# Using Vegetation Indices to Determine Vegetation Health After the East Palestine Train Derailment


**Abstract**

In February of 2023, a train derailed in East Palestine, OH causing 450 tons of vinyl chloride (VC) to be released and burned shortly after. This release of chemicals had caused concern in the local area about the effects of VC on the environment and humans. The objective of this project is to determine if vegetation health was affected by the train derailment and if vegetation indices are an effective way to measure vegetation health. To quantify these effects, Sentinel-2 imagery captured pre-incident in 2021 and post-derailment in 2023 was utilized, with analysis conducted using spectral indices. NDV, G-NIR and G-SWIR indices were calculated for each image and then compared using testing points across the vegetation classes Grass/Pasture, Forest, and Crops at distances 1 to 5 miles away from the derailment site. After various statistical analyses were performed on the testing points, it can be determined that May 2023 has a significant change from May 2021. It is challenging to definitively link the results to the derailment, given the possibility that the May 2021 values could have been an anomaly and thus not ideal for comparison with the May 2023 values. If additional research is undertaken, there is a possibility that vinyl chloride's impact on vegetation could be detected using advanced remote sensing techniques, including improved imagery, LiDAR technology, interdisciplinary efforts, and varying timing and distance of the chemical spill assessment.



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# Introduction

On February 3rd, 2023, around 9 pm, a Norfolk Southern train, carrying 1.6 million pounds of chemicals, was derailed near the town of East Palestine, OH. While no one was hurt, 11 of the 36 affected train cars contained hazardous chemicals (Sullivan, 2023). In the following days, authorities opted to perform a controlled burn of the spilled chemicals, to avoid a potential explosion.

A hazmat spill of this magnitude created concerns for human health due to hazardous materials seeping into the groundwater, soil, and air. While chemical concentrations will dissipate over time, long-term environmental impacts may be associated with this incident that can be monitored by using remotely sensed data to evaluate the health of vegetation. I propose utilizing the spectral characteristics of remote sensing imagery captured before and after the train derailment to assess vegetation health. This analysis not only aims to discern potential changes in vegetation health attributed to the derailment but also to evaluate the viability of using vegetation indices as a method to assess damage resulting from chemical spills.

# Literature Review

## Background

Shortly after the East Palestine train derailment occurred, news sources published articles that raised concerns about potential short-term and long-term impacts on the local area's economy, environment, and the population's health. The hazardous chemicals released were vinyl chloride (VC), butyl acrylate, isobutylene, ethylene glycol, and ethylhexyl acrylate (Chow & Abou-Sabe, 2023). These chemicals can cause skin/eye irritations, drowsiness, disorientation, numbness and tingling of extremities, dizziness, headaches, sore throats, and nausea (Chow & Abou-Sabe, 2023). Of the 11 train cars carrying hazardous materials, 5 contained 450 tons of VC (Sullivan, 2023). Vinyl chloride is used to create polyvinyl chloride (PVC) and can be in a gas or liquid form and seep into soil and groundwater. Shortly after the derailment, levels of VC in the air were considered safe, but another concern was dioxins, which are compounds created during the burn that can stick to surfaces and are toxic if ingested or inhaled (Chow & Abou-Sabe, 2023). The EPA monitored water and air quality and declared they were safe but encouraged people with private wells to have their water tested (Sullivan, 2023; Oladeji et al., 2023). Norfolk Southern removed 167,000 tons of soil and wastewater near the derailment site and stated they would continue monitoring the area until April 2024 (Morgan, 2023).

## Impact of Vinyl Chloride on Humans

Following the East Palestine train derailment, there was frequent mention of vinyl chloride (VC) in news reports, highlighting its well-known carcinogenic properties and negative impact on human health. Humans can be exposed to VC by inhaling polluted air near contaminated sites, drinking contaminated water, ingesting foods with VC or packaged in PVC, or by skin contact through PVC-wrapped cosmetics (Kielhorn et al., 2000). East Palestine residents experienced the side effects of exposure to VC like headaches, respiratory difficulties, and skin and eye irritations. In addition, Kielhorn et al. (2000) cited a study that strongly correlated angiosarcoma of the liver (ASL) to VC exposure. This condition is rare, difficult to diagnose, and fatal if undiagnosed. Kielhorn et al. discussed a train derailment, which carried VC and caught fire, in Germany in 1996. After the fire, measurements taken 14 hours later showed levels of 80 mg/m$^3$ of VC near the train, where 250 tons of VC had been burned. As a result of exposure, 29 individuals had increased chromosomal aberrations. Kielhorn et al. (2000) stated VC can degrade into nonchlorinated ethenes and then $CO_2$ and ethane, with half-lives around 1-2 years for each stage of chemical reaction. However, it is only under certain conditions that VC degrades at all, which raises concerns for VC in soil and water sources that could eventually be ingested by humans.

