A TIME SERIES OF NDVI AT A HIGH ARCTIC PEATLAND

An Undergraduate Research Scholars Thesis

by

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RESEARCH COMPLIANCE CERTIFICATION

Research activities involving the use of human subjects, vertebrate animals, and/or biohazards must be reviewed and approved by the appropriate Texas A&M University regulatory research committee (i.e., IRB, IACUC, IBC) before the activity can commence. This requirement applies to activities conducted at Texas A&M and to activities conducted at non-Texas A&M facilities or institutions. In both cases, students are responsible for working with the relevant Texas A&M research compliance program to ensure and document that all Texas A&M compliance obligations are met before the study begins.

I, Daniel Maraldo, certify that all research compliance requirements related to this Undergraduate Research Scholars thesis have been addressed with my Faculty Research Advisor prior to the collection of any data used in this final thesis submission.

This project did not require approval from the Texas A&M University Research Compliance & Biosafety office.

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ABSTRACT

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Arctic greening has been studied as a significant and accelerating environmental change throughout the past few decades; however, most studies focus on greening across scales as large as the entire terrestrial Arctic and lack smaller-scale observations of vegetation at individual sites. Conducting such studies on peatlands is especially important, considering Arctic peatlands' potential to act as an immense source of atmospheric carbon should they degrade as permafrost thaw accelerates. Additionally, while remote sensing studies cannot quantify any vegetation trends with complete accuracy, I aimed to prove the effectiveness of open-source, free satellite imagery in displaying the existence and strength of such trends. I produced a time series of NDVI at a well-studied catchment basin in the Canadian High Arctic, to illuminate trends of greening since the start of the 21st century. I compiled and analyzed MODIS imagery from peak growing seasons starting in 2000 until 2022. Without any *in situ* data to qualify the results from my analysis, I found a statistically significant trend in NDVI throughout the past 22 years; with *in situ* data, this data could be considered when mapping related physical attributes when trying to further quantify environmental changes at the site. Additionally, I found that, despite the

inherent flaws of remote sensing's accuracy when collecting data, remote sensing datasets with low resolution are effective in uncovering trends as long as the temporal resolution is high; with daily image products from a platform like MODIS, outliers of snow, ice, and cloud cover can be accounted for, which sensors like Landsat and Sentinel could not despite higher spatial resolution. Greening is likely to continue at this site with climate change, and future studies are warranted to observe the cascading effects of warming and permafrost thaw on vegetation cover in peatlands.

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1. INTRODUCTION

The Arctic is warming quickly leading to longer growing seasons, shorter periods of snow and ice cover on the surface, and the thawing of permafrost (Box et al., 2019). These changing conditions have led to observable changes in vegetation on the surface, in both productivity and area, together creating higher density in vegetation (McPartland et al., 2019). This trend in vegetation density, today commonly referred to as “greening”, has been a dominant circumpolar environmental change recently (Arndt et al., 2019). However, the causes for this “greening” are complex, and although such a trend has been observed broadly across the entire Arctic for a few decades (Box et al., 2019), greening may not occur equally across all Arctic regions. Local topography, hydrology, species phenology, and bedrock chemistry are all factors that work in tandem with broad climate changes to affect vegetation cover (Lemly & Cooper, 2011).

