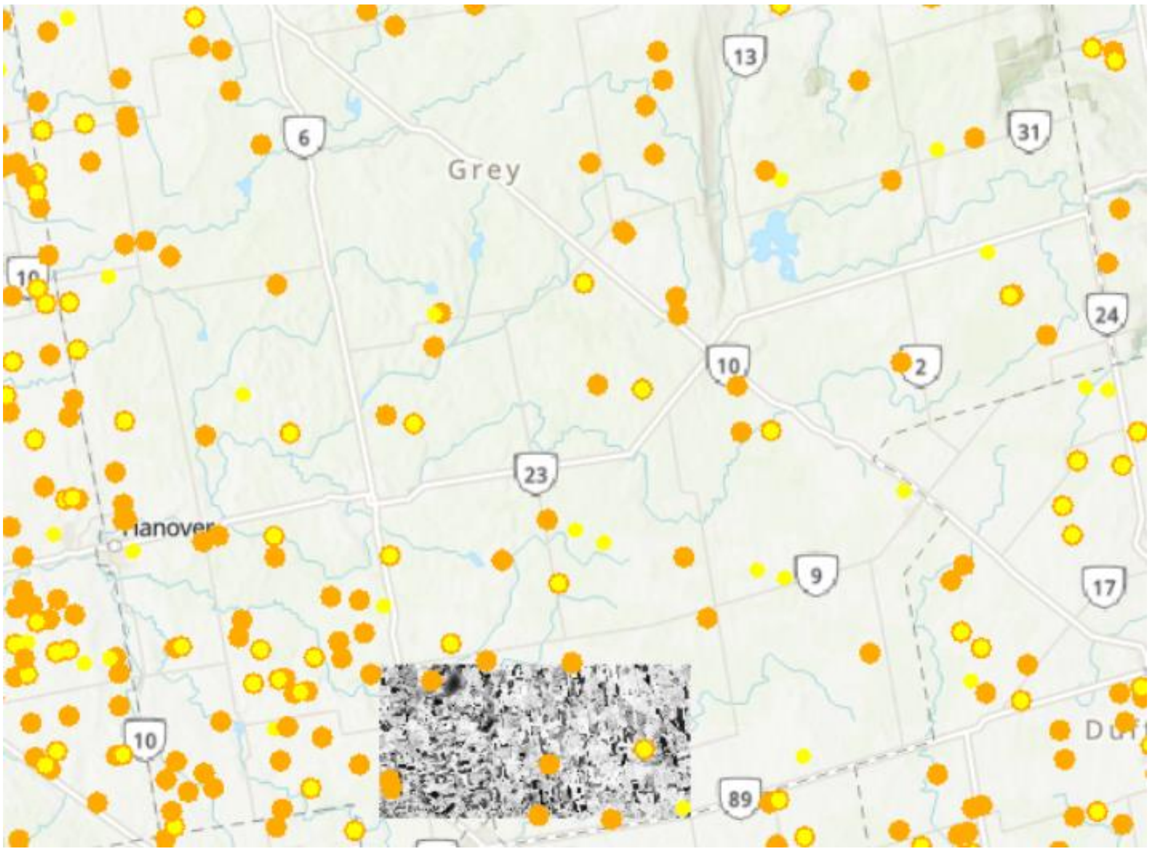
<u>Figure 3.1.2:</u> Oxford County NDVI Imagery sample with Corn and Soybean Lot/concession centroids (Corn: Green circle, Soybean: Red circle)



<u>Figure 3.1.3:</u> Lambton County NDVI Satellite Imagery sample on September 17



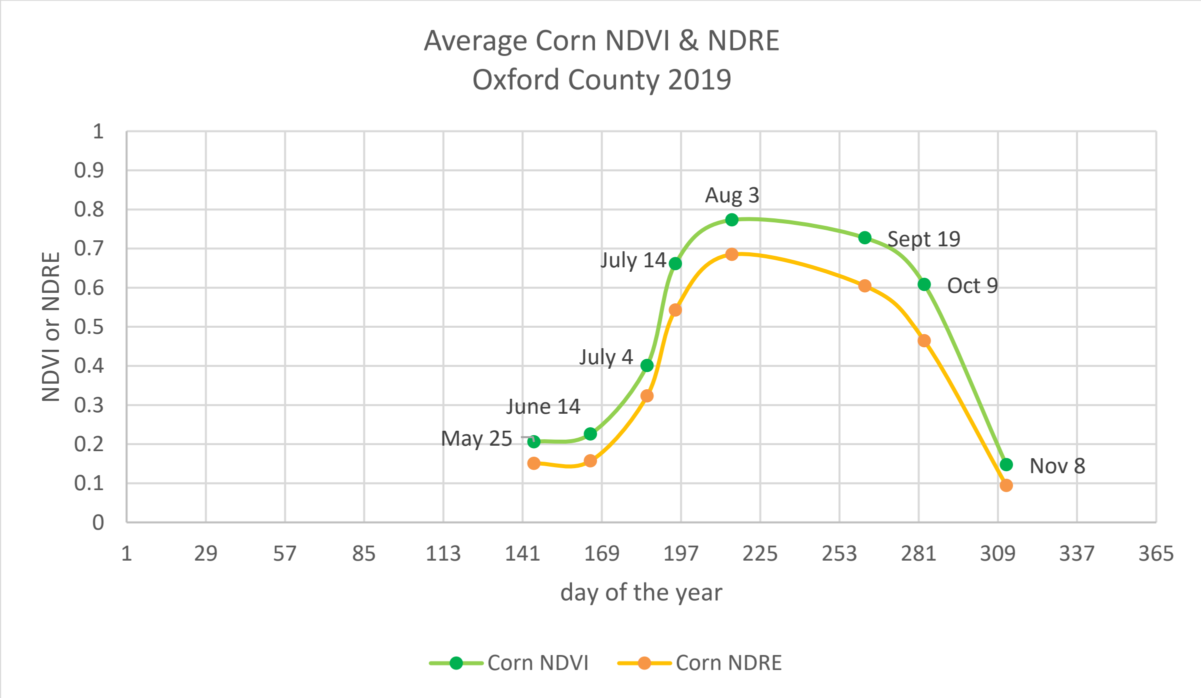
<u>Figure 3.1.4:</u> Lambton County NDVI Imagery sample with Corn and Soybean Lot/concession centroids (Corn: Purple circle, Soybean: Red circle)



<u>Figure 3.1.5:</u> Grey County NDVI Imagery sample with Corn and Soybean Lot/concession centroids (Corn: Yellow circle, Soybean: Orange circle)

3.2 Summary of Corn and Soybean NDVI & NDRE vegetation index values with Mean Temperature and Total Precipitation

The following scatter plots and line graphs below summarize the research data for Grey, Lambton and Oxford counties, extracted from the satellite imagery and the weather data.



<u>Figure 3.2.1:</u> Average Corn NDVI & NDRE for Oxford County from May to November 2019

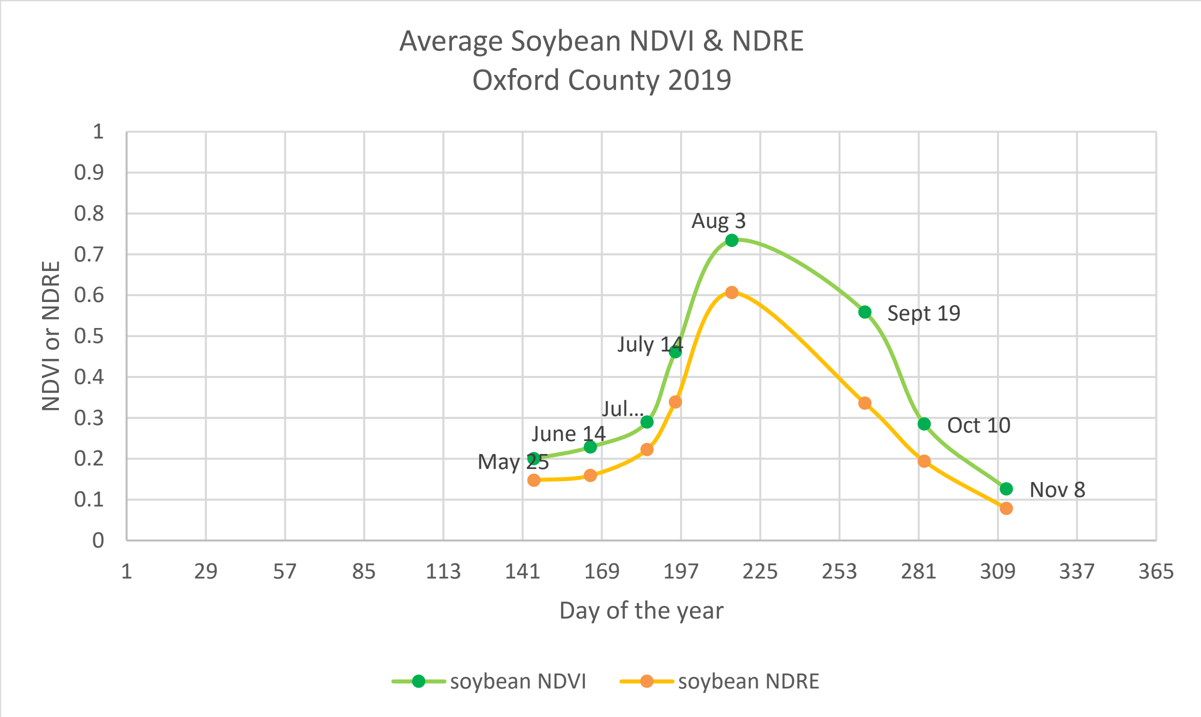


Figure 3.2.2: **Average Soybean NDVI & NDRE for Oxford County from May to November 2019**