## Environmental Impact Research on Chemical Spills

To grow, plants need exposure to sunlight, and good soil with nutrients and water. Chemicals seeping into the soil and groundwater could create challenges for local vegetation growth in East Palestine. Sebe et al. (2023) researched the area of East Palestine to determine if VC had seeped into local water sources by collecting rainwater and testing the pH levels and for the presence of VC. Sebe et al.'s (2023) research indicated levels of VC above what is considered permissible by the EPA (0.002mg/L), which was measured at 0.0035-0.0036 mg/L in East Palestine, other test locations ranged from 0.002-0.0028 mg/L, with only one test site at a permissible level. According to the EPA, acid rain leaches aluminum from the soil and removes key nutrients and minerals which would have negative ramifications for plant health and affect the local vegetation health.

News reports suggest that citizens distrusted the EPA results because of the tangible effects like the acrid smell in the air, the slimy substances found in creeks, and the physical symptoms local people felt. To assuage the public's fears of government deception, Oladeji et al. (2023) conducted mobile air quality samples on February 20$^{th}$ and the 21$^{st}$. Of the fifty chemicals present at the derailment site, nine were reported at higher-than-average levels. Most chemicals were below minimal risk levels, but acrolein (a common combustion product and respiratory irritant) levels were 6 times higher than the surrounding local area. Their results agreed with the EPA that the levels of hazardous chemicals decreased over time; VC varied more but stayed below levels of concern for human health (Oladeji et al., 2023).

Research was gathered by Singh et al. (2020) about emerging contaminants like hormones, pharmaceuticals, industrial additives, surfactants, and pesticides on crops leaching into the soil, and absorbed by crops. Water aids in contaminant mobilization into soil, and plants will absorb both beneficial minerals and contaminants equally. Municipal wastewater treatments are currently not effective enough at removing these pollutants from the water which allows them to persist in the environment, affecting microorganisms, and causing negative outcomes in crop productivity. Morphological and chemical makeup changes due to microcontaminants have been observed in produce such as lettuce and zucchini (Singh et al., 2020). Similarly to VC, these chemicals can persist in the soil for long periods, and due to the difficulty of breaking them down, they can accumulate within human bodies in fatty tissue, breast milk, and blood after being ingested (Singh et al., 2020).

This research demonstrates the presence of contaminants in our food sources and their impact on vegetation within the hydrological cycle. The introduction of chemicals from the train derailment may have additional and potentially long-lasting adverse effects on vegetation, which might not be immediately apparent. Therefore, evaluating vegetation health serves as a crucial initial step in comprehensively assessing the ecological damage stemming from the East Palestine train derailment.

## Remote Sensing Research Methods on Vegetation Health

Current research shows a gap in using remote sensing to evaluate hazmat spills regarding plant health. Gaseous chemicals are more difficult to relate to positive or negative outcomes on plants without extensive lab work. As shown by Oladeji et al., chemicals created as byproducts in hazmat spills can add variables that are difficult to track. However, oil spill research using remote sensing with Vegetation Indices (VIs) has been well documented to assess the impact on vegetation near spill sites.

Different materials have different spectral characteristics due to how they absorb and reflect electromagnetic energy. Vegetation strongly reflects the Green region and the Near Infrared (NIR) region, and these can be used to assess the condition of plants (Adamu et al., 2016). Spectral indices are calculated using imagery bands. The most common index for vegetation is the Normalized Difference Vegetation Index (NDVI) which utilizes the red and NIR regions to measure greenness and aids in monitoring stress in vegetation. Rivard et al.'s (2008) research how NDVI can be used to detect early signs of stress in vegetation, through spectral signatures, after 48 hours to 1 week in lab plants. This information could mean that vegetative stress can be detectable using spectral indices within one week of the East Palestine derailment and the subsequent burning of chemicals.

Oil spill research conducted by Adamu et al. (2016) using Landsat 5 Thematic Mapper (TM) and Enhanced TM (ETM) imagery in the Niger Delta region showed that the visibility of oil spills by spectral indices on vegetation is affected by the toxicity of oil spilled, the volume of oil spilled, and the length of time between imagery acquisition and the spill event. They utilized NDVI among other indices on pre-spill and post-spill imagery and noticed that on average, the longer period between the oil spill and image acquisition, the more the NDVI values improved. Similarly, Oladeji et al. (2023) and the EPA report diminished traces of hazardous materials in the water and air samples over time. Further research done in 2018 by Adamu et al. showed lower values for all VIs at oil spill sites compared to non-oil spill sites. This was done using Landsat 8 Operation Land Imager (OLI) imagery to create five VIs: NDVI, G-NIR, and G-SWIR. Plant vigor is assessed using G-NIR (Green-Near Infrared) and nitrogen content in plants and moisture in soil and vegetation is sensed by G-SWIR (Green-Short Wave Infrared). This research shows that VIs like NDVI, G-NIR, and G-SWIR would be suitable for examining vegetation health in the derailment area.

The methods used by Adamu et al. (2016 & 2018) are effective at examining the effects of oil spills on vegetation. These methods could also be applied for evaluating vegetation health before and after chemical spills using spectral data and Sentinel-2 imagery. Sentinel-2 Imagery is 10m-20m resolution for bands required for NDVI, G-NIR, and G-SWIR, and would be more adequate for the East Palestine area.

# Data

## Setting the Scene

The location of the derailment, depicted in Figure 1, was determined based on data provided by the Pennsylvania Department of Environmental Protection (2023). This point served as the center for creating buffers and assessing distances from testing points. A polyline layer from the U.S. Department of Transportation (2023) was utilized to visualize the railroad network within the study area, while county boundaries were sourced from the U.S. Census Bureau (2022).