1.1 Peatlands

Peatlands are widespread and diverse terrestrial ecosystems that exist in climates around the world. They are important soil organic carbon (SOC) reserves; like forests, they absorb carbon from the atmosphere over time, but generally at a slower rate, storing carbon as dead organic matter accumulates over millennia - much longer than forest ecosystems (Joosten et al., 2016). Peatlands today, while only covering about 3% of the planet’s terrestrial area, contain 450 Gt of SOC (Joosten et al., 2016). Peatlands are not necessarily defined by any specific vegetation type; only that whatever vegetation present consistently grows and dies over time and does not decompose completely which allows for organic matter accumulation (Rydin & Jeglum, 2015). In the Arctic, most peatlands are composed of a matrix of sedge, moss (including *Sphagnum*), and dwarf shrubs (Minayeva et al., 2016). Changes in vegetation type tend to correlate with climate, and to that extent, latitude. Peatlands are not beholden to any climatic regions across the world; they exist in virtually all latitudes and exercise different attributes at each, for example, peatlands in tropical regions tend to have a larger thickness than their high-latitude counterparts, accumulating tens of meters of decaying organic matter. In the Boreal zone and the Arctic, a lot of peatlands are locked in sporadic to continuous permafrost (Olefeldt et al., 2021). Permafrost in the Arctic is thawing at an accelerating rate, and active layers are getting deeper (Schuur et al., 2015). As permafrost thaws, the ensuing moisture changes the hydrology of a given area, and exposes once shielded carbon reserves to decomposition, emitting the greenhouse gasses (GHGs) carbon dioxide (CO2) and methane (CH4) back into the atmosphere (Olefeldt et al., 2021). This feedback loop between warming temperatures, thawing permafrost, and carbon emission from peatlands could significantly add to the amount of GHGs in the atmosphere (Schuur et al., 2015). However, because greening trends are leading to denser vegetation cover on the surface, there is potential for peat accumulation to continue or perhaps accelerate (Loisel & Yu, 2013). There exists a possibility that process could tilt the Arctic's carbon balance back in favor of sequestration over emission to an extent, but with greening trends themselves, the factors that fuel carbon balance in the Arctic are complex and multivariate.

Arctic peatlands are difficult to access *in situ*. Extended field campaigns that require overnight camping can only take place in the summer months when snow and ice have melted, and air temperatures are not hazardous. The Arctic is also quite desolate, with only a few population centers with commercial flights available. Peatlands in Nunavut, the Arctic portions of the Yukon and Northwest Territories, and much of Alaska's North Slope are also inaccessible by roads, requiring the financial burden of air travel to small population centers nearby. These challenges open the door for remote sensing applications, which are conductible at home or anywhere the user works, and at a relatively low or nonexistent cost. There exist many pathways to evaluate environmental change using remotely sensed data, which vary in cost, resolution, file size, and data/sensor type.

1.2 Remote Sensing Applications

To map vegetation, NDVI can be extrapolated from satellite or airborne imagery to estimate the productivity of vegetation on the surface (Pettorelli et al., 2005). NDVI has often been used to measure bulk biomass greenness across study sites, particularly at peak-growing seasons to determine the density of green vegetation on the surface (Crichton et al., 2022; McPartland et al., 2019). The NDVI of a particular point on the surface is derived from the reflectance ratio of red and near-infrared (NIR) bands through the following equation, where NIR and Red represent the spectral reflectance values captured by the sensor for each respective spectral band.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

What's communicated when analyzing NDVI at a particular site is the "green-ness" of the surface; NDVI values range from -1 to 1, where positive values indicate dense vegetation and negative values indicate snow, ice, or clouds. Therefore, the NDVI of a region could increase both as vegetation expands in quantity over a landscape, or as individual plants grow and become more productive. The data are compiled in a grid of pixels to form a raster, where the NDVI can be computed in the aggregate of a particular region in a geographic information system (Pettorelli et al., 2005).

NDVI is an effective tool for estimating how greening has occurred over time, with some caveats. Because the presence of snow, ice, clouds, and water on the surface is a potent influence on the NDVI of an area, they must be accounted for when performing a study of vegetation alone, since persistent cloudy weather or later-than-typical snowmelt can influence NDVI without communicating anything about vegetation density (Pettorelli et al., 2005). Although NDVI can be used to estimate annual snowmelt dates and surface water levels, which are useful attributes of how climate change may be affecting a region, their impact on NDVI for a study that focuses merely on vegetation cover is too great (McPartland et al., 2019). I address how I arranged NDVI data to account for these pitfalls in the following section.

NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) is a specific sensor equipped on a constellation of two satellites: Terra, launched in 1999, and Aqua, launched in 2002. Images of every point on the Earth's surface are taken daily, with images stratified by data applications (land use, NDVI, etc.). Since MODIS began in 2000, it has published data spanning 36 different spectral bands at spatial resolutions of 250 meters, 500 meters, or 1 kilometer. MODIS also publishes a vegetation index product that computes NDVI at 16-day increments, somewhat effectively neutralizing days with unusable data like high cloud cover, and forgoing imagery collection for winter months when snow and ice cover makes detection of vegetation cover impossible. For this study, NDVI data at 250-meter resolution were compiled beginning in the year 2000s growing season, which at my site, spans from the beginning of July to near the end of August, and each of the following growing seasons until 2022. MODIS' 250-meter resolution for NDVI data isn't poor, but is low compared to other open-access sensors on Sentinel and Landsat satellites. MODIS image products from each day are available free of charge from NASA's Worldview website, where the user can browse the entire globe for a specific point, and can scroll through time from the year 2000 up to the date of access. However, NASA forgoes taking imagery in certain locations that would not yield any benefit, such as vegetation indices in the Arctic during winter months, when snow and ice cover is present until the start of the next growing season. Because of MODIS' excellent temporal resolution, it emerged as the primary source of data for this study.

Because NDVI trends correlate with warming temperatures and permafrost thaw across the Arctic, it is important to quantify NDVI trends across the Arctic in smaller bits and pieces instead of broad, pan-Arctic studies so that any emergent trends can be tied to environmental changes at each site, coming together to paint a picture of how the Arctic peatlands are responding to climate change. There have been studies that observe trends in NDVI within a time series, but most of them apply these over large scales that span most or the entirety of the Arctic or limit their study boundary to certain well-studied sites (Crichton et al., 2022; McPartland et al., 2019). However, these studies often do not reveal local attributes in particular regions that can illuminate trends, such as unique surface hydrology, topography, or ecology. To investigate and piece together trends in Arctic greening, understudied sites must be studied individually to uncover unique local environmental qualities that might explain trends. While remote sensing has many advantages over *in situ* data collection, it alone cannot perfectly replace it to draw definitive conclusions for a site. Regardless, using remote sensing to add to the bank of knowledge regarding trends in smaller sites in the Arctic is a step in the right direction at worst and a revealing investigation at best.

A proxy to be applied in tandem with others (soil moisture, GHG emissions, etc.), an empirical measure of NDVI in this region can support future studies to determine how peatlands have and will continue to respond to climate change. In this study, I investigated two specific research questions: 1) Has the NDVI of the study site increased among each growing season since the year 2000? 2) What are the successes and shortcomings of a study that focuses solely on remote sensing to identify such trends?

2. METHODS

Figure 1: Study site, ~2 km North of Greiner Lake

2.1 Study Site

While the Arctic is quite large in area and there is no objectively perfect site, the factors that went into choosing a location were relative accessibility for field study, unique characteristics of some kind (i.e. unique vegetation phenology), and a site that has had little analysis of NDVI throughout the past few decades, but has had some sort of other research presence recently. I chose a particular basin (Figure 1) near Cambridge Bay, Nunavut, Canada, a hamlet in the Canadian High Arctic where the Canadian High Arctic Research Station (CHARS) is located.

Figure 2: CHARS Campus, Field Operations building and Main building.

CHARS (Figure 2) is supported by Polar Knowledge, a division of the Government of Canada aimed at "…advancing Canada's knowledge of the Arctic, strengthening Canadian leadership in polar science and technology, and promoting the development and distribution of knowledge of other circumpolar regions…" (Government of Canada, 2023). Studies in a wide variety of subdisciplines within geosciences are conducted year-round by visiting scientists from around the world, making it an optimal location to base fieldwork operations for nearby potential sites. By choosing this site to begin a primitive time series analysis of carbon balance, the research in the scope of this study can be expanded upon with relative ease compared to peatlands in more remote locations.

Figure 3: The Greiner Lake watershed. Greiner Lake is highlighted in dark blue, along with a central body of water spanning from the eastern extremity of the watershed to the lake.

Figure 4: Boundaries of the study site relative to notable locations nearby.

CHARS has nearby field observation sites for different applications. The Experimental and Reference Area (ERA), mapped in Figure 3, is a particular observation site defined by the boundary of the Greiner Lake watershed, a ~1500 km2 basin that extends east from the physical Cambridge Bay. Greiner Lake itself is a ~6 km wide glacial lake situated 10 km north of CHARS. Within the ERA exists the Intensive Monitoring Area (IMA), mapped in Figure 4, which contains a second-order catchment basin on the north shore of Greiner Lake. The IMA is equipped with a weather station and has been the site for numerous field campaigns measuring attributes of peat accumulation there. Because of its relative ease of access from CHARS and the increasing volume of research being conducted there, I delineated the boundaries for my study as the boundaries of the main catchment basin within the IMA.