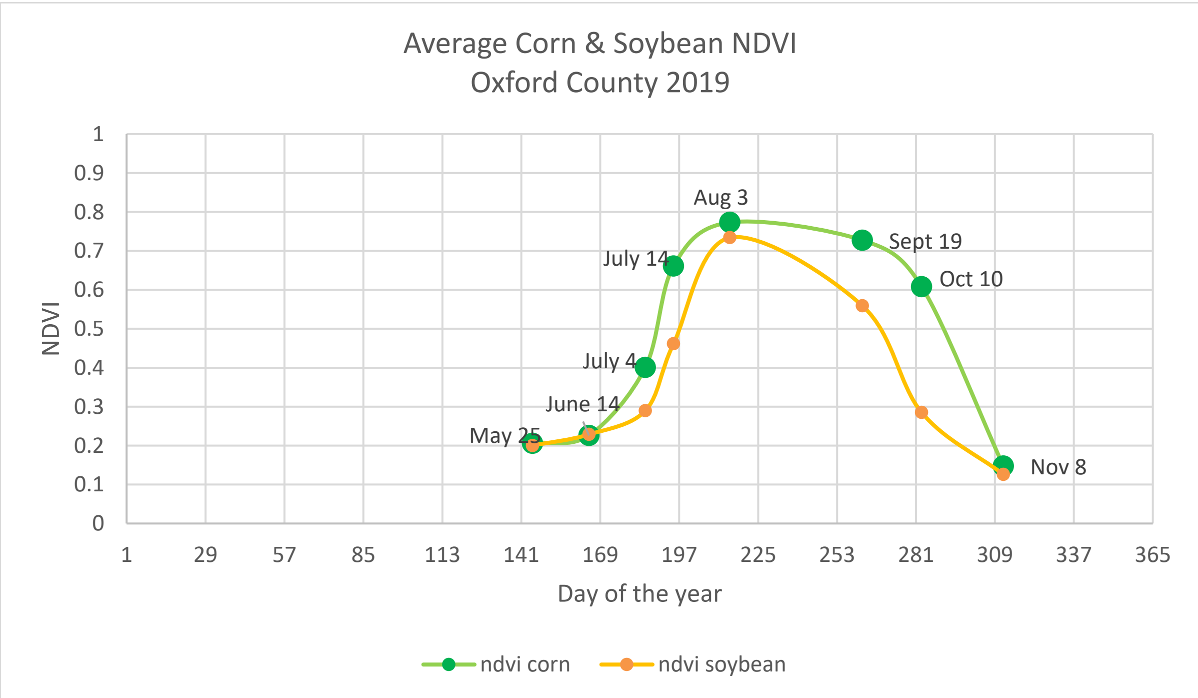


Figure 3.2.3: **Average Corn and Soybean NDVI for Oxford County from May to November 2019**

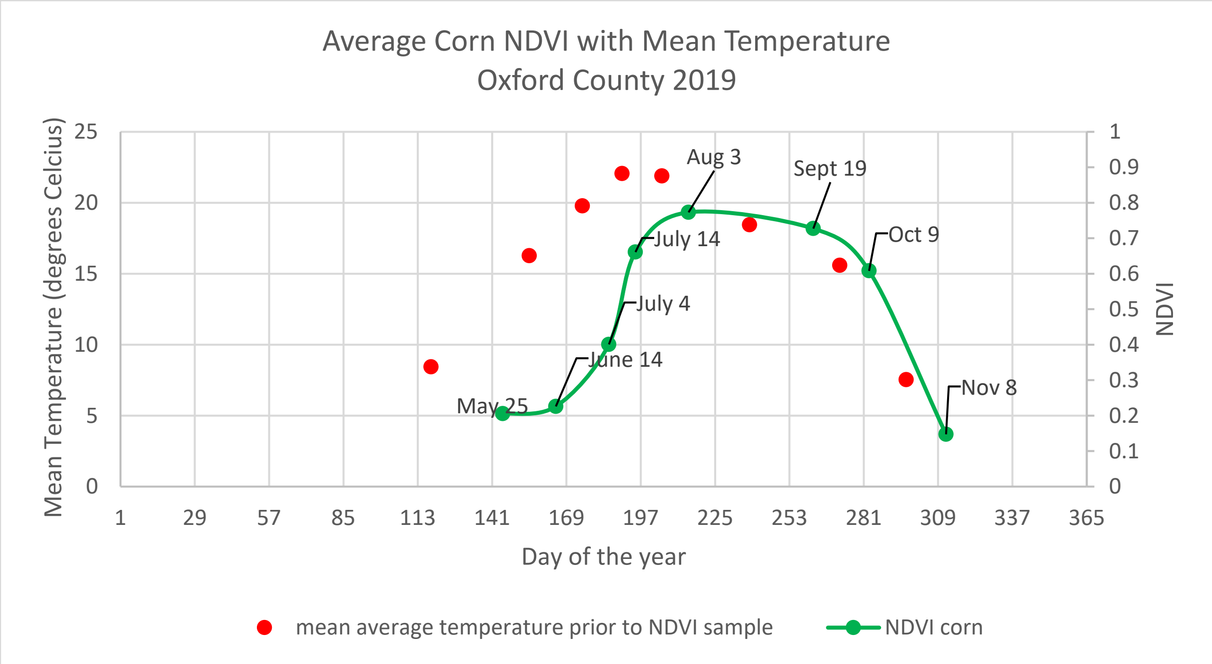


Figure 3.2.4: **Average Corn NDVI with Mean Temperature for Oxford County from May to November 2019**

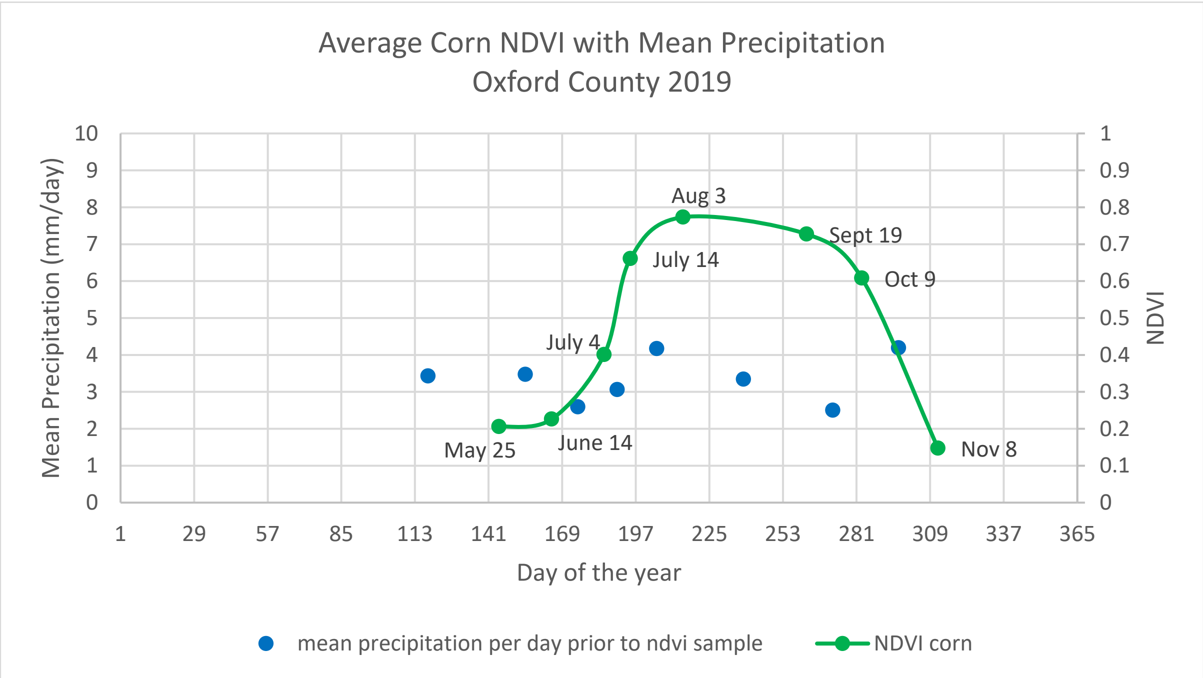


Figure 3.2.5: **Average Corn NDVI with Mean Precipitation/day for Oxford County from May to November 2019**