## Data For Analysis

Sentinel-2 Level 2A imagery spanning the years 2021 to 2023 was obtained via the Copernicus Browser across four dates: 5/1/2021, 7/5/2021, 5/21/2023, and 7/5/2023. These dates were chosen based on crop growing seasons to ensure the best spectral reflectance for vegetation. The imagery from 2021 was chosen for comparison with post-derailment data from 2023. These images were used to calculate key VIs such as the NDVI, G-NIR, and G-SWIR which are measured on a scale of -1 to 1. These indices are crucial for detecting vegetative stress through remote-sensed imagery by combining spectral bands.

The U.S. Department of Agriculture's National Agricultural Statistics Service (USDA NASS) provided a detailed crop cover data layer (2022) showing specific crops grown across the United States. This data, available at a 30-meter resolution in GeoTIFF format, encompasses deciduous forests, various crop types (e.g., soybeans, corn, barley), water bodies, and developed areas.

To create a comprehensive testing framework, a point layer was generated based on the USDA NASS crop cover data (2022), imagery visibility considerations, and proximity to the derailment site. These points were strategically distributed within three distinct vegetation classes derived from the USDA NASS data: deciduous forests, various crop types, and other land categories. The randomness of point placement within each class ensured a representative sampling approach for analyzing the three different variables of interest.

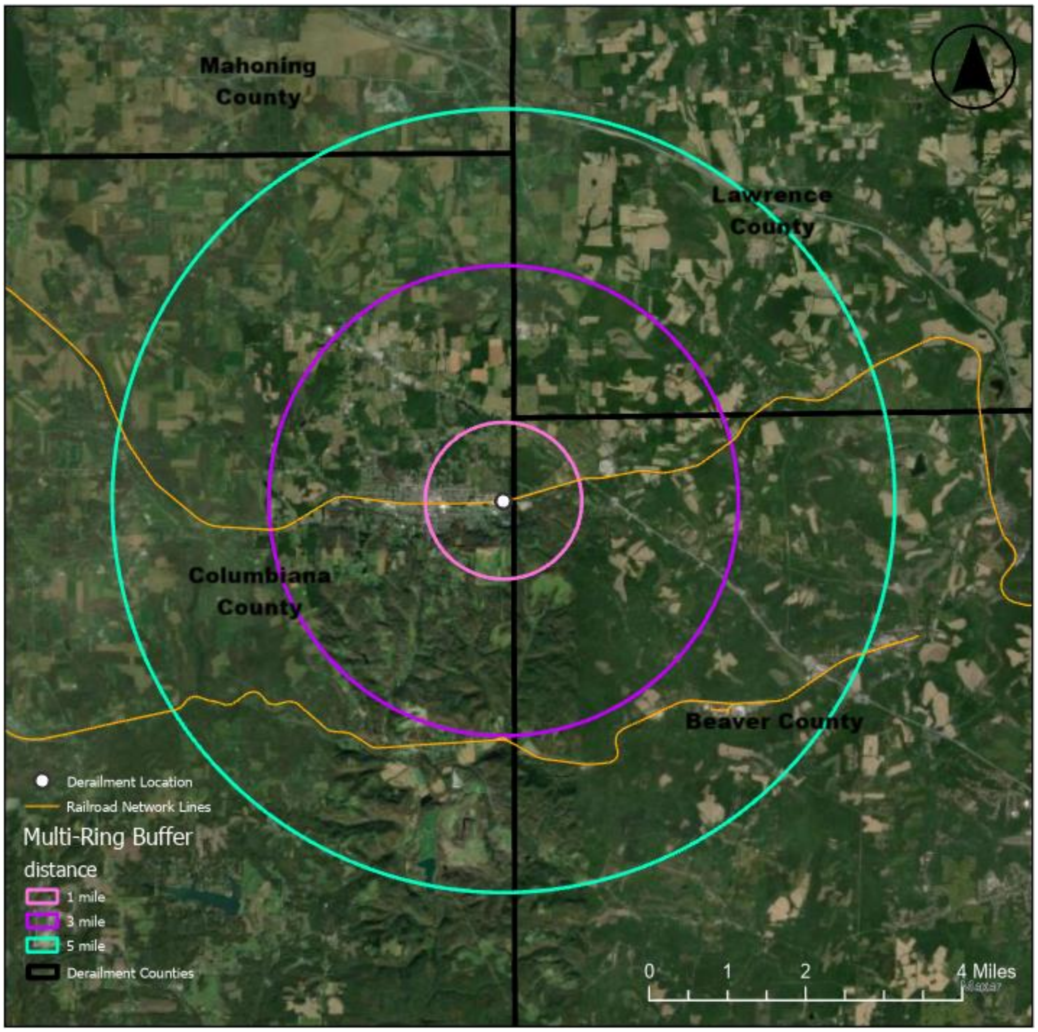


***Figure 1:*** *This map shows the area of East Palestine, the derailment location, the surrounding counties, railways, and the multi-ring buffer used to group points into buffers.*

# Methodology

## Image Processing and Data Preparation

ArcGIS Pro was used for all the image processing and data preparation steps.