The wetland site is dominated by herbaceous plants (sedge) and mosses. A notable point is the absence of Sphagnum moss, the most dominant moss genus in peatlands across the Arctic. Reasons for this absence could include alkaline bedrock chemistry or the peatlands' shallow depth. The site's shallow peat accumulation depth is notable compared to most peatlands, even in the Arctic. From field campaigns to this site in 2019 and 2022, we found that, with the exception of samples taken along permafrost polygon edges where peat depth is uniformly thicker, peat depth across the basin is about 30 cm on average.

Figure 5: Edge of a permafrost polygon, where peat accumulation is notably deeper than in the center of polygons or where polygons are absent. This polygon is located in a wet sedge fen.

Because peat depth across the basin does not continuously reach 40 cm in depth, the Government of Canada, ironically, would not define this site as a peatland (Government of Canada, 2023). However, it exercises all the attributes of classic peatlands that do meet that depth threshold, so it’s useful to study so that it could be compared with other emerging, or “proto-peatlands", across the Arctic (Yu et al., 2010). Finally, while this site has been the location for some past remote sensing-based studies for reconnaissance purposes (Ponomarenko et al., 2019), to my knowledge there has not been any published analysis of NDVI on a multidecadal scale. After deciding to apply my study in one or many basins around CHARS, the next step was to delineate the specific boundaries of a site.

2.2 Satellite Imagery

MODIS data are available from an online, open-access platform. While MODIS was the only satellite imagery source used in this study, attempts were made to apply data from four other platforms: Landsat 5, 7, and 8, and Sentinel 2. However, while each has certain benefits over the other, each of the forgone satellite imagery sources’ respective drawbacks prevents a successful analysis of long-term changes in vegetation cover at my study site. Sentinel-2 and Landsat 8 have a much higher spatial resolution than MODIS at the Red and NIR bands, but their images are taken at a much sparser time interval, 5 and 16 days respectively. Because the peak growing season of the study area is so short, about two months, only 5-10 images can be used per year of analysis, and that figure excludes imagery that is unusable due to cloud cover. More importantly, they were launched in 2015 and 2013 respectively, which is quite recent compared to other platforms. Landsat 5 and 7 do have a multidecadal catalog of data but have the same issue of too few images captured at the Red and NIR bands. These attributes make the total amount of usable imagery quite small, so it would be quite difficult to uncover any sort of spatial trend in the data with so few examples. Although MODIS data's highest spatial resolution product is 250 meters, which is usable but quite coarse compared to the other platforms, it was effective enough in conveying trends in vegetation growth.

2.3 Google Earth Engine

An automated method of processing and compiling the data from each of the 2,087 images was necessary to fit time constraints. I synthesized JavaScript code that I wrote with code that I accessed on open Google forums and rewrote to apply to my data and methodology. Using the finished code, I was able to retrieve, compile, and process the NDVI value from each image into a comma separated values (CSV) table. Google Earth Engine (GEE) is an efficient and useful platform for applying this code, because of its many built-in tools and simplicity in operating. The full extent of GEE can be accessed and operated from an internet browser on any computer, while other more powerful geoprocessing software like ArcGIS Pro cannot.

Using GEE's map window, I hand-delineated a boundary containing the study site, an area of ~15 km. Using the compiled Java code, GEE compiled all MODIS NDVI data from the months of June-August, 2000-2022 within the boundary. I created a histogram of this data to determine the average peak growing season of all years in the study and found that NDVI typically began to increase drastically around June 30 (DOY 181) and decline again around August 26 (DOY 238). Although this 57-day window isn't a perfect representation of the peak growing season of each year, it effectively accounts for the thawing of snow and ice in early summer and ends before plants begin to die as temperatures plummet in late summer. I then re-ran the same code but adjusted the image date window to DOY 181-238 instead of all photos from June, July, and August. GEE then produces a feature with the 2,087 data points, which was processed into a downloadable CSV file that could be cleaned in spreadsheet editing software.