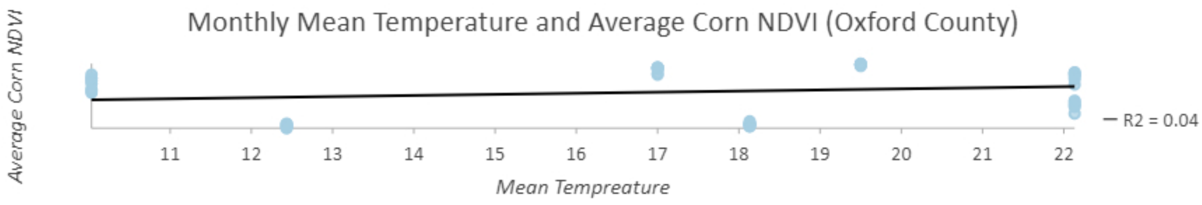


Figure 3.2.6: Scatter Plot of Average Corn NDVI with Mean Temperature for Oxford County from May to November 2019

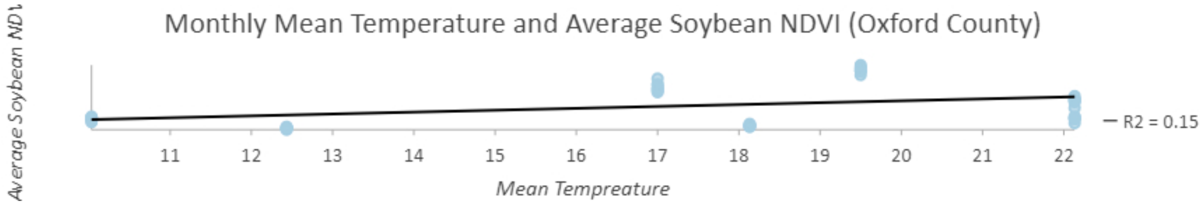


Figure 3.2.7: Scatter Plot of Average Soybean NDVI with Mean Temperature for Oxford County from May to November 2019

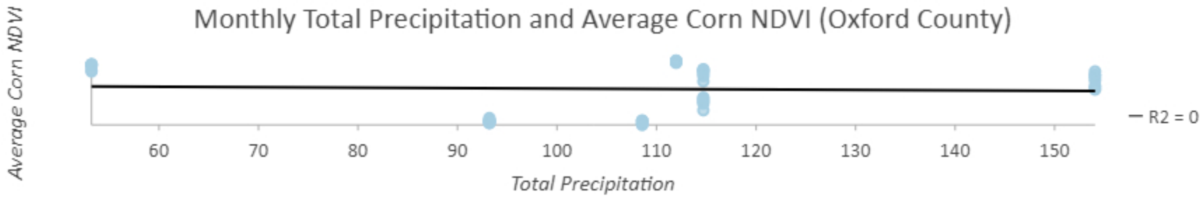


Figure 3.2.8: Scatter Plot of Average Corn NDVI with Total Precipitation for Oxford County from May to November 2019

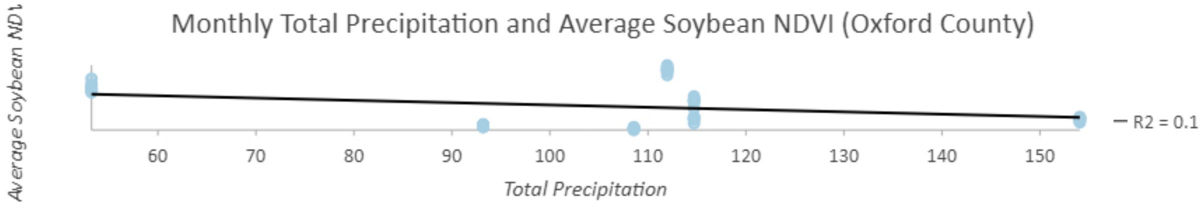
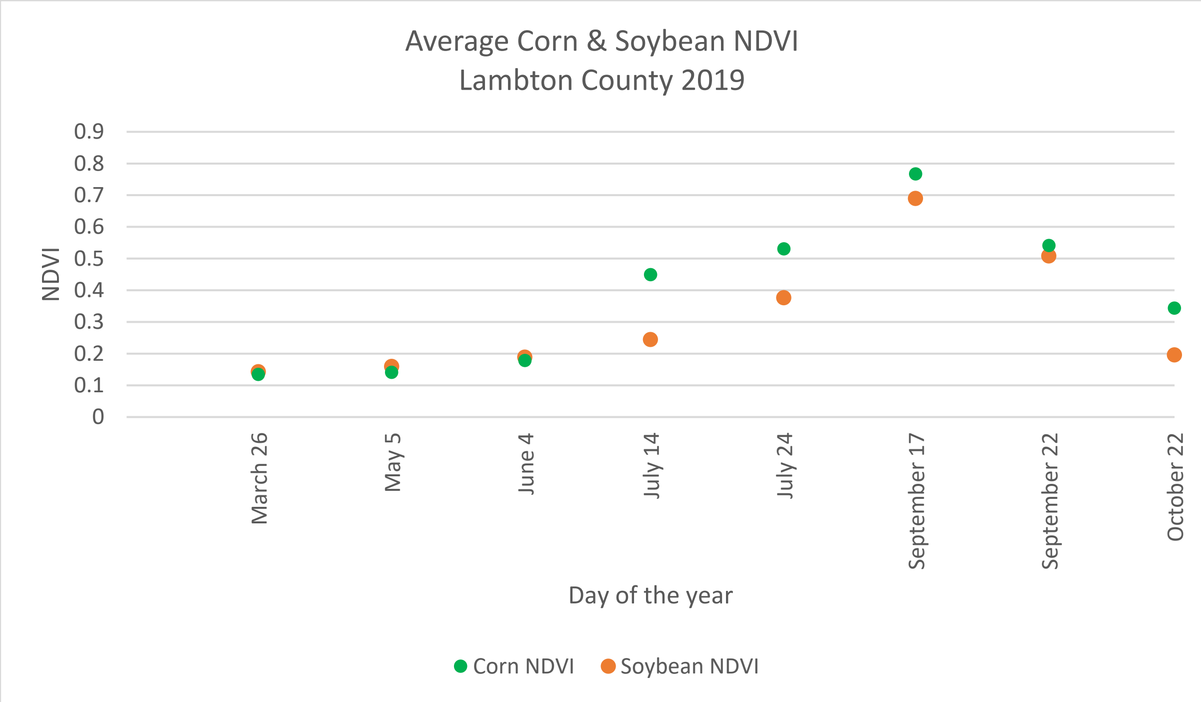
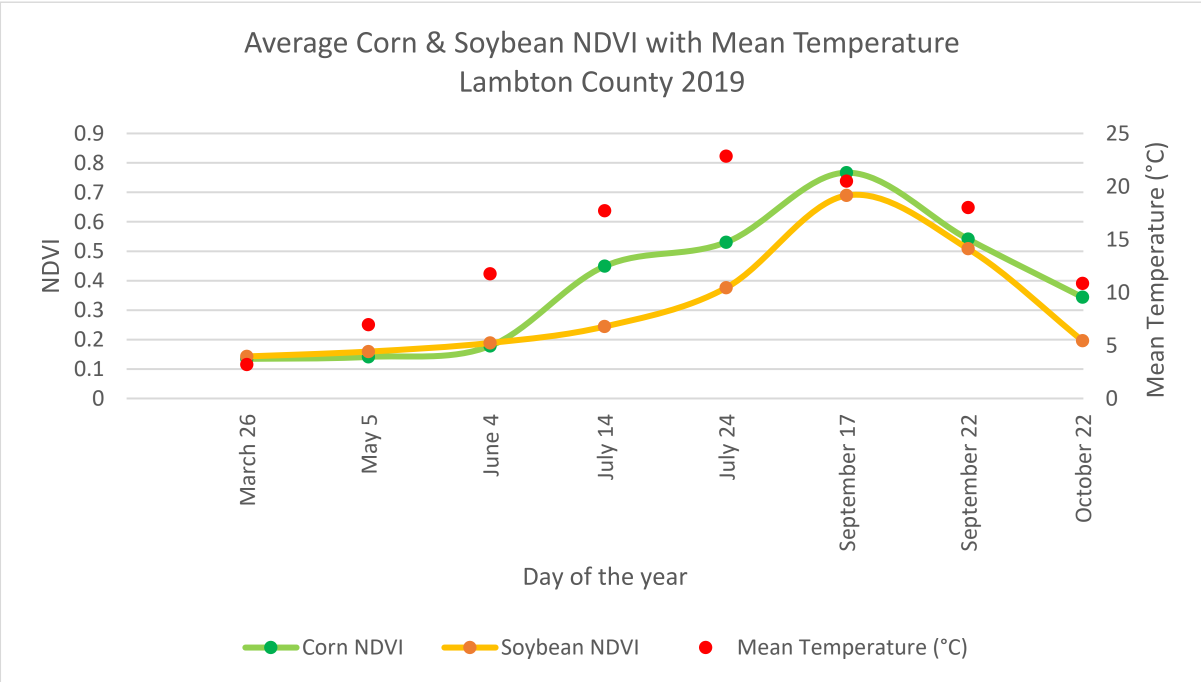


