STUDYING THE EFFECTS OF LARGE-SCALE SOLAR FARMS ON PLANT ECOSYSTEMS IN NEW YORK STATE USING NDVI BASED GEOSPATIAL ANALYSIS

A Project Report

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Professional Studies in Agriculture and Life Sciences

Field of Natural Resources

by

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ABSTRACT

The state of New York launched the 2015 New York State Energy Plan, which details goals of reducing greenhouse gas emissions by increasing renewable energy generation to 50% by 2030. To meet this energy demand, multiple large-scale solar energy facilities have been proposed for construction by 2030. However, this requires abundant land use for solar site establishment, creating a land use conflict with the surrounding vegetation and the environment. This report details the preliminary effects that solar farms will have on nearby vegetation, such as shading from solar panels. The subsequent study utilizes remote sensing in Google Earth Engine, geospatial applications in QGIS, and statistical analysis in R to analyze satellite imagery over New York State. Sentinel-2 land surface reflectance is processed to calculate normalized difference vegetation index to determine a significant change pre- and post-construction of solar farms. Results indicate that solar farms improve vegetation growth by providing shade and pooling water during the summer growing seasons, yet reduces growth during other months.

BIOGRAPHICAL SKETCH

Matthew Norman Gee is an environmental nut and a native of the San Francisco Bay Area in California. Given the opportunity to be the Gator Gears Robotics Team's Head Software Programmer and the Advanced Placement Environmental Science Teacher's Assistant, Matthew developed his interest in the intersection between technology and the environment. This passion led to his inquisitive pursuit of how computer-based aerial and satellite spatial analysis can be utilized for resource assessment as an undergraduate at the University of California, Davis. There, he examined desert kit fox response to solar energy development in the Mojave Desert as a student researcher and diurnal viticulture response to variable irrigation regimes during summer heat waves while employed as a laboratory & field technician. He received his Bachelor of Science in Environmental Science and Management at UC Davis with a specialization in Geospatial Information Sciences in December 2019.

His drive to seek how geospatial analysis can further natural resource management for industries, researchers, and policy makers led Matthew to pursue his Master of Professional Studies in Agriculture and Life Sciences through the field of Natural Resources at Cornell University. He centered his research on renewable energy ecology and geospatial applications while being part of the United States Geological Survey New York Cooperative Fish and Wildlife Research Unit.

ACKNOWLEDGEMENTS

I would like to thank Dr. Steve M. Grodsky for facilitating the foundational concept for this project and being an advisor throughout my tenure in the Natural Resources and the Environment program. His insight on renewable energy ecology as it pertains to stakeholders was vital to the approach in my work. I am grateful for his guidance in my scholastic endeavors prior and during my study at Cornell, as well as his support to include me with the USGS New York Cooperative Fish and Wildlife Unit. I am truly thankful to have his broad-ranging mentorship that fostered this project.

I would like to thank Dr. Stephen J. Morreale for nurturing the Natural Resources and the Environment MPS program, as well as providing thoughtful advice regarding methodology for my research. Due to the data's small sampling size, he proposed the use of paired t-tests for statistical analysis that is now implemented in this project. His knowledge on scientific geospatial theory had also helped me with the overall brainstorming process. Additionally, I am wholeheartedly appreciative for his devotion to establishing an inclusive and enriching academic environment to all students regardless of background.

I want to also thank Dr. Ying Sun for offering critical input on the research variables for this study. Her intricate comprehension of available satellite data, remote sensing, and GIS-oriented agroecosystem science helped me understand the importance of data precision. Her instruction regarding spatial and temporal resolution between satellite measuring instruments allowed me to assess the feasibility of applying certain data that was instrumental to the creation of the project.

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LIST OF ABBREVIATIONS

BOA	Bottom-Of-Atmosphere
BTU	British Thermal Unit
EPSG	European Petroleum Survey Group
GIS	Geographic Information System
HA	Hectares
KM	Kilometer
MSI	Multispectral Instrument
MW_{ac}	MegaWatt Alternating Current
NDVI	Normalized Difference Vegetation Index
NYS	New York State
NYSERDA	The New York State Energy Research and Development Authority
QGIS	Quantum Geographic Information System
REV	Reforming the Energy Vision
TIF	Tag Image File Format
WGS	World Geodetic System

INTRODUCTION

On June 25th, 2015, New York State Governor Andrew M. Cuomo released the final version of the 2015 New York State Energy Plan. It was created to set forth a vision for New York's energy future and lay out a clear roadmap to achieve the state's 2014 Reforming the Energy Vision (REV) goals. The Plan is centered on coordinating the efforts of state agencies to improve market-driven adoption of clean energy technologies into statewide energy demand budgets. It outlines initiatives, alongside private sector innovation and investment from REV, that will place New York State on a path to achieve its clean energy goals (NYSERDA). These goals are a 40% reduction in greenhouse gas emissions from 1990 levels, 50% of energy generation from renewable energy sources such as solar and wind by 2030, and 600 trillion British thermal unit (Btu) increase in statewide energy efficiency (Sen 2015).

The New York State Energy Research and Development Authority, or NYSERDA for short, has overseen many renewable energy projects from the 2015 New York State Energy Plan through government incentive programs. A majority of these programs are targeted towards clean solar energy generation which supports the construction of recently proposed, large-scale solar farms known as Tier 1 - New Renewables. While these solar energy facilities may help NYS reach its ambitious goal of reaching 50% renewable energy generation by 2030, many solar companies focus more on the aspect of novel energy production rather than how solar farm construction will affect the nearby environment. Site selection, construction, and maintenance of solar sites often neglect environmental ramifications as these sites compete with vegetation for space and resources, creating a land-use conflict. Current societal concerns with vegetation cover change from renewable energy development also focus on potential effects it may have on protected area conservation and endangered species. Abrupt changes, known as "breakpoints", in plant cover may have negative ramifications that affect habitat of wildlife, which may not adapt quick enough to new conditions (Nghiem et al. 2019).

This report aims to develop a framework that can eventually predict the effects that solar site selection and construction in New York State will have on nearby native vegetation. To study this effect, it shall detail the use of geospatial analysis and remote sensing to compare pre- and post-construction of multiple current operational solar farms, focusing on changes in normalized difference vegetation index (NDVI). This report shall test the alternative hypothesis that solar site establishment will decrease nearby vegetation health and greenness due solar panel shading which inhibits plant accessibility to sunlight needed for photosynthesis.