2.4 Data Processing Workflow

Once the CSV file was downloaded, I opened it in Microsoft Excel to format it to perform a time series analysis. To begin creating a dataset containing a 7-day maximum value for the data to reduce the impact of single-day NDVI outliers, I first arranged the original CSV file, which was arranged in two rows with 2,087 columns, into a standard, two-column table. The Cut & Transpose functions were used to rearrange the data into a two-column table. After the metadata was cleared from the table to leave only the image date and NDVI values, the table was brought to the Transform from Table/Range editor. The date text was delimited by the underscore (_) symbol that the image dates were automatically formatted in, to create 3 more rows each containing the date, month, and year of the image capture respectively. The table was brought back to a standard Excel window to create a new column with the image capture date in the proper date format. Containing the columns for Year, Month, Day, Date, and NDVI, the table was brought back to the Transform from Table/Range editor.

By copying the date column two different times and transforming the values to new formats, two new columns were created displaying each image capture's day of the year (DOY) and week of the year (WOY). From there, using the "Group By" tool, two additional columns were created, one with each week in the peak season and the week's maximum NDVI value. With these two columns completed, the data was ready for time series analysis of NDVI over the past two decades.

Although Excel is useful for creating a wide variety of charts that could be used to visualize the data and any trends within it, the most powerful statistical analysis in Excel that could be used to perform trend analysis comes at the price of purchasing a license for an add-on. To streamline the data analysis and create aesthetically pleasing visualizations, I opted for the free statistical analysis software RStudio. Before switching over to R, the data from the columns containing the 7-day maximum NDVI and the dates starting each week in the peak season were copied and placed into a fresh Excel file.

The packages “readxl”, “trend”, and “ggplot2” were accessed in a new R script. The data from excel was then read into the script and set as the data frame. The package “readxl” allows Excel sheets to be imported directly from Excel, instead of having to save a spreadsheet as a CSV file which can affect date formatting (Wickham, Bryan, et al., 2023). The package “trend” is designed to run non-parametric trend tests and conduct change-point detection (Pohlert, 2023). Finally, the package “ggplot2” is a widely used package with a suite of tools that allow the user to create aesthetically pleasing visualizations beyond the scope of RStudio’s basic plotting functions (Wickham, Chang, et al., 2023).

The Mann-Kendall trend analysis test was applied to the data using a function within “trend” on the NDVI values of the data frame alone. The Mann-Kendall test is a particular method of regression analysis that can identify the existence and strength of a monotonic trend, either positive or negative, of any variable over time, represented by Kendall’s τ (Gilbert, 1987; Kendall, 1948; Mann, 1945). The test may identify a positive trend, but it may not necessarily be linear. The test assumes a normal distribution and can account well for seasonal variations, making it the most effective regression analysis method for a study such as this one that focuses only on values during the peak growing season.

3. RESULTS

The workflow was successful in identifying a positive trend in NDVI over time, however, the exact slope of the trend should be qualified as potentially affected by errors, as with any remote sensing analysis. Among the four different data sets analyzed, there existed different levels of statistical significance and strength of trends in NDVI over time. The two statistically significant data sets came from the 7-day averaged data and the 7-day averaged data with outliers removed. Both exhibited positive trends in NDVI over time. The all-data and annual peak data sets were not statistically significant; however, with that qualification given, the annual peak data did have a positive trend, while the all-image dataset had no trend at all, due to the strong presence of outliers among the data from cloud cover. Also, because image resolution is too coarse to visualize specifics into how certain species of vegetation at the IMA have changed over time, NDVI was calculated only in the aggregate of all vegetation types combined, without revealing trends among individual species.

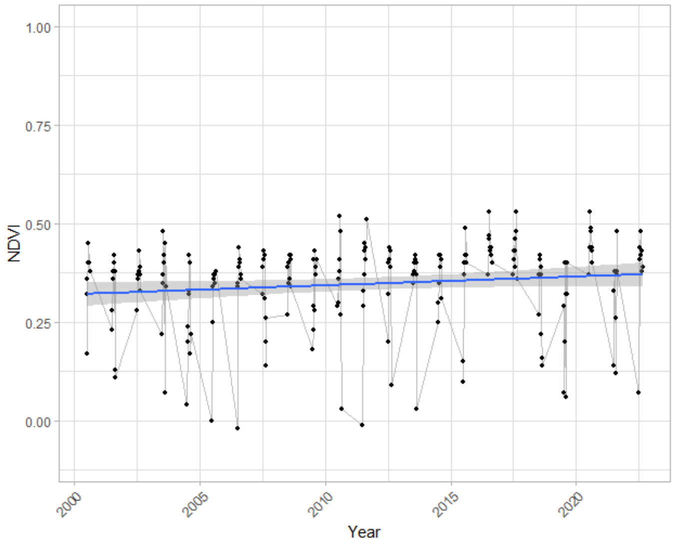

Figure 6: Graph of 7-day average data.