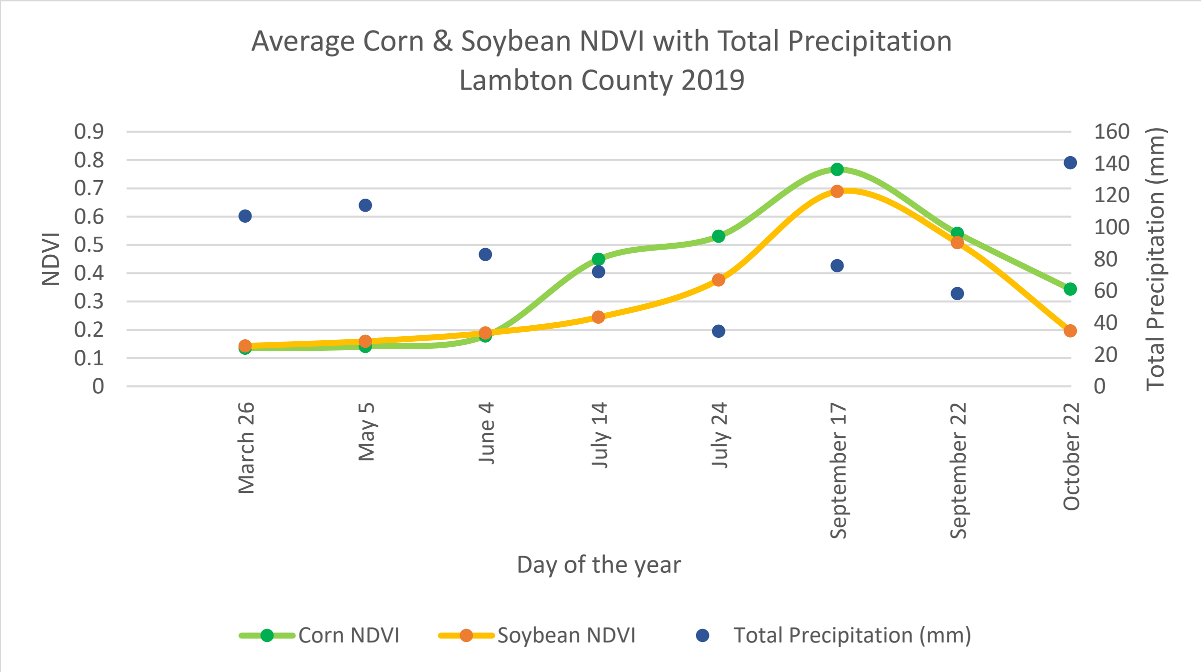
Figure 3.2.9: Scatter Plot of Average Soybean NDVI with Total Precipitation for Oxford County from May to November 2019



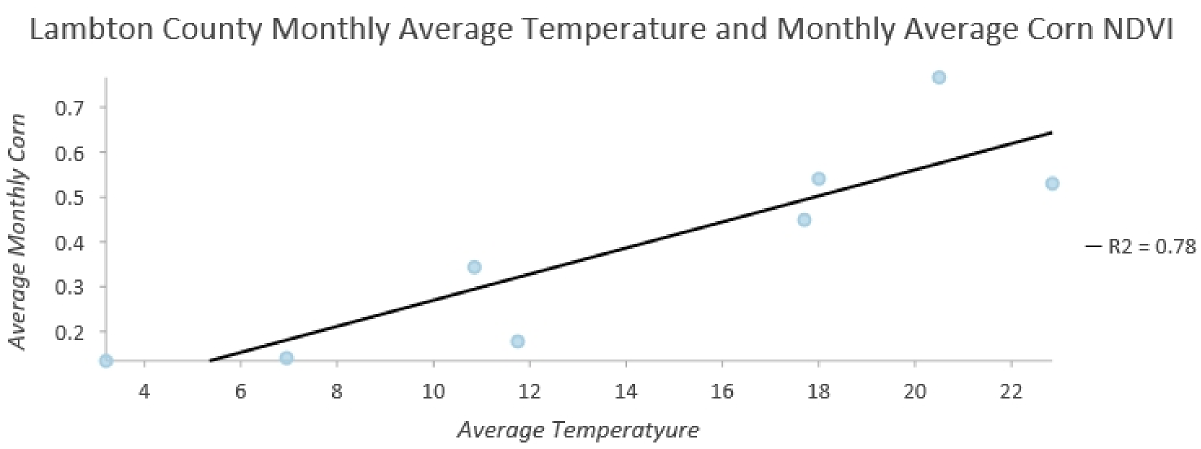
<u>Figure 3.2.10:</u> Average Corn and Soybean NDVI for Lambton County from March to October 2019



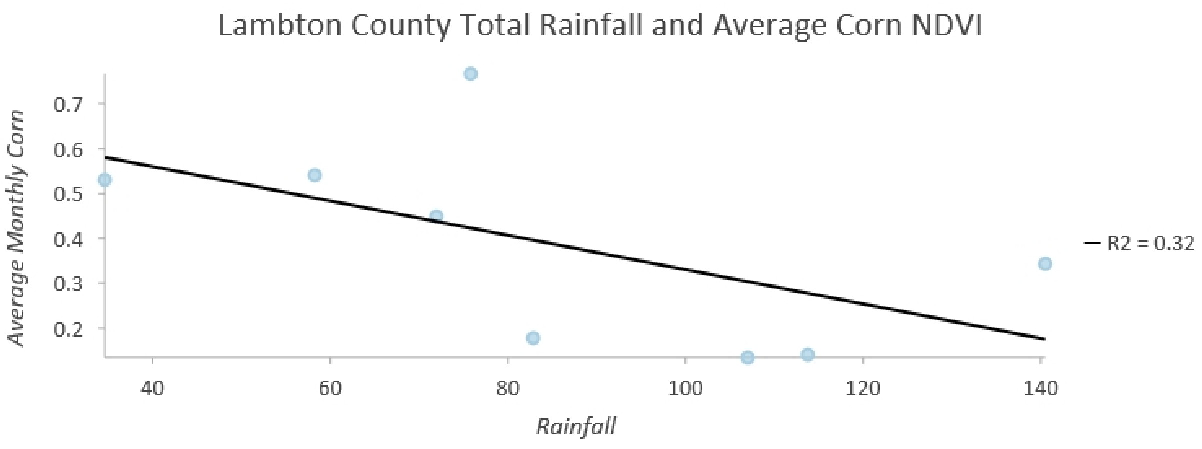
<u>Figure 3.2.11:</u> Average Corn and Soybean NDVI with Mean Temperature for Lambton County from March to October 2019