DATA AND METHODS

To scrutinize temporal differences in NDVI near the edge of a solar farm, annual information that monitors vegetation cover breakpoints can be obtained through biometeorological satellite data. A suitable spaceborn instrument for retrieving high resolution NDVI data is the Harmonized Sentinel-2 MSI: Multispectral Instrument carried on the Sentinel-2A optical imaging satellite from the European Space Agency's Copernicus Programme. This instrument provides imagery for a 10-day Bottom-Of-Atmosphere (BOA), orthorectified surface reflectance through the Sentinel-2 Level-2A Collection 1 product. These images include atmospheric correction of the absorbing and air molecule scattering (known as Rayleigh scattering) for atmospheric gasses such as oxygen, ozone, aerosol particles, and water vapor (Copernicus Sentinel-2, 2020-23). It can be used to calculate NDVI processed for opaque and cirrus cloud-shadow masking and low cloud probability. Availability of continuous global observations on a thrice a month basis since June 2015 makes this sensor versatile for many smaller-scale vegetation and climate change studies.

The study domain includes aggregated data from seven of the first operational Tier-1 solar farms in the state of New York: Branscomb Solar, Darby Solar, ELP Stillwater Solar, Grissom Solar, Pattersonville Solar, Puckett Solar, and Regan Solar. Developed by MN8 Energy Operating Company LLC, these solar farms each have a nameplate capacity of 20 MW_{ac} and altogether total to 3.6 km^2/359.5 ha in area. They have been commissioned and built from 2020-2022 in Washington, Chenango, Saratoga, Schenectady, and Montgomery County. These facilities were chosen since they are spatially-heterogeneous throughout New York State and possess NDVI measurements one year before and after construction. Information of these solar farms is complemented by data from NYSERDA, which denotes over 200 complete or under development large-scale renewable energy projects reported since 2004 (State of New York).

To conduct this study, a shapefile for each of the seven Tier-1 solar facilities was created then merged in QGIS version 3.30.0 - Hertogenbosch, an open-source geographic information system application, to establish the boundaries of the property, aggregating to a sample size of 29 solar panel collections. The independent variable is solar farm establishment and the dependent variable is NDVI. Seven shapefiles encompassing a total of 29 nearby, randomly-selected grassfields were also made to be treated as a control variable due to its similar vegetation cover. These shapefiles are then imported to Google Earth Engine[1][2][3][4][5][6][7], a cloud-based catalog of satellite imagery and geospatial data sets, for determining the location needed to compare changes in NDVI before and after establishment. A low cloud probability of less than 20%, alongside an opaque and cirrus cloud-shadow mask, are used on Sentinel-2A surface reflectance to filter for clear weather condition imagery over the study domain. To compare pre-construction (2019-2021) and post-construction (2021-2023) changes, average NDVI is then calculated from the surface reflectance during 3 four-month periods (January-April, May-August, & September-December) for 2019-2023. These images are exported as .tif raster data back to QGIS and reprojected to EPSG: 3857 - WGS 84/Pseudo-Mercator, where each post-construction, four-month NDVI is subtracted from their respective pre-construction measurements through QGIS' Raster Calculator. Figure 1 below shows normal distribution pixel frequency histograms for this difference in NDVI from 2019-21 to 2021-23, which is required to conduct paired t-tests.

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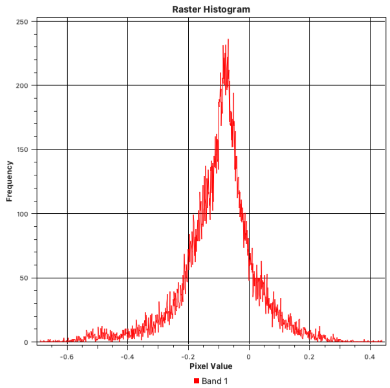
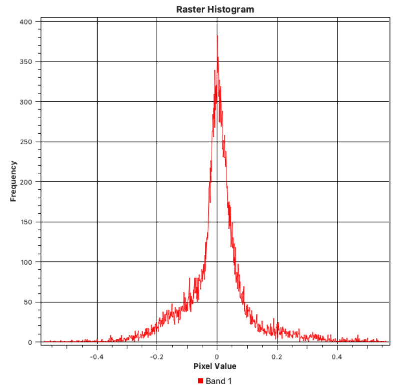
[1] Branscomb Solar - GEE code: https://code.earthengine.google.com/4285f41658355d010f4139ba75cf7480
[2] Darby Solar - GEE code: https://code.earthengine.google.com/f85d8bc21faf4b136bf4b605d26032ac
[3] ELP Stillwater Solar - GEE code: https://code.earthengine.google.com/66be3fc47897c37f83a780f387850b6f
[4] Grissom Solar - GEE code: https://code.earthengine.google.com/bb359fa3bbe8bde7a09ca4a215d45ca7
[5] Pattersonville Solar - GEE code: https://code.earthengine.google.com/e372525b8082ade639b4f7f9481fcfa4
[6] Puckett Solar - GEE code: https://code.earthengine.google.com/e18525be75718568bbcd3ceee9cdfa6c
[7] Regan Solar - GEE code: https://code.earthengine.google.com/e90e128395c5752284ae53b43927200e

Branscomb Solar

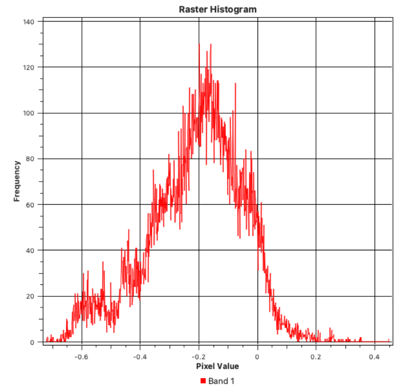
Jan-Apr 2020-22 Change



May-Aug 2020-22 Change

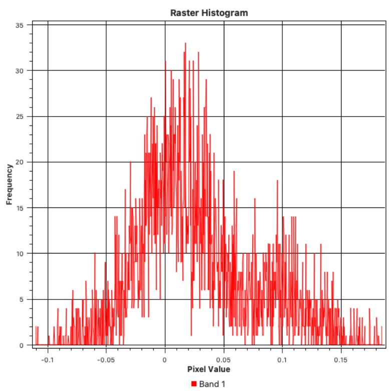


Sep-Dec 2020-22 Change



Darby Solar

Jan-Apr 2021-23 Change



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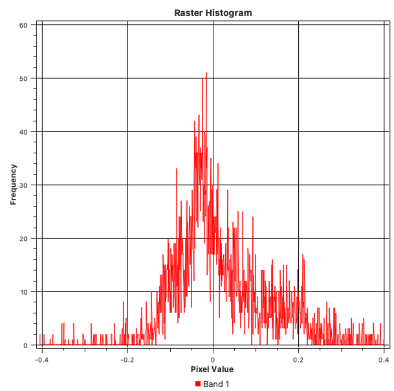