Figure 6 shows the 7-day average data. With a null hypothesis claiming that the Kendall's τ is equal to 0, and an alternative hypothesis of Kendall's τ being greater than or less than but not equal to 0, the 7-day averages data set exhibited a Kendall's τ of .15, which indicates a slight yet certainly present trend in NDVI since 2000. To confirm the significance of the data, it required a p-value less than .05. This data had a p-value of .0016 among 206 samples, so I was able to reject the null hypothesis and accept the alternative hypothesis, confirming that a positive trend does exist between NDVI and time within this data set. However, I felt that a stronger trend could be produced with cleaner data.

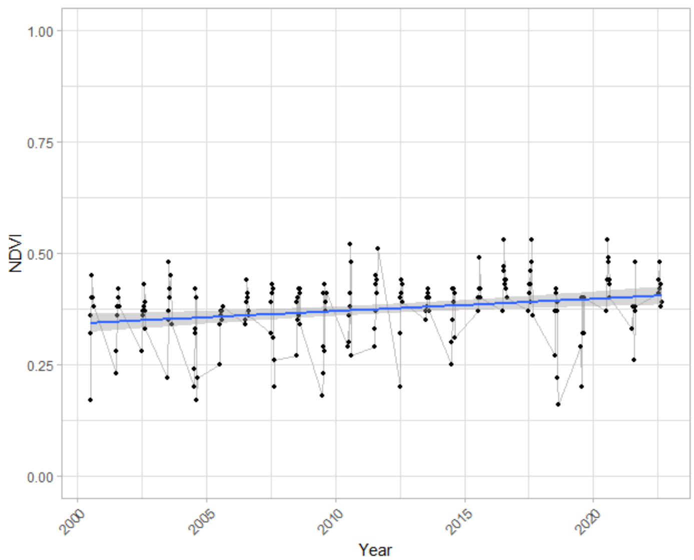

Figure 7: Cleaned 7-day average data.

Figure 7 shows the 7-day averaged data with statistical outliers removed. With a null hypothesis claiming that the Kendall's τ is equal to 0, and an alternative hypothesis of a Kendall's τ greater than or less than but not equal to 0, the 7-day averages with outliers removed data set exhibited a Kendall's τ of .19, which indicates a more positive trend than the 7-day averages data set without the outliers removed. This data had a p-value of .00009 among 187 samples, so I was able to reject the null hypothesis and accept the alternative hypothesis, confirming that a positive trend between NDVI and time does exist within this data set, a trend stronger than the data set with 7-day average values with the outliers.

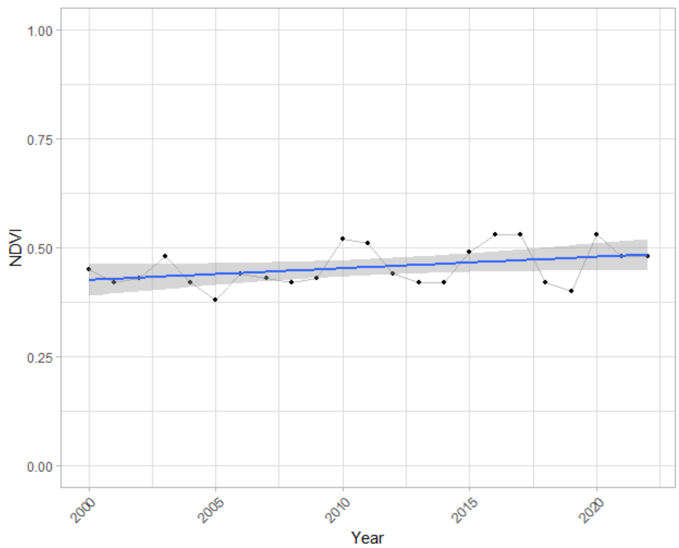

Figure 8: Annual NDVI Highs.