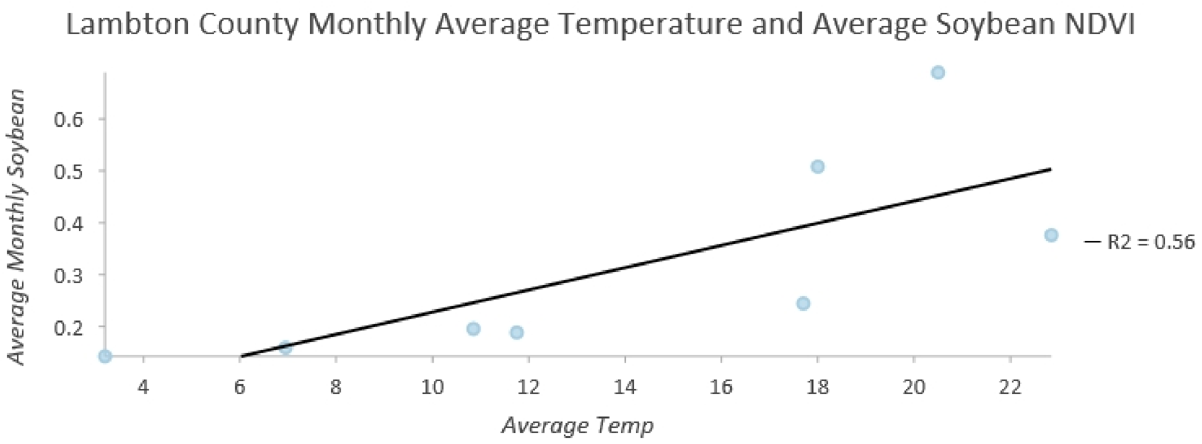
<u>Figure 3.2.12:</u> Corn and Soybean NDVI values with Total Precipitation for Lambton County from March to October 2019



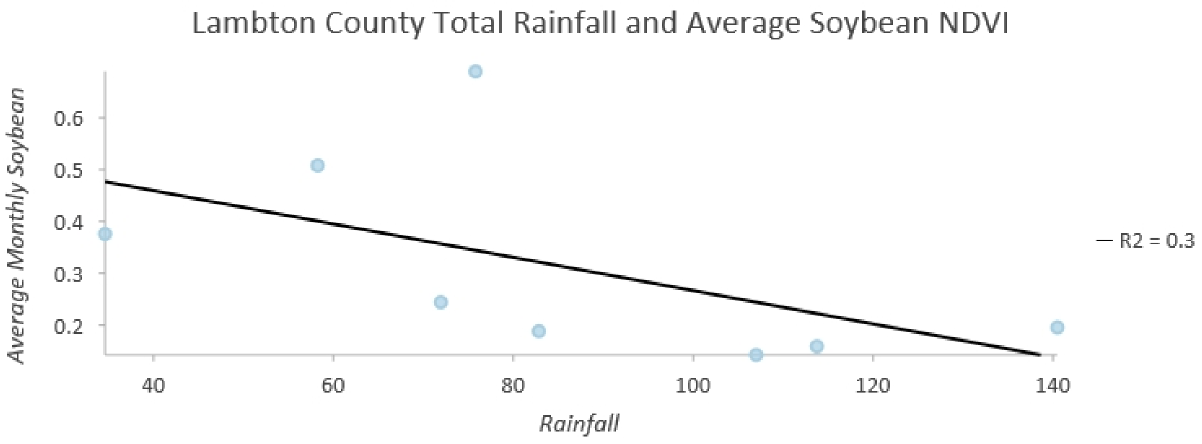
<u>Figure 3.2.13:</u> Scatter Plot of Average Corn NDVI with Mean Temperature for Lambton County from March to October 2019



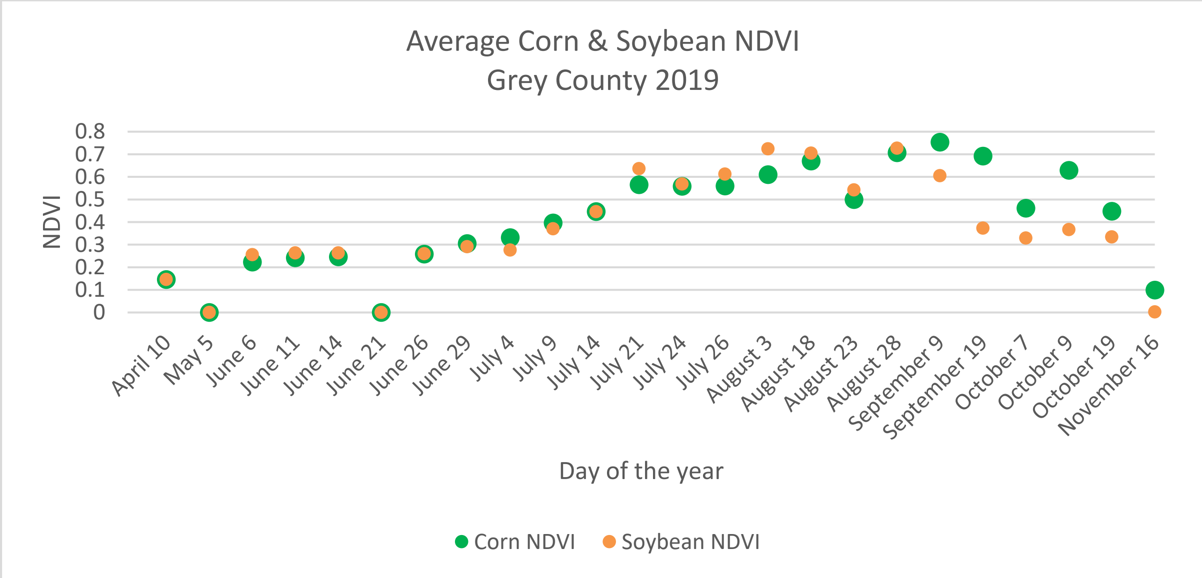
<u>Figure 3.2.14:</u> Scatter Plot of Average Corn NDVI with Total Rainfall for Lambton County from March to October 2019



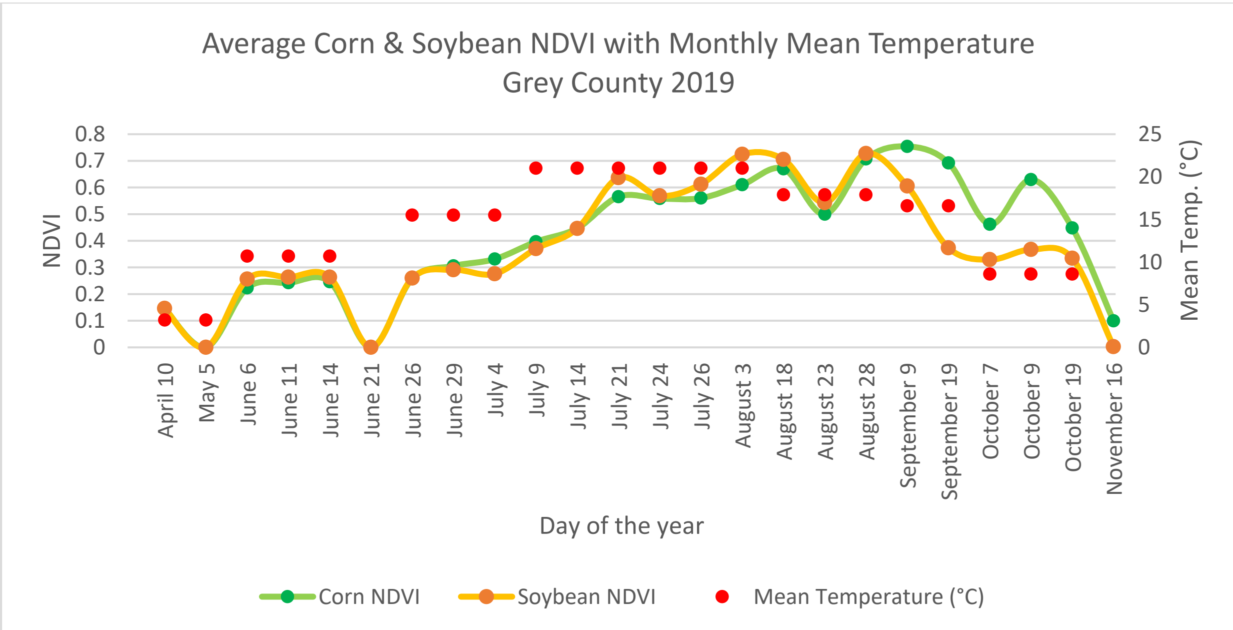
<u>Figure 3.2.15:</u> Scatter Plot of Average Soybean NDVI with Mean Temperature for Lambton County from March to October 2019



<u>Figure 3.2.16:</u> Scatter Plot of Average Soybean NDVI with Total Rainfall for Lambton County from March to October 2019



<u>Figure 3.2.17:</u> Average Corn and Soybean NDVI for Grey County from April to November 2019



<u>Figure 3.2.18:</u> Average Corn and Soybean NDVI with Monthly Mean Temperature for Grey County from April to November 2019