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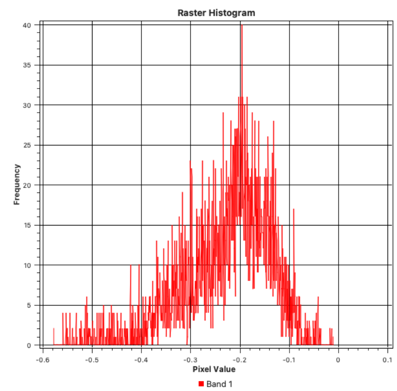
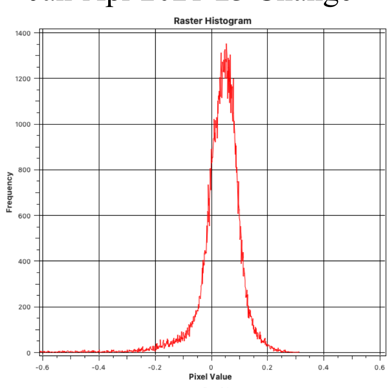
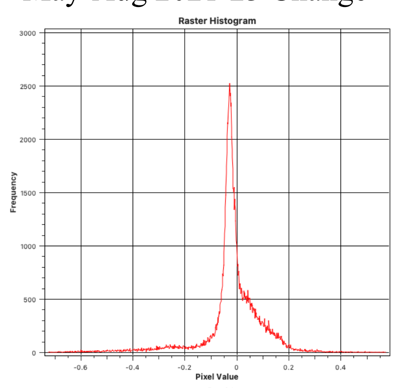


ELP Stillwater Solar

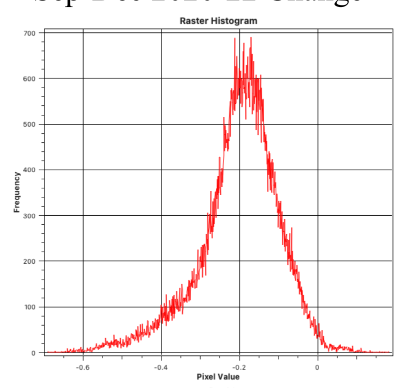
Jan-Apr 2021-23 Change



May-Aug 2021-23 Change

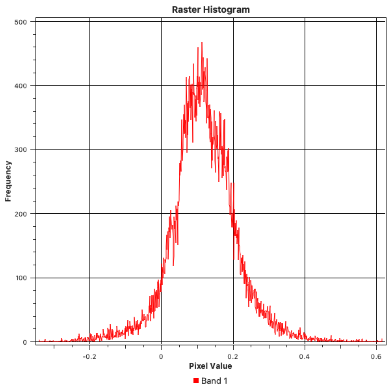


Sep-Dec 2020-22 Change



Grissom Solar

Jan-Apr 2021-23 Change



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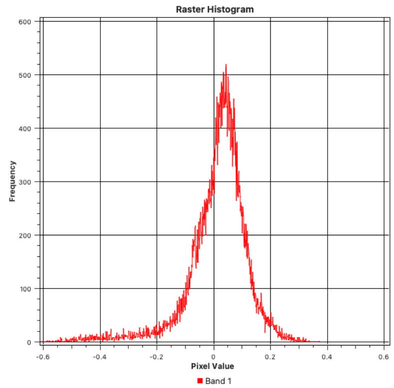

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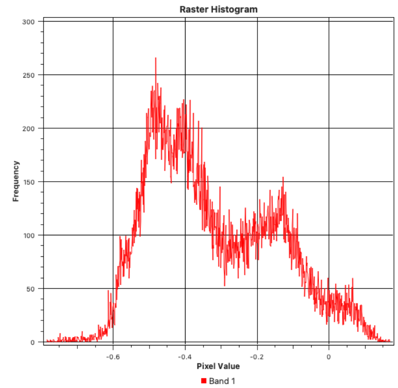
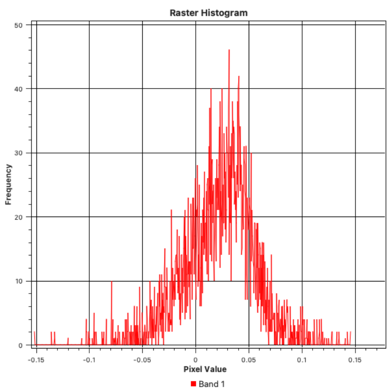
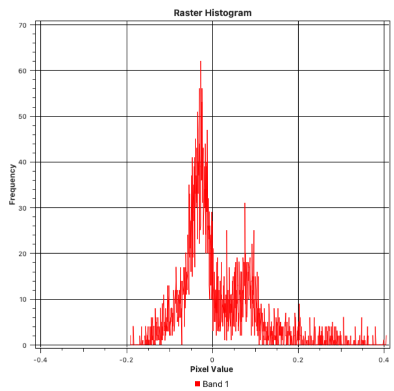