Figure 8 shows the peak NDVI value at the site every year. With a null hypothesis claiming that the Kendall's τ is equal to 0, and an alternative hypothesis of a Kendall's τ greater than or less than but not equal to 0, the annual peaks data set exhibited a Kendall's τ of .2, which indicates a more positive trend than all other data sets compiled in this study. However, because the data had a statistically insignificant p-value of .208 among 23 data points, I had to reject the alternative hypothesis, qualifying the positive trend peak annual NDVI highs as intriguing yet not meaningful for this study. This result is most likely related to the low number of data points (n=23); over the next few decades, with many more data points, the same analysis could be done and the statistical significance may improve.

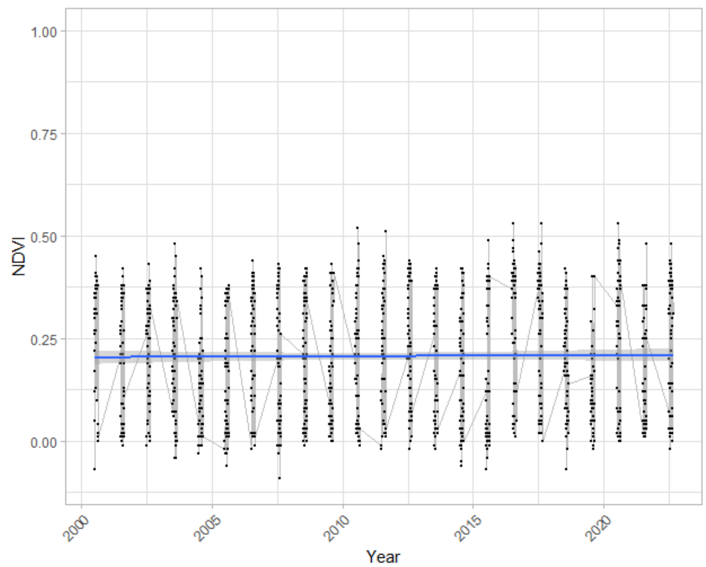

Figure 9: NDVI values from all images.

Figure 9 shows the NDVI values of every day captured by MODIS during each peak season. With a null hypothesis claiming that the Kendall's τ is equal to 0, and an alternative hypothesis of Kendall's τ greater than or less than but not equal to 0, the data set containing all 1,297 images exhibited a Kendall's τ of .013, which indicates an extremely slight positive trend in annual NDVI. However, because the data had a statistically insignificant p-value of .49, I had to reject the alternative hypothesis, qualifying the already very slight trend as not meaningful to the goals of this study.

4. CONCLUSION

The study of Arctic peatlands is becoming vital to assessing the Arctic's capacity to become either a net carbon source or sink, in a future characterized by warming temperatures and increasing soil moisture amid permafrost thaw. Pathways in both *in situ* investigation and the utilization of remote sensing applications have been useful for such assessment at regional scales, but in order to identify environmental attributes unique to local ecosystems, it becomes important to decrease the scale of analyses.

Similar to scales that quantify greening trends across the entire Arctic, there appears to be a significant increase in NDVI at the CHARS IMA site since 2000. The strongest trend in NDVI over time appeared in the 7-day averaged data with outliers removed. Because observed NDVI values are extremely sensitive to abnormalities in surface color, such as clouds or ice, there existed many outliers even among the 7-day averaged data on account of persistent cloudy weather, despite the MODIS imagery product already pooling together images to neutralize such outliers. Although the actual value of the trend over time isn't extreme, its robust statistical significance confirms that trend's presence, and I can conclude that this site has gotten significantly greener since 2000. An increasing NDVI, indicating an increase in plant productivity, could indicate that this site is increasing in its carbon sequestration potential. Besides increasing atmospheric CO_2 absorption, high biomass could lead to an increased rate of peat accumulation. However, it is yet to be seen whether the same warming and wetting processes will influence the depth of the active layer of permafrost, increasing degradation and decomposition of peat, causing wide-scale emission of GHGs back into the atmosphere (Olefeldt et al., 2021).