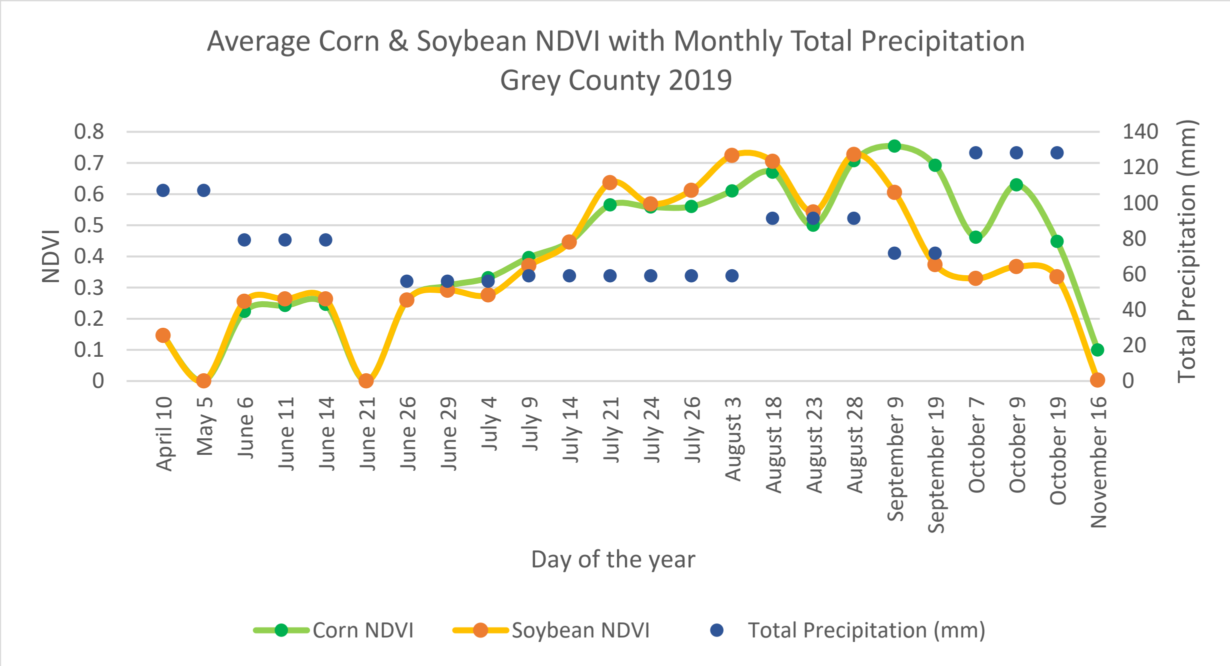


Figure 3.2.19: Average Corn and Soybean NDVI with Monthly Total Precipitation for Grey County from April to November 2019

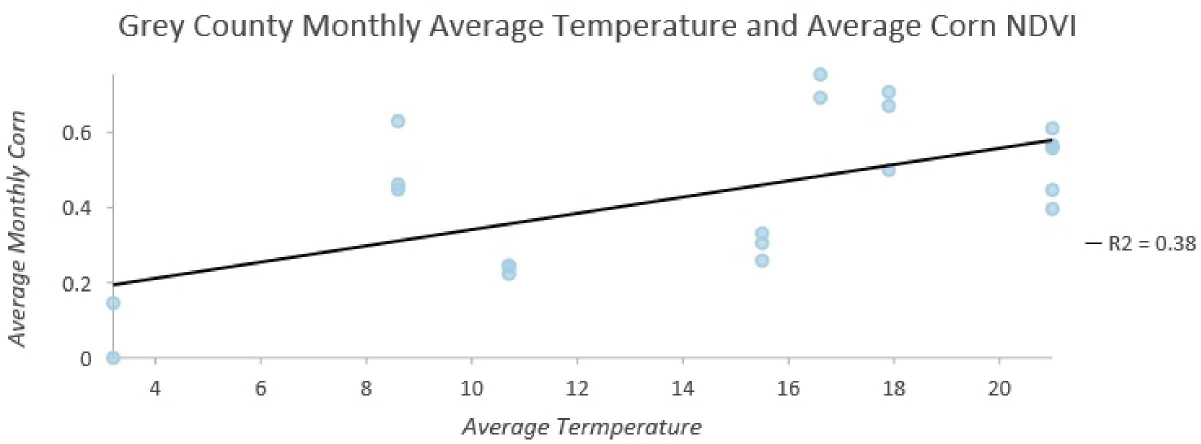
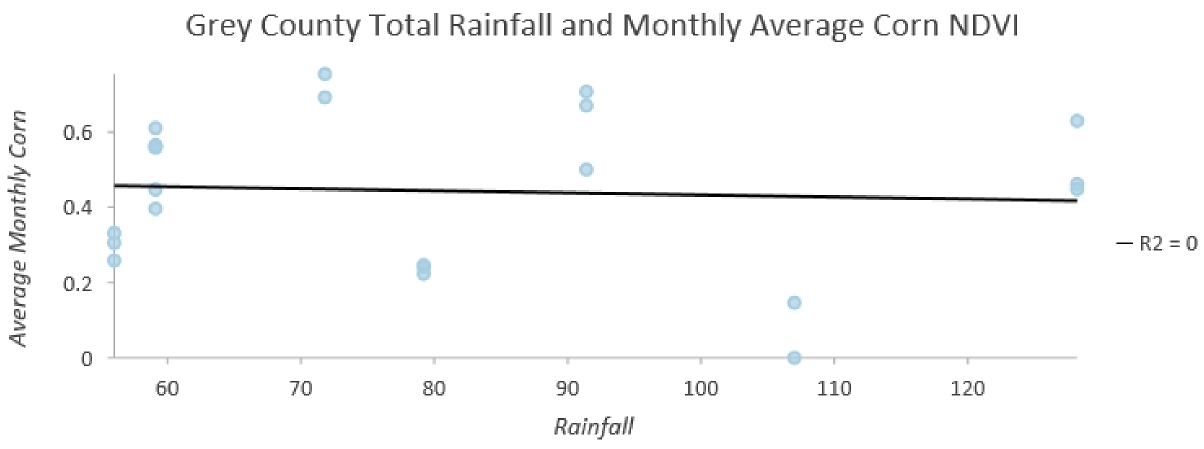
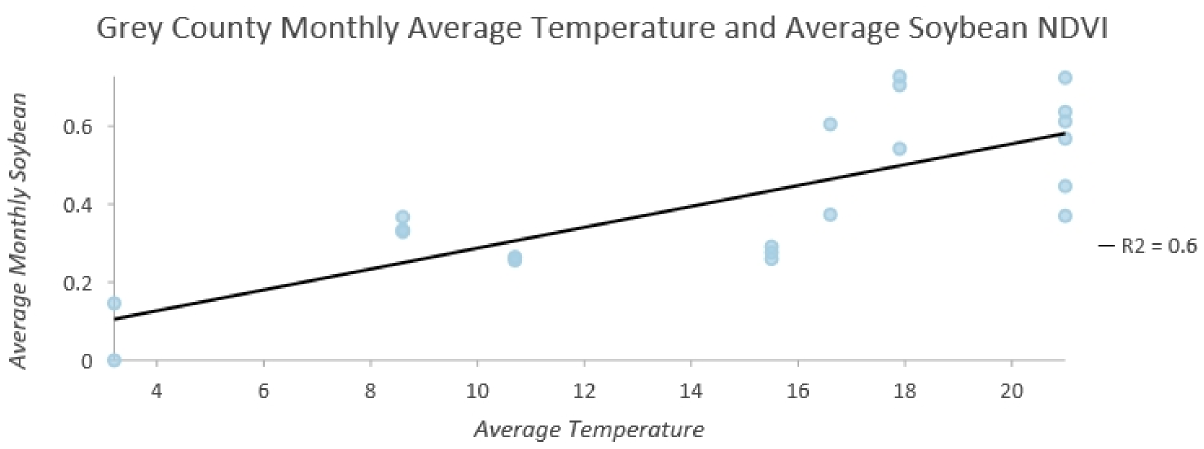