Pattersonville Solar

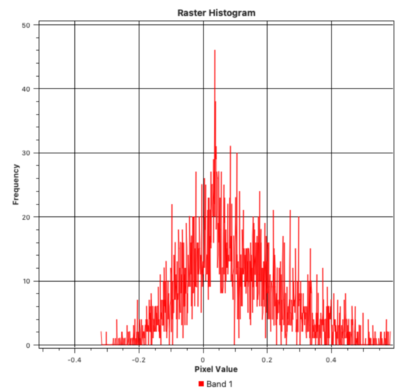
Jan-Apr 2019-21 Change



May-Aug 2019-21 Change

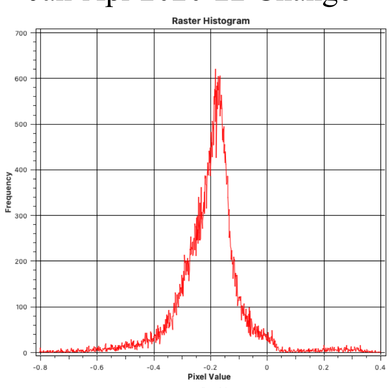


Sep-Dec 2019-21 Change

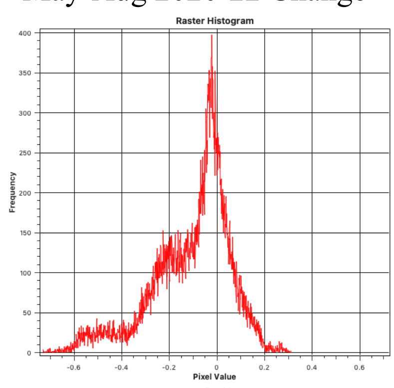


Puckett Solar

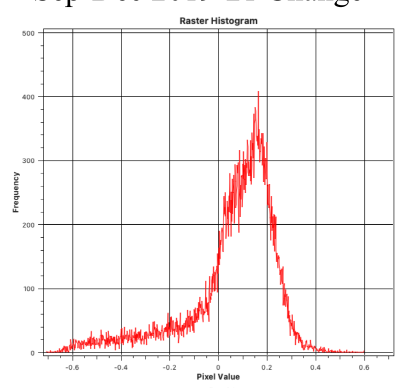
Jan-Apr 2020-22 Change



May-Aug 2020-22 Change



Sep-Dec 2019-21 Change



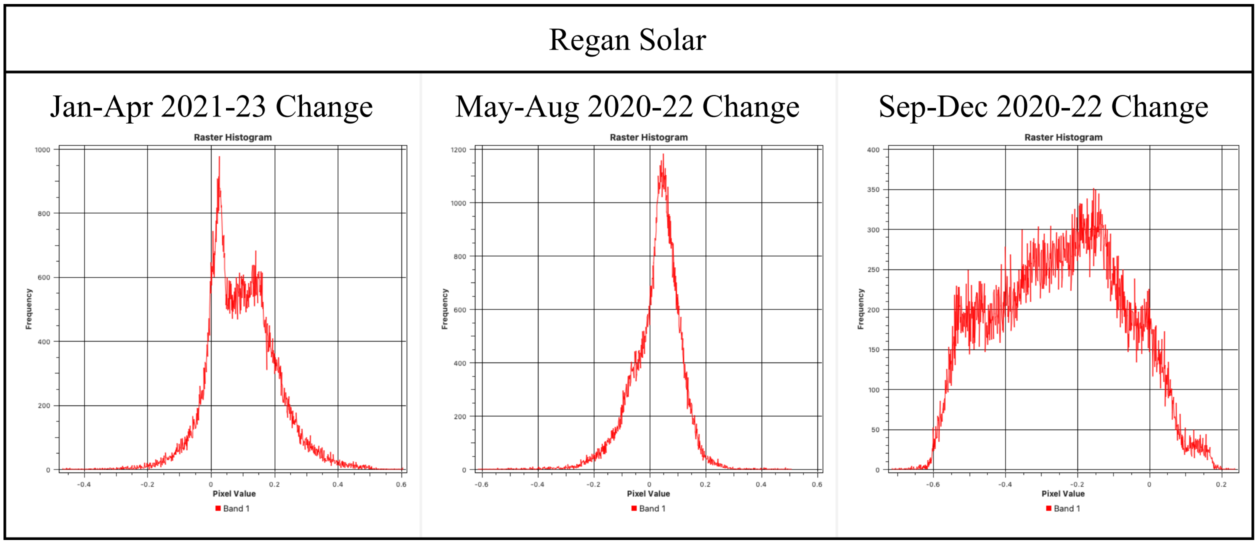
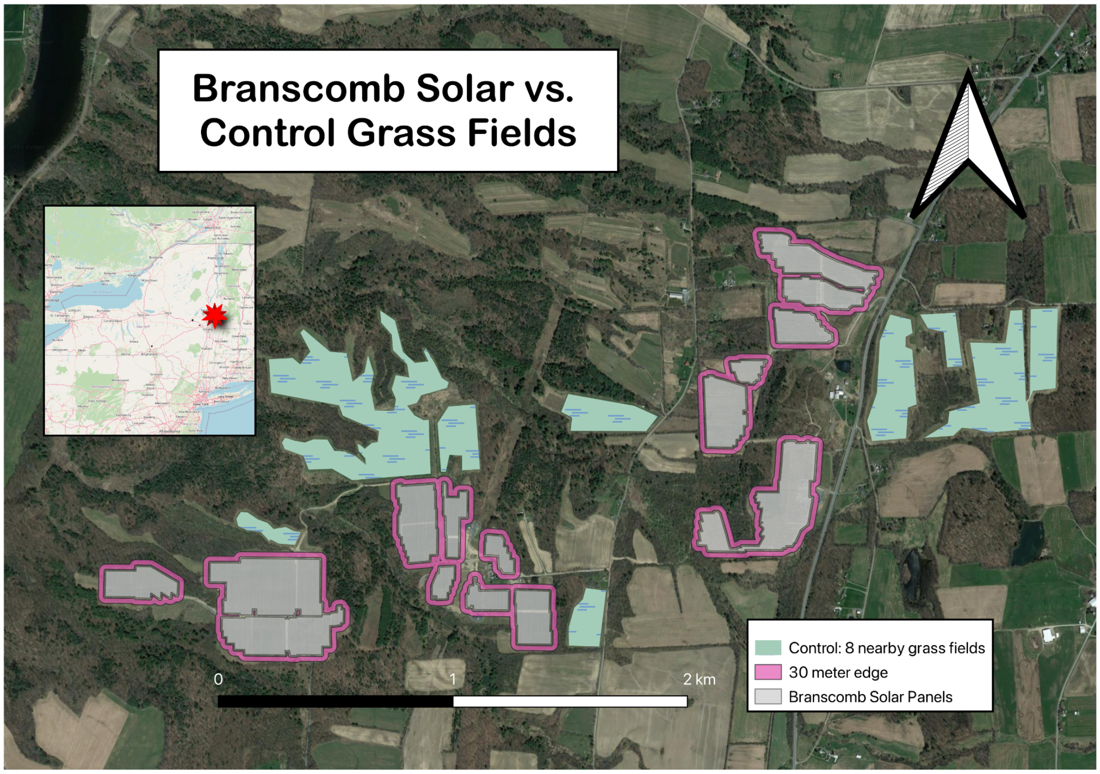
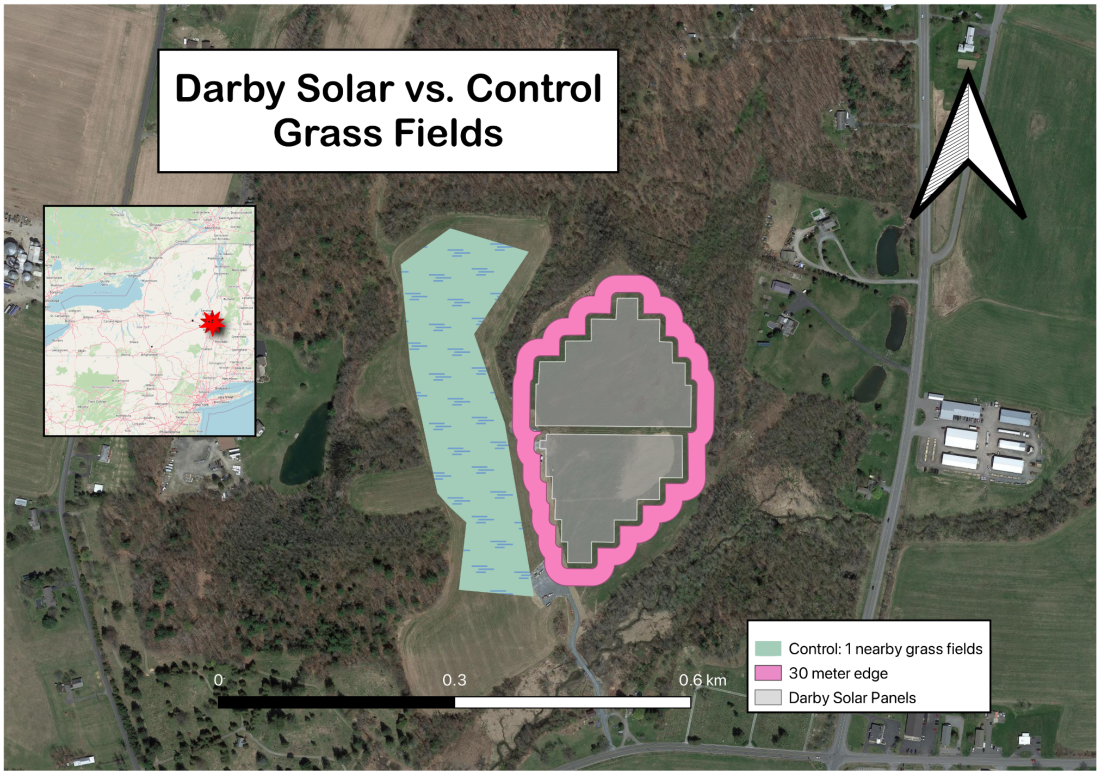
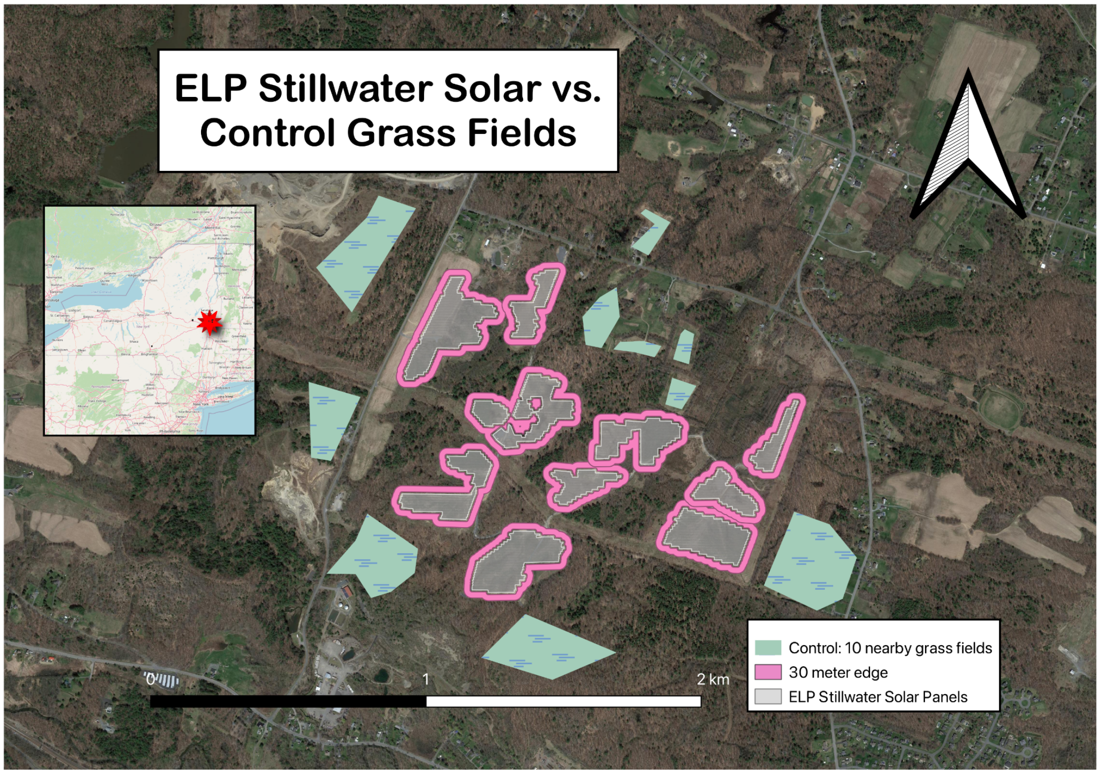