For each Sentinel-2 L2A image, a composite image was created by combining the bands Blue (B2), Green (B3), Red (B4), NIR (B8), and SWIR (B11). This process aimed to enhance the spectral information for subsequent analysis.

To test for distance effects, a 3-ring buffer was established around the derailment location at distances of 1 mile, 3 miles, and 5 miles. These specific distances were chosen to investigate potential variations in spectral indices, presuming that the effects of the derailment would be most pronounced near the site and diminish with increasing distance.

Spectral indices, including NDVI, G-NIR, and G-SWIR, were calculated to quantify vegetation health, near-infrared reflectance, and shortwave infrared reflectance, respectively.

USDA NASS crop cover classes were consolidated into general categories such as water, developed areas, grass/pasture (G/P), crops, forests, wetlands, and barren lands. Subsequently, only the classes relevant to the study—G/P, forests, and crops—were retained for further analysis.

Systematic testing points were then generated within each selected vegetation class approximately 40 meters apart. These points were used to capture NDVI, GNIR, and GSWIR values from the composite images, along with precise distance measurements from the derailment location, vegetation class, and information about the buffer ring (BR) distance.

Testing points with NDVI values below 0.2 were excluded to ensure data quality, as they likely represented shadowy or cloudy areas in certain images, which could skew the analysis.

## Statistical Analysis

The testing points table was exported to Excel for comprehensive analysis. Summary statistics such as mean, median, minimum, maximum, and standard deviation were calculated for each spectral index and image, to help create a quantitative overview of the dataset.

To determine if there is a relationship between VI and derailment distance, RStudio was utilized for conducting linear regression testing for each vegetation class per image and spectral index. The results were represented using scatter plots, where VI values served as the dependent variable on the y-axis, and derailment distance acted as the independent variable on the x-axis. To enhance clarity in the scatter plots, a randomized subset of 40 points per Buffer Ring (BR) and vegetation class was selected for generating regression lines.

Additionally, an independent samples t-test was performed in RStudio to evaluate temporal changes between the 2021 and 2023 NDVI means across each BR for both May and July. The resulting data was exported to a CSV file and subsequently utilized to create line graphs illustrating the mean changes from 2021 to 2023 for May and July per BR.

# Results

While noticeable changes were observed in the G-NIR and G-SWIR indices across the years, the literature review did not yield sufficient insights to interpret these changes effectively. Consequently, I refrained from utilizing these indices to draw any conclusions.

## Statistical Testing

There was a very noticeable change from May 2021 to May 2023 across all 3 classes shown in Figure 2. However, there were minor changes between July 2021 to July 2023. Overall classes, NDVI values decreased by 0.187 from May 2021 to May 2023. Between May and July 2021, there was a decline in NDVI of 0.179, whereas in 2023, the values remained relatively stable during the same period. The most significant change occurred in the crops category, with a decrease of 0.06.

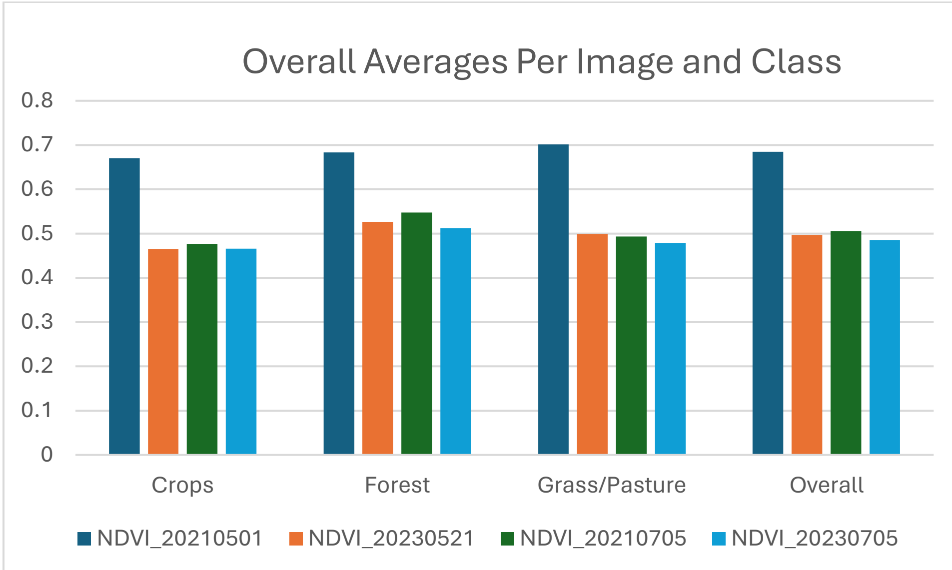


**Figure 2:** *This bar chart shows the overall class averages for each image per vegetation class and index.*

An independent sampling t-test was run to compare the means of the two independent variables to determine if there was a significant difference between them. The variables being compared are May 2021 and May 2023 NDVI values (Table 1) and July 2021 and July 2023 NDVI values. The null hypothesis was that there was no change in data between 2021 and 2023 NDVI values and the alternative hypothesis is that there is a change in data between 2021 and 2023. The difference in t-test results, shown in Tables 1 and 2, indicated that there was a change in data. All classes had P-values of less than $p > 0.05$, which means the alternative hypothesis can be accepted. However, the change in July data was slim, varying from -0.056 to 0.009.