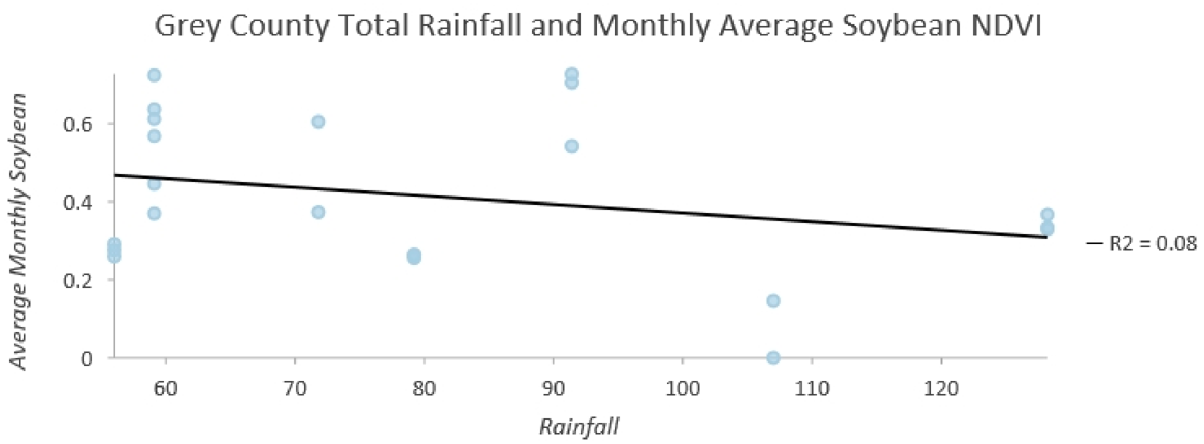
Figure 3.2.20: Scatter Plot of Monthly Average Corn NDVI values with Mean Temperature for Grey County from April to November 2019



<u>Figure 3.2.21:</u> Scatter Plot of Monthly Average Corn NDVI values with Total Rainfall for Grey County from April to November 2019



<u>Figure 3.2.22:</u> Scatter Plot of Monthly Average Soybean NDVI values with Mean Temperature for Grey County from April to November 2019



<u>Figure 3.2.23:</u> Scatter Plot of Monthly Average Soybean NDVI values with Total Rainfall for Grey County from April to November 2019

3.3 NDVI/NDRE Statistics at Lot/Concession Spatial Extent

The average pixel/acre value across all 3 Counties which we were able to measure covering the spatial extent of a lot/concession area was close to 8 pixels/acre. The average range of NDVI/NDRE values which we measured for a lot/con across all 3 Counties was 0.595. And finally the average Standard deviation in the NDVI/NDRE values which we measured for a lot/con across all 3 Counties was 0.246. See the data output tables mentioned in Appendix 7.2 for actual calculations.

4 Discussion

In this section we will discuss the results from Section 3 above and include possible explanations for the trends and patterns we see in the data. We will also discuss the implications of these results on the objectives of this research project. And any limitations in the research which might have affected our results.

Regarding the line graphs shown in Figure 3.2.1 and 3.2.2 comparing the NDVI index with the NDRE index for corn and Soybean crops in Oxford County, we can see that NDRE values are slightly lower than the NDVI values and the gap between the NDVI and NDRE does increase in the later stages of the growing season when the plant develops a significant canopy. However, since our research was focused more towards monitoring at high spatial resolutions and not actually trying to determine the health of plant itself we did not see a benefit of continuing to use both indexes and in order to save time and effort we only looked at the NDVI value for the rest of our research study.

First we examined the results of the statistical calculations we did on the vegetation indexes outlined in Section 3.3. As discussed earlier in Section 2.1, our research design was to study the results at the lot/con spatial extent in order to prove one of our objectives that public domain satellites such as Sentinel 2 can be used to monitor crop health more accurately at higher spatial resolutions. Other public domain satellites such as Landsat 8 have a spatial resolution of 30m by 30m and a pixel density of 4.5 pixel/acre. The Red and Near Infrared bands on Sentinel 2 which are used to calculate NDVI and NDRE vegetation indexes have a resolution of 10 m by 10 m. The average pixel/acre value of 8 that we measured shows that the satellite imagery we used had a high spatial resolution of 16.8m x 16.8m. The reason our imagery's spatial resolution was not as high as the 10m resolution the Sentinel 2 satellite provides could have been because we used the Sentinel 2 explorer app for downloading the satellite imagery with less effort and time instead of downloading it directly from the European Space Agency's SNAP platform which requires more processing. This can be classified as a possible limitation of our research which could be improved upon if the imagery is downloaded directly suing the SNAP platform. Moreover, as mentioned in Section 3.3, the average range of NDVI/NDRE values at the lot/concession level was measured at 0.595 and the standard deviation was measured at 0.246. This was done to evaluate the amount of variation in the data at the farm level as these measurements are for satellite imagery on the same day in each lot/con area. A standard deviation of 0.246 and a range of 0.595 shows that we were able to measure some variation in the index values inside each lot/con area on the same day. This coupled with the measured pixel density of 8 pixel/acre means that the spatial resolution of our imagery was high enough to pick up variations throughout different parts of the same lot/con area and it is possible to use this kind of satellite imagery to monitor farm level variations.

Apart from monitoring at high spatial resolution, the other main objective of our research was to be able to monitor crops at a high temporal resolution using the Sentinel 2 satellite imagery. We were hoping to be able to monitor the farms on a weekly basis throughout the growing season, since the Sentinel 2 satellite's revisit time in mid-latitude regions is 2-3 days. As seen in Figures 3.2.10, 3.2.11 and 3.2.12 which contain the line graphs for Corn and NDVI for Lambton County, there are gaps in the data with the months of April and August missing. This was due to cloud cover present throughout those months over Lambton County. The cloud cover was less for Oxford County, where we could gather data at least once every month, as seen in Figures 3.2.3, 3.2.4 and 3.2.5. The highest frequency of data collection was possible in the County of Grey, where we could gather bi-weekly or even weekly data for most of the months in the growing season as seen in Figures 3.2.17, 3.2.18 and 3.2.19 due to a lack of cloud cover hindering data collection. Therefore, we discovered that cloud cover is a very important factor and it can cause gaps in the data and continues to be a limiting factor in using only public domain satellites in precision agriculture.

By examining the scatter plots created for all 3 Counties we can determine if there is a significant correlation between the weather and the NDVI measurements. Although proving a relationship exists between the weather and the NDVI of crops was not the objective or scope of this research project, we included these plots to determine what kind of weather measurements can play a major role in determining the NDVI values of a crop. Scatter Plots in Figure 3.2.20 and 3.2.22 look at the relationship between NDVI and mean temperature in Grey County. The closer the value of the coefficient of determination, R^2 is to 1, the stronger the relationship. In these scatter plots we can see a R^2 value of 0.38 for Corn and 0.6 for Soybean crops when compared with the mean temperature which shows significant correlation between NDVI and temperature. Also in Figures 3.2.13 and 3.2.15, R^2 values of 0.78 for Corn and 0.56 for Soybean for Lambton County can be seen on the scatter plots when comparing NDVI with mean temperature which shows significant correlation. However, the scatter plots correlating the mean temperature and NDVI for Oxford County don't have significant R^2 values at 0.04 and 0.15 for Corn and Soybean respectively, as seen in Figures 3.2.6 and 3.2.7. This can be explained because of the high mean temperatures we can see in Figure 3.2.4 at the start of the growing season in Oxford County, when the crops would not have yet grown big and thus the NDVI would still be low. No significant correlation was found between NDVI and total precipitation as seen from the low R^2 values in the scatter plots of both Corn and Soybean crops for all 3 Counties in Figures 3.2.8, 3.2.29, 3.2.14, 3.2.16, 3.2.21 and 3.2.23. Therefore, although temperature naturally plays a big factor in crop health, weather is not the only factor which affects crop NDVI. There can be other unique local factors affecting NDVI values such as different planting dates, different soil health or different dates of fertilizer application between farms.

5 Recommendations

At the end of the research project we discovered that some of the limitations in our research occurred due to gaps in the data due to the cloud cover reducing the availability of satellite imagery. Also, other limitations which were encountered was a lack of accurate weather data, soil quality data, planting dates and fertilizer application dates for individual farms, all of which would play an important role in determining crop health and NDVI throughout the growing season. Therefore, if possible, conducting a research study comparing different years of NDVI data for the same set of farms with their yields spanning over many years, would reduce the impact of these unique and local variables on the research results. Also, this type of research would allow us to study issues of lower NDVI areas within specific farms more accurately. To conduct this type of research you would have to involve the farmers themselves to provide for more localized and accurate yield data, soil quality data and climate data for their individual farms.

The research highlights that public domain satellites can be used in precision agriculture to monitor crop health at high spatial resolutions at the farm level thereby increasing crop yields, farm productivity and thus the overall profitability of agriculture and the economy as a whole. The limitation of acquiring imagery at a higher frequency or high temporal resolution remains an issue due to cloud cover. This gap is currently being overcome in the private sector remote sensing market by creating imagery packages which combine Sentinel 2 data with other public domain satellites such as Landsat 8 and private satellites, but these are not ideal due to high cost and inconsistent spatial resolution data, since satellites like Landsat 8 have a 30m by 30m spatial resolution, which is much lower than the 10 m x 10m resolution of Sentinel 2. However, future public domain satellite launches such as Landsat 9 in 2021 may eliminate the need to rely on older satellites like Landsat 8 or more expensive private domain satellites to fill in the gaps and thus greatly increase the adoption of precision agriculture.