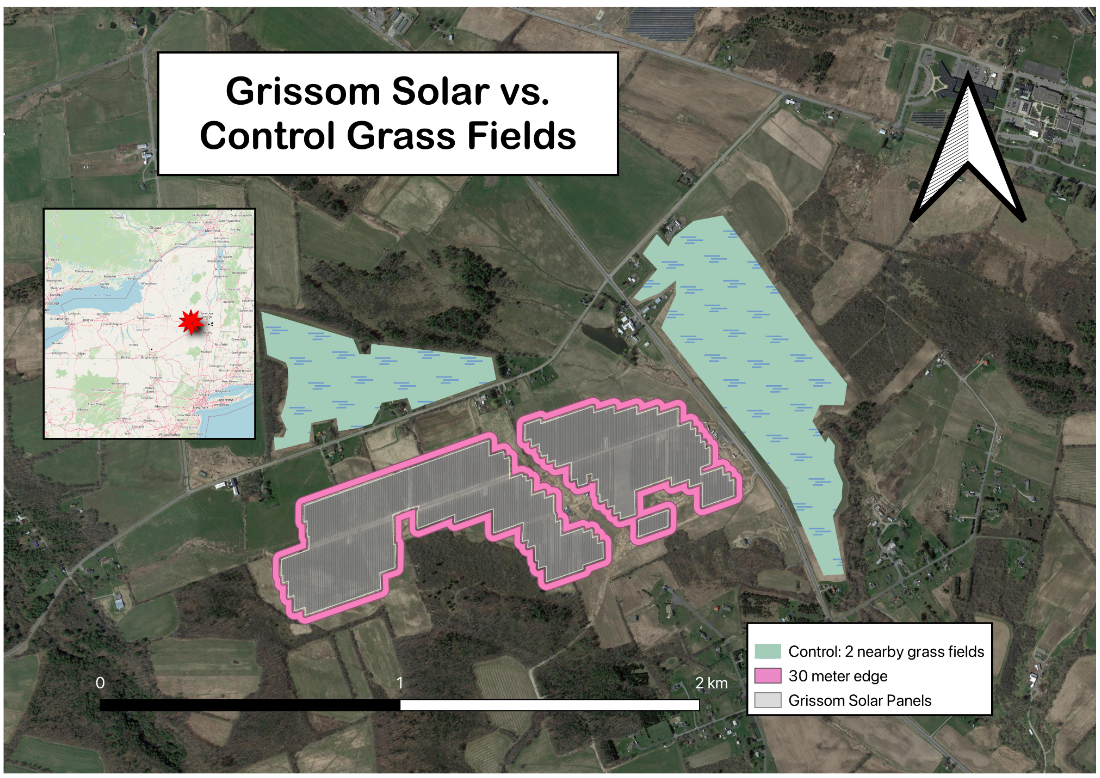
Figure 1. Pixel frequency histograms of differences in mean NDVI rasters during four-month periods pre-construction for 2019-21 and post-construction for 2021-23 near each of the seven Tier-1 solar farms. Note that each histogram roughly reflects a normal distribution needed for paired t-tests.