The line graph in Figure 3 shows across all classes that the July data was at a low of 0.05 near the derailment within the 1-mile buffer. Within the 3-mile buffer, the mean difference values increased and then lowered again slightly in the 5-mile buffer. While the difference was less, it varied more between BRs. The May mean difference values did not vary much over distance although the overall mean difference is higher. The May values also had a minor peak around the 3-mile buffer. If the distance from the derailment affected the mean NDVI values, we would anticipate a more significant difference in means near the derailment site, with the variability decreasing as the derailment distance increases.

| Grouping | Difference_mean of x | ConfidenceInterval95_Lower | ConfidenceInterval95_Upper | Degrees of Freedom | p-value |
|---|---|---|---|---|---|
| Crops 1 Mile | -0.191893 | -0.238016 | -0.145769 | 59.000000 | 0.000000 |
| Crops 3 Mile | -0.194195 | -0.205631 | -0.182760 | 832.000000 | 0.000000 |
| Crops 5 Mile | -0.209521 | -0.216911 | -0.202130 | 2011.000000 | 0.000000 |
| Forest 1 Mile | -0.162415 | -0.179647 | -0.145184 | 139.000000 | 0.000000 |
| Forest 3 Mile | -0.152790 | -0.159287 | -0.146293 | 1210.000000 | 0.000000 |
| Forest 5 Mile | -0.158086 | -0.162813 | -0.153359 | 2419.000000 | 0.000000 |
| Grass/Pasture 1 Mile | -0.203683 | -0.218723 | -0.188643 | 248.000000 | 0.000000 |
| Grass/Pasture 3 Mile | -0.199721 | -0.204844 | -0.194599 | 2257.000000 | 0.000000 |
| Grass/Pasture 5 Mile | -0.202550 | -0.206013 | -0.199087 | 5447.000000 | 0.000000 |

**Table 1**: *Independent Samples t-Test created in RStudio to compare May 2021 to May 2023 mean values.*

| Comparison | Difference_mean of x | ConfidenceInterval95_Lower | ConfidenceInterval95_Upper | Degrees of Freedom | p-value |
|---|---|---|---|---|---|
| Crops 1 Mile | -0.042075 | -0.082375 | -0.001774 | 59.000000 | 0.041021 |
| Crops 3 Mile | 0.009032 | 0.001121 | 0.016942 | 832.000000 | 0.025294 |
| Crops 5 Mile | -0.018195 | -0.024047 | -0.012343 | 2011.000000 | 0.000000 |
| Forest 1 Mile | -0.056851 | -0.078706 | -0.034995 | 139.000000 | 0.000001 |
| Forest 3 Mile | -0.033085 | -0.040169 | -0.026001 | 1210.000000 | 0.000000 |
| Forest 5 Mile | -0.034392 | -0.039266 | -0.029518 | 2419.000000 | 0.000000 |
| Grass/Pasture 1 Mile | -0.035606 | -0.052372 | -0.018840 | 248.000000 | 0.000040 |
| Grass/Pasture 3 Mile | -0.010748 | -0.015758 | -0.005739 | 2257.000000 | 0.000027 |
| Grass/Pasture 5 Mile | -0.015187 | -0.018531 | -0.011843 | 5447.000000 | 0.000000 |