6 References

"Crop Monitoring & Damage Assessment." *Natural Resources Canada*, Natural Resources Canada, 25 Nov. 2015, nrcan.gc.ca/node/14652.

Darr, Matt, et al. "The Source Matters for Getting the Most out of Aerial Imagery." *Soil and Management Factors Influence Seeding Depth | Integrated Crop Management*, Iowa State University, 10 Mar. 2016, crops.extension.iastate.edu/cropnews/2016/03/source-matters-getting-most-out-aerial-imagery.

"Insuring America's Farmland." *ESRI*, ArcNews, 2011, www.esri.com/news/arcnews/spring11articles/insuring-americas-farmland.html.

Jaramaz, Darko, et al. "RESPAG 2013." 2013, pp. 1–2, www.researchgate.net/publication/267981491_The_ESA_Sentinel-2_mission_Vegetation_variables_for_Remote_sensing_of_Plant_monitoring.

Soukup, Cara. "NDVI vs. NDRE: What's the Difference?" *Sentera*, 11 Mar. 2020, sentera.com/ndvi-vs-ndre-whats-difference/.

"Weekly Best-Quality Maximum - NDVI Anomalies." *Open Government*, Agriculture and Agri-Food Canada, 26 Sept. 2016, open.canada.ca/data/en/dataset/ea6b4be2-9826-47f3-a387-33ddf02592f4.

Zhang, T. et al., 2018. Potential bands of sentinel-2A satellite for classification problems in precision agriculture. International Journal of Automation and Computing, DOI: 10.1007/s11633-018-1143-x

7 Appendices

7.1 2019 Corn and Soybean Yield/Acre Maps from Agricorp

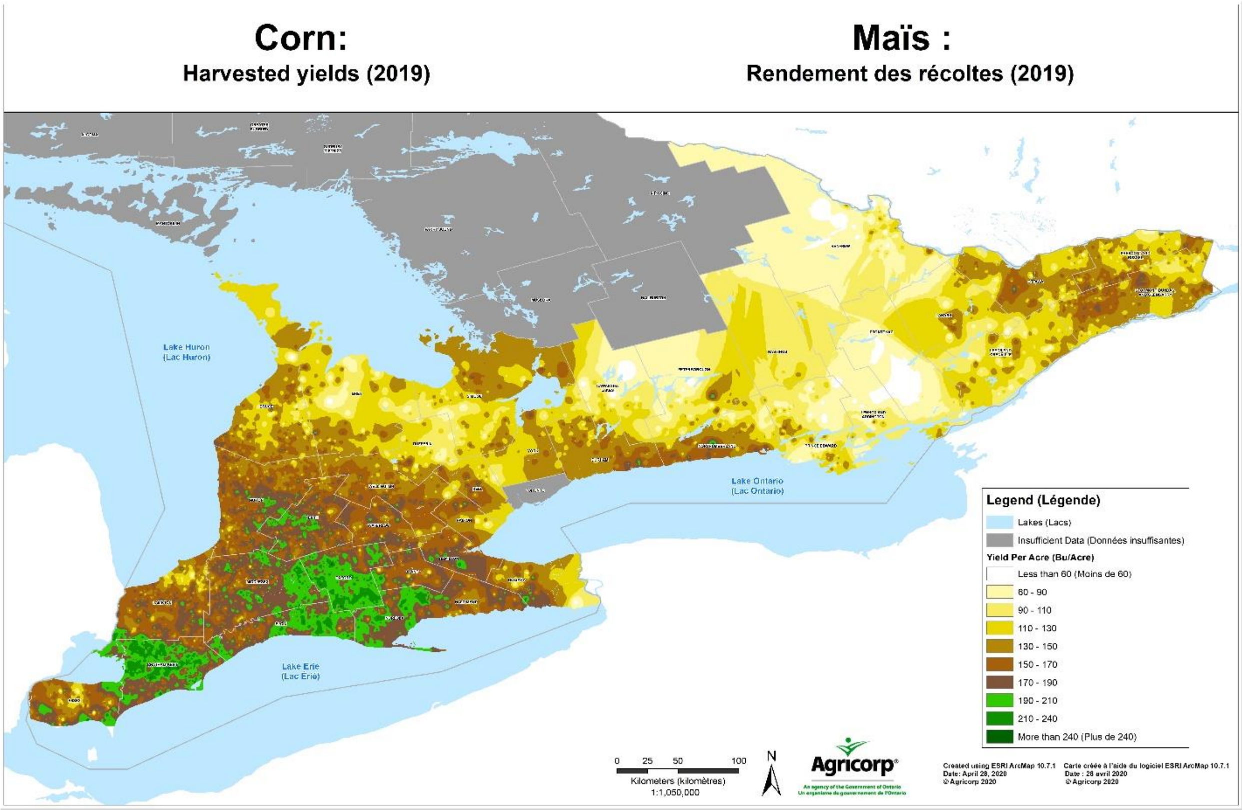


Figure 1: **2019 Corn Harvested Yield Map for Ontario**

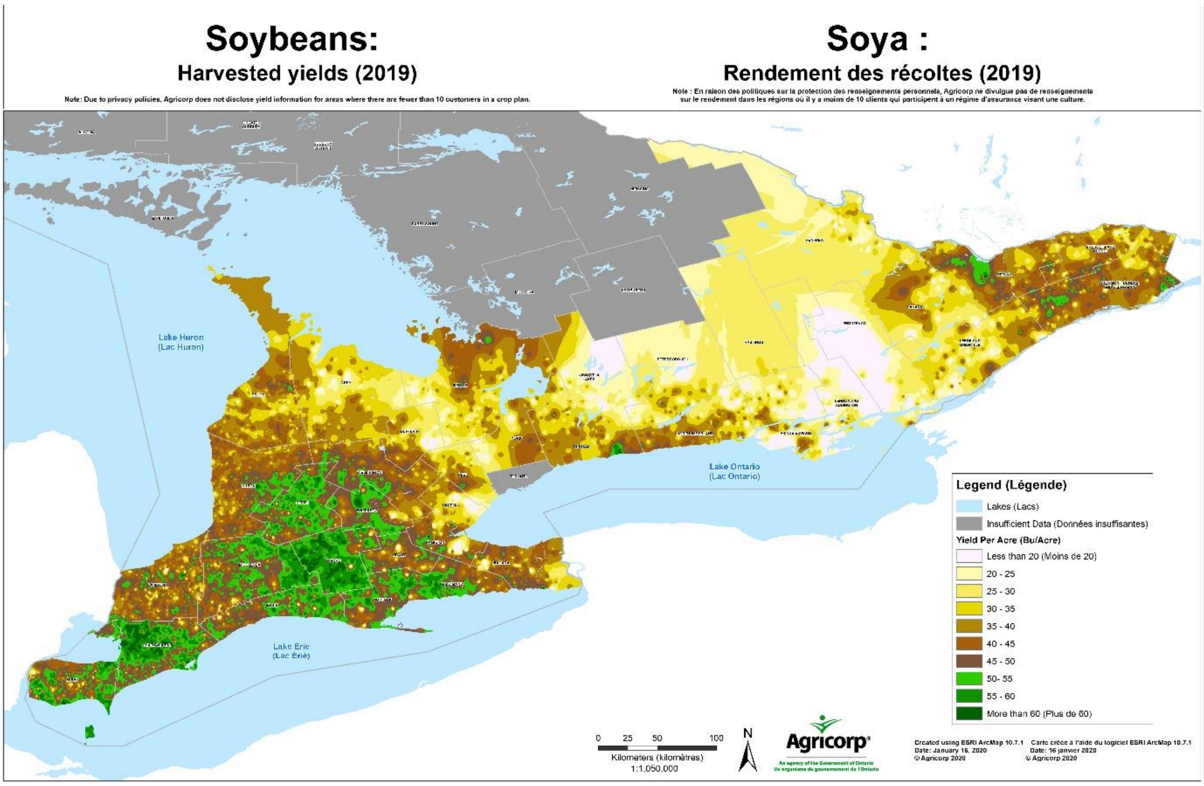


Figure 2: **2019 Soybean Harvested Yield Map for Ontario**

7.2 Extracted Satellite Imagery and Data Outputs

The satellite imagery downloaded for this research project can be found in the OneDrive folder here. Also, located in this same folder as well as attached to this report are excel files containing data outputs produced during this research project.