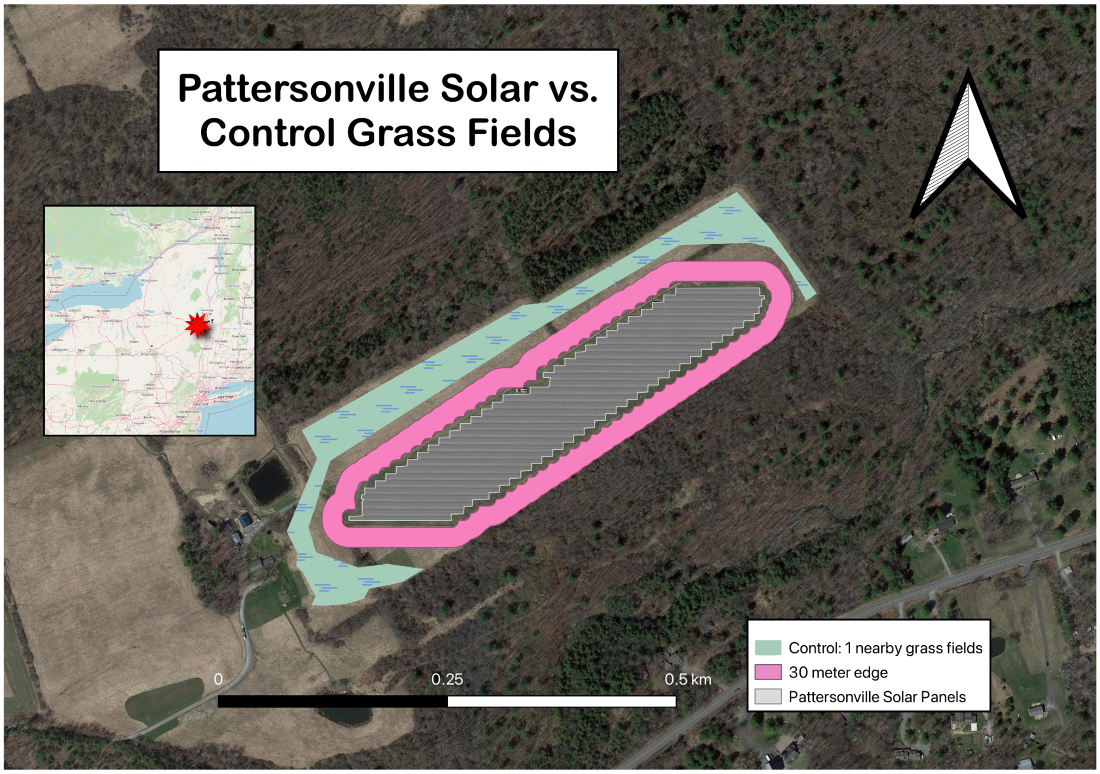
To quantify NDVI change along the solar farm edge, a multi-ring buffer (4 rings, 10 meters each) around each Tier-1 solar shapefile is created. The interior feature is then deleted, which removes NDVI measurements on top of and 10 meters away from the solar panels. Due to Sentinel-2A's 10 meter spatial resolution, this is necessary to prevent accidentally measuring NDVI on the built environment. The buffer is then dissolved to create a continuous 30 meter buffer, which is a 10-40 meter distance from the edge of the solar panels. Zonal statistics, found under 'raster analysis' in the processing toolbox of QGIS, extracts and averages NDVI within the 29 solar panel collections and 29 control grassfields during the 3 four-month periods pre- and post-construction. Figure 2 below highlights the relative locations of each Tier-1 solar farm, the 10-40 meter buffer, and control grassfields. Figure 3 shows the spatial difference in pre- and post-construction NDVI per four-month period for the two solar farms with the most solar collections, Branscomb and ELP Stillwater Solar. The green areas represent an increase, red areas represent a decrease, and white areas show insignificant changes in NDVI.