**Table 2:** *Independent Samples t-Test created in RStudio to compare July 2021 to July 2023 mean values.*

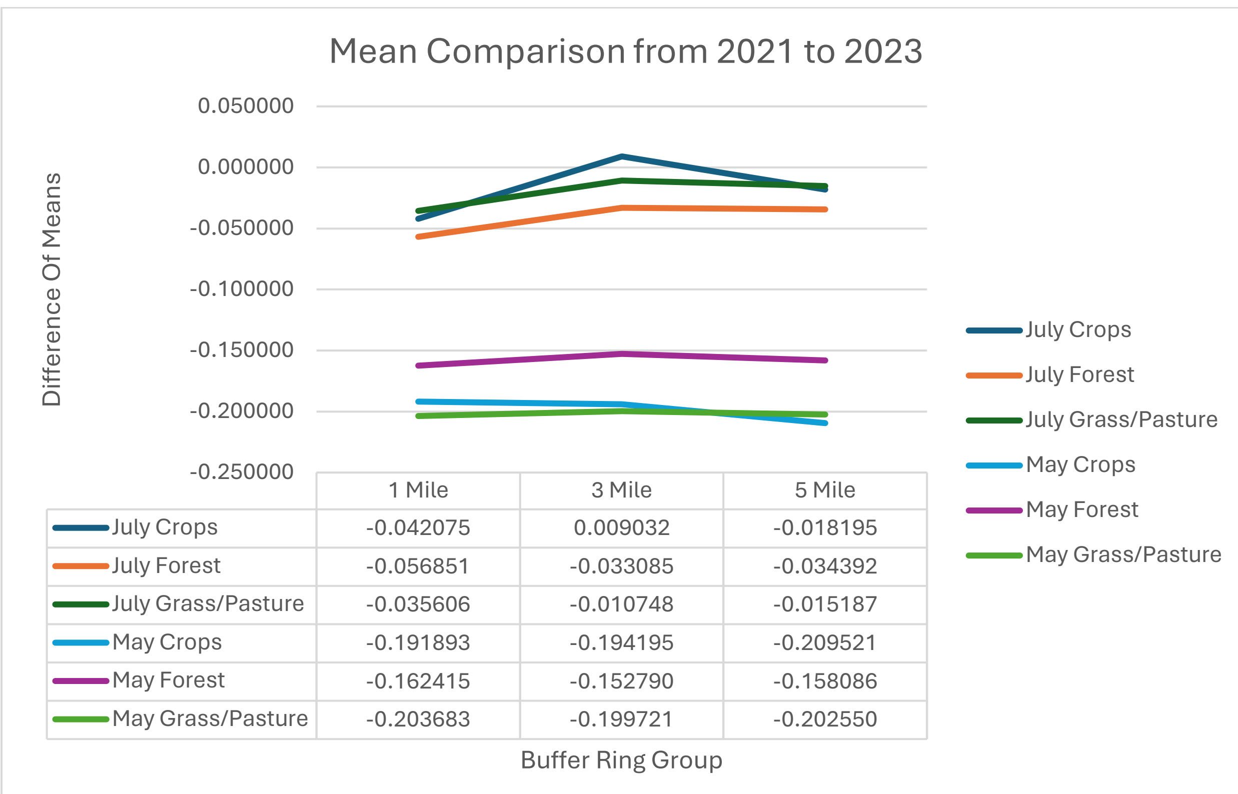


***Figure 3:*** *Independent Sampling t-Test in RStudio to compare NDVI mean values May 2021 to May 2023 and July 2021 to July 2023. Represented as a line graph.*