Such a strong trend did not exist when the highest NDVI value of every year in the study was compiled, or when every single data point was compiled. In theory, if this site has gotten greener over time, which it appears to have from the cleaned data, then it would make sense for there to be a trend present in the high points of every year and raw data sets. However, colder years, cloudy growing seasons, or late snowmelt dragged down the average to create an imperfect timeline of NDVI over time.

For this study, I forewent any image pre-processing that could have more effectively revealed a more accurate trend in NDVI averages, particularly the removal of clouds from images where clouds shroud the study site and register negative NDVI. It would be plausible to mask clouds out of MODIS images using software like ArcGIS Pro or ENVI; however, with more than 1,000 total images, this process would have taken an immense amount of time, which I did not have in the scope of this study. By keeping these images and accounting for them on the statistical analysis side of the data processing workflow, a trend was still observed, albeit at a value that may not be completely accurate. In the future, given more time and a savvy processing workflow, I would preprocess these images to produce a more accurate, and perhaps stronger, trend. Regardless, such inaccuracy comes with the territory of studies focusing heavily on remote sensing.

Remotely sensed data should always be treated as supplementary to data taken *in situ*. While monitoring NDVI using satellite imagery is extremely useful for tracking plant productivity across a vast array of applications, conclusions from the data must be qualified by the fact that the data itself isn't a true representation of activity on the surface, but only a register of certain aspects of that activity by a sensor hundreds of miles above it. For example, while quite unlikely, it's possible that cloudiness drastically decreased at the site over twenty years, displaying a perceived increase in NDVI. The opposite could also be true; perhaps cloudiness increased over time, but so too did the NDVI of the site, and so the data set has a weaker trend than it should have. These problems could be resolved through the usage of high-resolution data, but the process of gathering, processing, and analyzing that data would be costly and time-consuming. High-resolution satellite imagery is available to commission through companies like Planet Labs, which can take a picture at a specific site at a specific date and time, which could potentially resolve the issue of cloud cover and changes in annual snowmelt. With accessibility to such higher-resolution imagery, specific variations among specific plant communities may also reveal themselves; for example, shrubs may be responsible for more greening than mosses or grasses in fens (Mekonnen et al., 2021). These specific trends could be compared to data from other sites across the Arctic, which would better identify any environmental controls unique to the ERA. However, compiling a number of images near the amount of MODIS images may yield a similar result to MODIS, but only after exhausting much time and resources to obtain the data. Generally, while remote sensing provides the capability to analyze data from anywhere and at any time over the past few decades, which *in situ* analysis cannot, remote sensing cannot be the only aspect of a study meant to draw definitive conclusions about a site.

The two purposes of this study were to identify trends in NDVI at the site since 2000, and identify shortcomings of the use of remote sensing to identify those trends. There has been a trend in NDVI at the catchment basin within the CHARS IMA site since 2000, indicating that Arctic Greening is occurring there and warranting future studies at other sites that may very well reveal the same result. However, given the opportunity to conduct this study with more time and a larger budget, I would adjust aspects of the main questions of this study as well as the means to answer them. Assessing ecosystem carbon balance capabilities requires the study of more than just the surface; analysis of the depth of peat accumulation, soil moisture, GHG flux, vegetation species, and mapping of elevation to visualize catchment basins and surface hydrology. Using these data, questions of not only vegetation productivity, but also wide-scale carbon potential could be answered at the local scale, which would be much more revealing than simply looking at how NDVI has changed. The CHARS IMA site is equipped to handle these questions in the future, so continuous monitoring of NDVI there is warranted via studies similar to this one.

Highlighted as a significant player in climate change in both the Arctic and the entire world by the IPCC in 2019 (Shukla et al., 2019), peatlands are hanging in the balance. Their growth in the Arctic could help soothe the adverse effects of rising GHG emissions by sequestering atmospheric carbon for the long term. Or just the opposite; should permafrost thaw disturb peatlands, a vicious positive feedback loop between rising temperatures and GHG emissions could be on our hands (Schuur et al., 2015). Much future study is needed to analyze peatlands at smaller scales, to identify the environmental controls that may have cascading effects on the health of the planet in the years to come. As innovations in sensor technology and processing software continue, accessibility to the Arctic will improve in the future, affording the ability to monitor climate change dynamics as they become more complex.

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