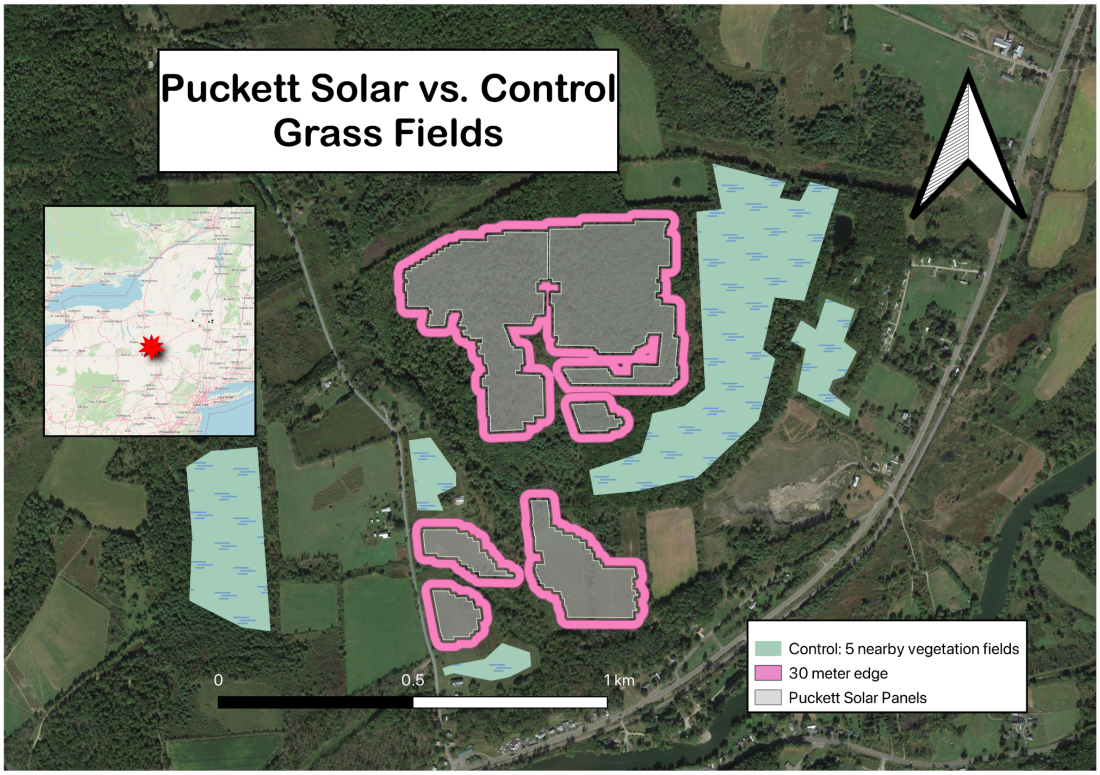

Branscomb Solar vs. Control Grass Fields
0
1
2 km
Control: 8 nearby grass fields
30 meter edge
Branscomb Solar Panels


Darby Solar vs. Control Grass Fields
0
0.3
0.6 km
Control: 1 nearby grass fields
30 meter edge
Darby Solar Panels


ELP Stillwater Solar vs.
Control Grass Fields
Control: 10 nearby grass fields
30 meter edge
ELP Stillwater Solar Panels
0
1
2 km


Grissom Solar vs.
Control Grass Fields
Control: 2 nearby grass fields
30 meter edge
Grissom Solar Panels
0
1
2 km


Pattersonville Solar vs. Control Grass Fields
0
0.25
0.5 km
Control: 1 nearby grass fields
30 meter edge
Pattersonville Solar Panels


Puckett Solar vs. Control Grass Fields
0
0.5
1 km
Control: 5 nearby vegetation fields
30 meter edge
Puckett Solar Panels