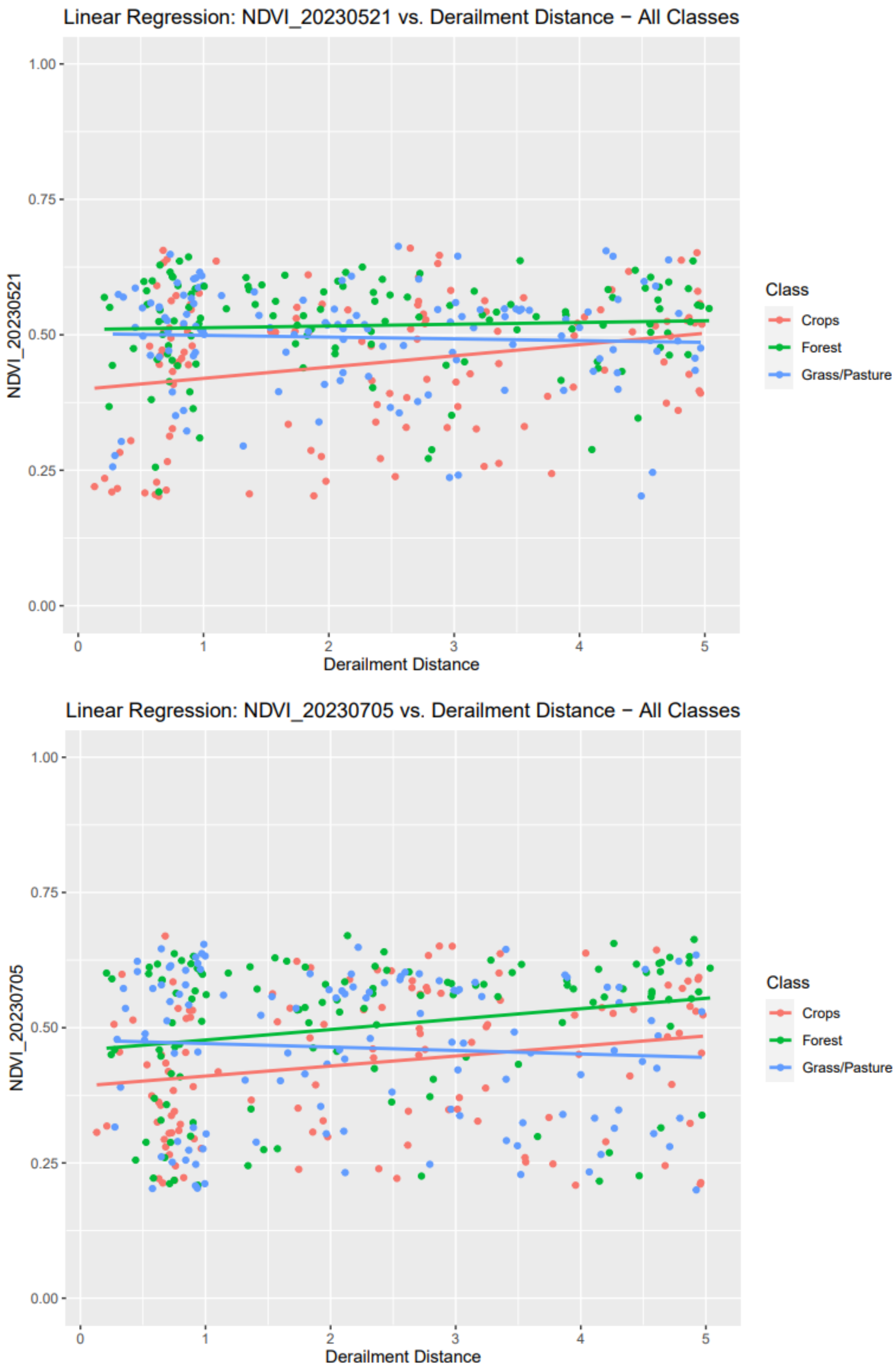


***Figure 4***: *Scatterplots created using RStudio, showing the relationship between NDVI and distance from the derailment, from the derailment on May 21st, 2023 (top) and July 5th (bottom) for the classes crops, forest, and G/P. These scatterplots were created to select 40 random points per BR and class.*

The scatterplots displayed in Figure 4 illustrate the linear regression analysis conducted for NDVI values in May and July post-derailment, focusing on the crops, forest, and grass/pasture (G/P) classes, with NDVI values ranging from 0.2 to 0.7. A subtle rise in NDVI is noticeable within the forest class over distance in July, as well as in the crops class during both May and July. In contrast, the NDVI values for the G/P class remain stable across both months. The dispersion of data points around the regression lines suggests a weak correlation between distance from the derailment site and NDVI values.

The Linear Model used in the linear regression analysis assumes a relationship between the independent variable (distance) and the dependent variable (NDVI). However, the low R-squared values presented in Table 3 indicate that only a small portion of the variability in NDVI values can be attributed to distance from the derailment. Notably, the highest slope and R-squared values are observed in the crops class for May 2023, explaining 4.8% of the NDVI variability based on derailment distance. Conversely, the G/P class exhibits the lowest R-squared and slope values, corroborating the weak relationship observed in the scatterplots, where the regression line appears nearly flat. It's important to note that the limited range of NDVI values can influence slope values; for instance, a change from 0.39 to 0.50 in NDVI represents a substantial shift considering the overall NDVI range in the May 2023 imagery (0.2 to 0.7).

The scatterplots were generated using 40 random points per Buffer Ring (BR) and vegetation class. This sampling strategy may have been influenced by the clustering of points within the one-mile range, along with the distribution of other points between 2 and 3 miles for the 3-mile BR, and 4 to 5 miles for the 5-mile BR.

| ID | Variable | Class | Intercept | Slope | R_squared |
|---|---|---|---|---|---|
| 1 | NDVI_20210501 | Crops | 0.58053 | 0.02878 | 0.04228 |
| 2 | NDVI_20230521 | Crops | 0.39900 | 0.02119 | 0.04812 |
| 3 | NDVI_20210705 | Crops | 0.44952 | 0.00709 | 0.00820 |
| 4 | NDVI_20230705 | Crops | 0.42010 | 0.01337 | 0.01917 |
| 5 | NDVI_20210501 | Forest | 0.66415 | 0.00555 | 0.00420 |
| 6 | NDVI_20210705 | Forest | 0.55744 | 0.00077 | 0.00026 |
| 7 | NDVI_20230705 | Forest | 0.47754 | 0.01172 | 0.01684 |
| 8 | NDVI_20230521 | Forest | 0.51646 | 0.00467 | 0.00661 |
| 9 | NDVI_20210501 | Grass/Pasture | 0.69672 | -0.00241 | 0.00049 |
| 10 | NDVI_20230521 | Grass/Pasture | 0.50248 | -0.00195 | 0.00067 |
| 11 | NDVI_20210705 | Grass/Pasture | 0.51482 | -0.00538 | 0.00674 |
| 12 | NDVI_20230705 | Grass/Pasture | 0.46261 | 0.00803 | 0.00734 |

***Table 3****: Linear regression intercept, slope, and R squared values per NDVI output and class.*

## 2020 NDVI Sample Check

Due to the difference in May 2021 NDVI values to the rest of the dataset, additional Sentinel-2 L2A imagery was acquired from 2020 on May 21$^{st}$ and July 25$^{th}$. The July values remained consistent from 2020 to 2021 and 2023. Figure 5 shows the change in May values, these show the 2021 values had a NDVI value of 0.2 higher than other years across all classes. This could be due to 2021 values being the earliest date on May 1st for May data, whereas, the 2020 and 2023 dates were both taken on May 21st. This could be due to more moisture from spring rains causing NDVI values to be higher or another unique event or weather scenario that explains the 2021 data but it is outside of the scope of this project to research further.

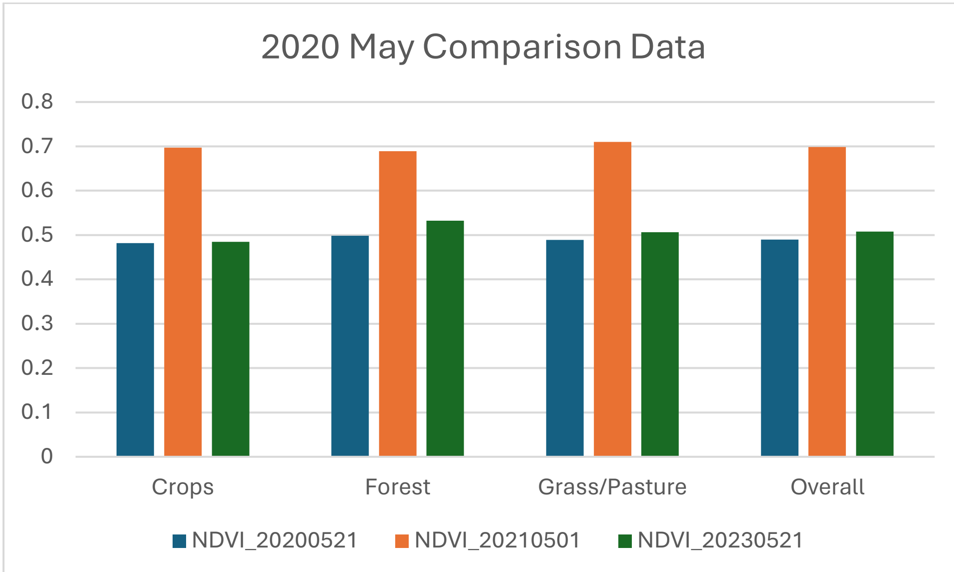


***Figure 5:*** *Additional Sentinel-2 L2A images were acquired for May and compared to other May data in 2021 and 2023 as a bar graph per class.*

# Discussion

The results of the independent samples t-test suggest that there was an overall change in NDVI from 2021 to 2023 in May, but it is difficult to associate with the derailment location without further data and analyses. The comparison of means from July 2021 to 2023 suggests very little change.

The results of the linear regression plots indicate that crops could have been impacted since NDVI values increased over distance in May and July, while forest values increased in July only. More imagery should be acquired and examined over greater distances to see if these results are meaningful or coincidental. There was also a series of forest fires in Canada from March to October 2023 that could have been a more likely contributor to the change in VI values from 2021 to 2023.

May 1st, 2021 may not have been the best choice for comparison with May 21st, 2023, as the 20-day difference and seasonal plant changes could lead to value fluctuations. Weather variations like an early or late frost that year might also add to the variability. It's hard to tell if these fluctuations are normal. Still, given the potential outlier status of May 1st, 2021, caution is needed when comparing it with other data points.

## Recommendations for Future Studies

This study had inherent difficulties due to the time of the train derailment in February. VIs could be more beneficial as a tool if the chemical spill occurred during the spring or summer months when vegetation growth is more active. For spectral properties of vegetation to be useful, the imagery had to be chosen for the summer months, which was 3 months after the derailment. This also made it more difficult to determine if the results of this research were even related to the derailment. This approach could be taken for a different chemical spill during warmer months and potentially yield more distinct results.

It would be preferable to have access to 2022 data for comparison with the 2023 imagery, however 2022 experienced significant cloud cover, resulting in limited availability of suitable imagery for selection.

Selecting different vegetation indices that have better documentation would also improve the results of this research. While G-NIR and G-SWIR were used in the oil spill research used by Adamu et al. (2016, 2018) in the literature review, they appear to be unique to that research and only briefly mentioned in others. In addition, it could be beneficial to expand the study area to 10 or more miles away from the derailment to see if there was a more noticeable change farther away.

Finer resolution imagery could benefit this research and the availability of LiDAR. The original intention for this project was to classify the imagery by hand using Object Based Image Analysis (GEOBIA) using eCognition to determine vegetation classes. However, no source of LiDAR covered the entire study area at the time of this study. An nDSM would be necessary to differentiate forest cover from crops and G/P. To generate vegetation classifications, the USDA NASS 30-meter resolution Cropland Data layer was utilized, which would naturally produce some mixed pixels from the Sentinel-2 10-meter resolution imagery. Given more resources and time, acquiring drone imagery at a finer resolution, LiDAR, and employing GEOBIA for classification could have produced more precise and accurate results.

This study is inherently interdisciplinary, bridging the fields of botany, agriculture, and remote sensing. Drawing upon expertise from agricultural research could significantly enhance the quality of this study. To further validate the results obtained from NDVI or other vegetation indices, conducting water and soil sampling in the vicinity to test for vinyl chloride could provide additional credibility to the research findings.

# Conclusion

The desired outcome of this study was to provide evidence that remote sensing can be used as an effective way to monitor vegetation health after chemical spills and determine if there was a change in vegetation health after the chemical spill in East Palestine. While the data analysis revealed a noticeable change in overall vegetation health between May 2023 and May 2021, the evidence linking this change directly to the chemical spill is not sufficiently robust without further investigation. The reliability of using May 2021 as a reference point for comparison also raises some concerns. As such, this study's findings remain inconclusive regarding the effectiveness of spectral indices for assessing vegetation health post-chemical spill. It is beneficial to observe no discernible impact on local vegetation from the train derailment with this method, possibly due to the remediation efforts by the EPA and Norfolk Southern (Morgan, 2023). The results could have turned out differently had the EPA and Norfolk Southern not been so quick to react. Nonetheless, with recommended adjustments and more rigorous research methodologies, NDVI and other indices could potentially prove valuable in evaluating vegetation health in future chemical spill scenarios.

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