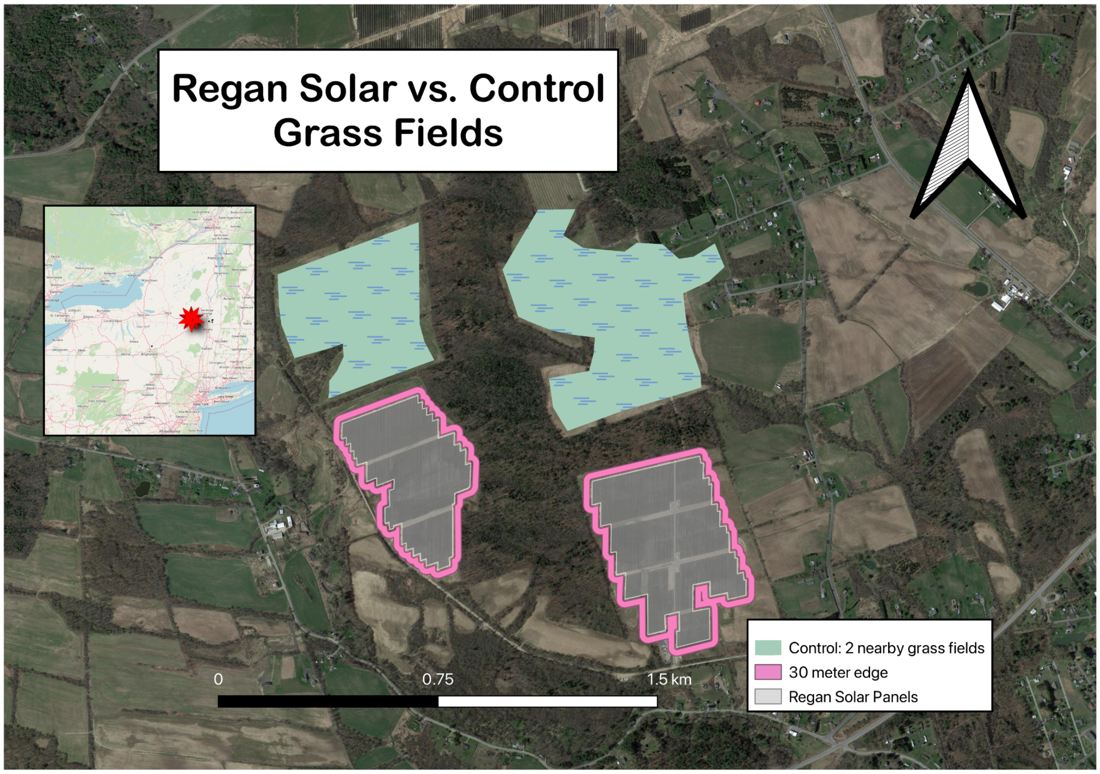
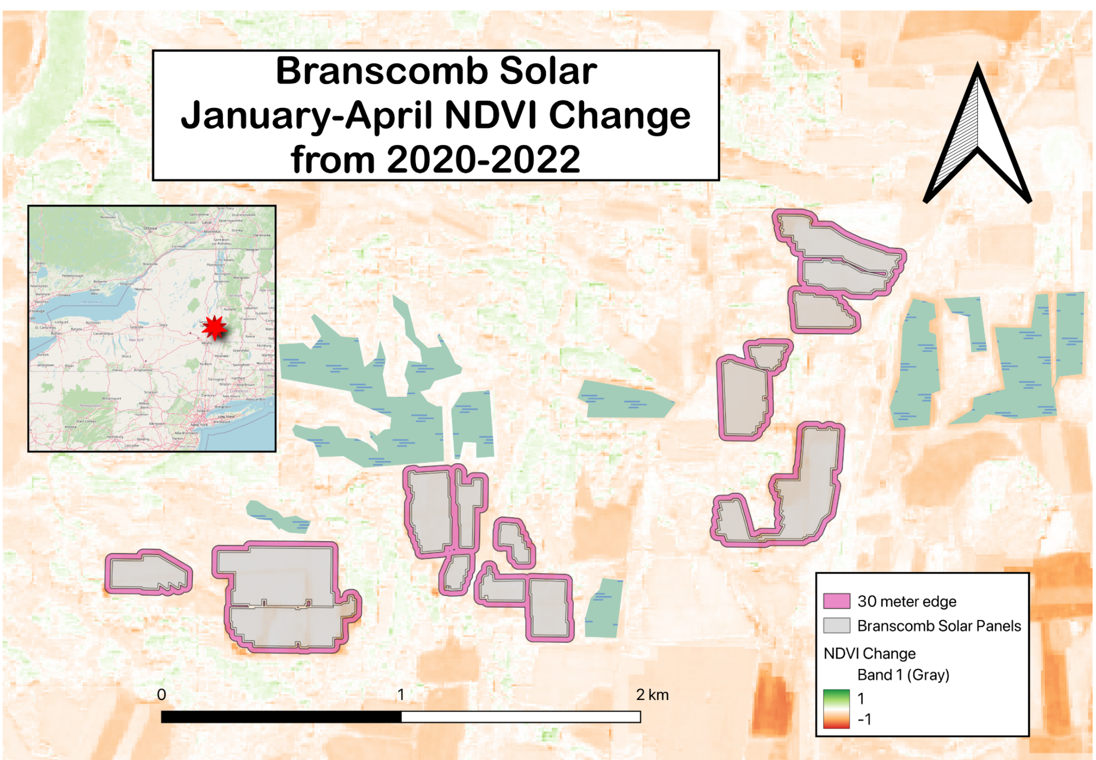
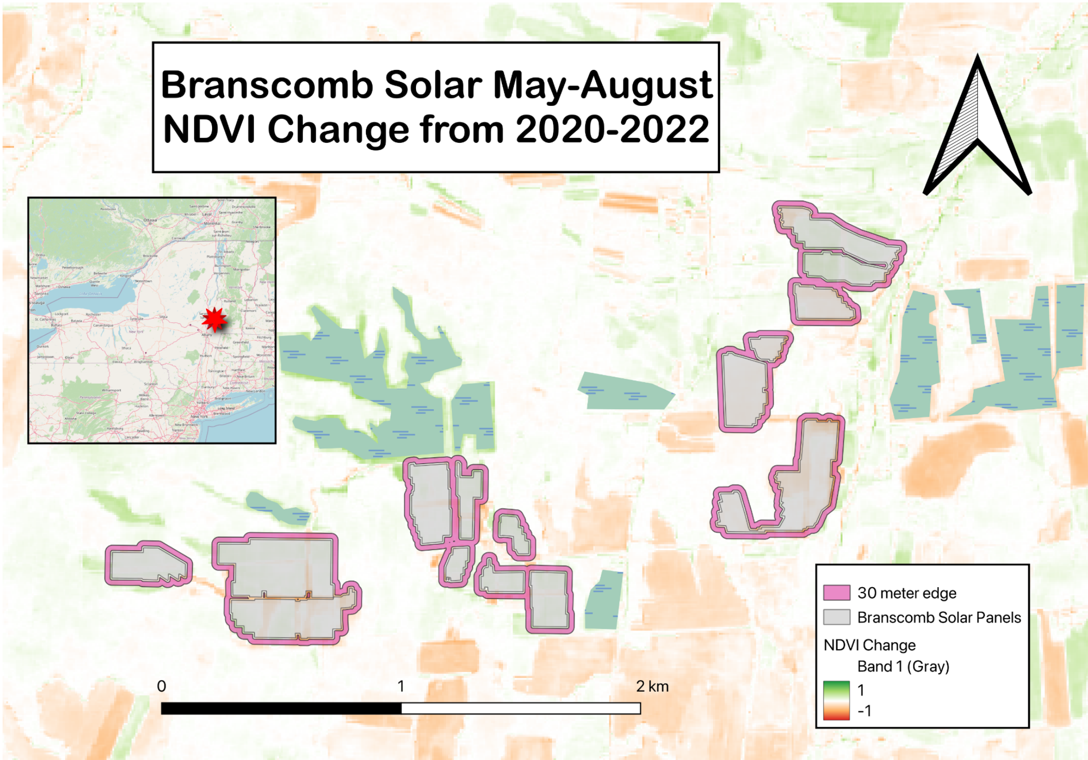
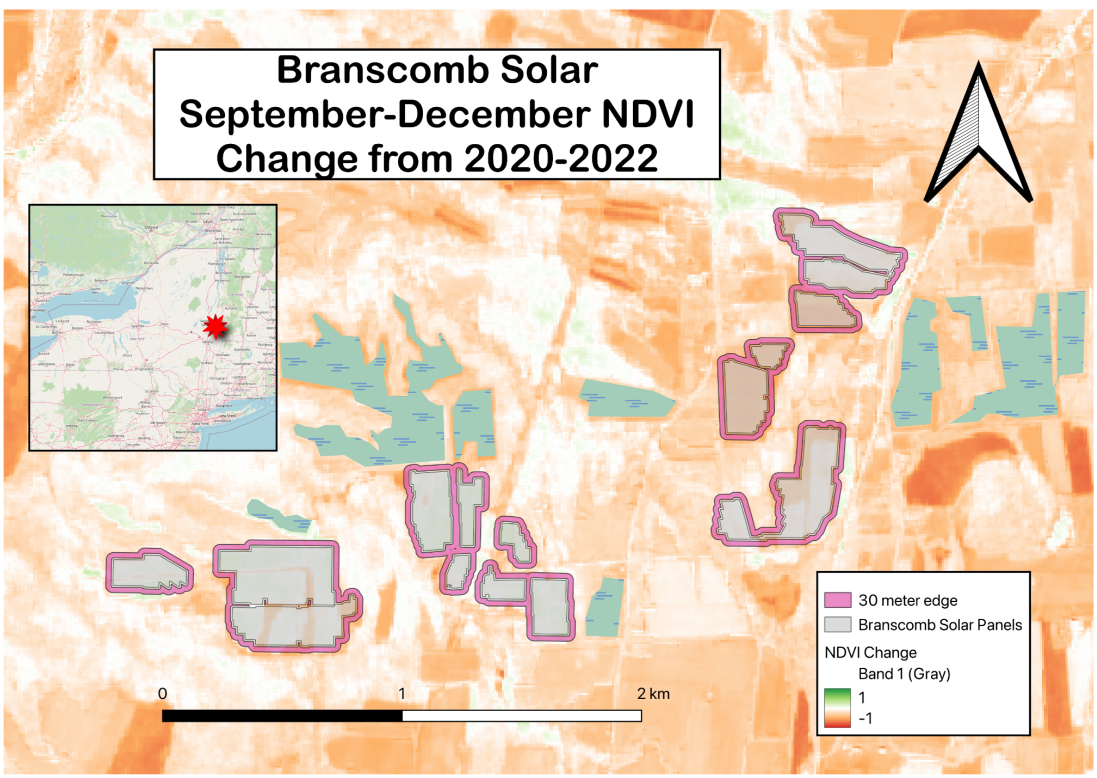
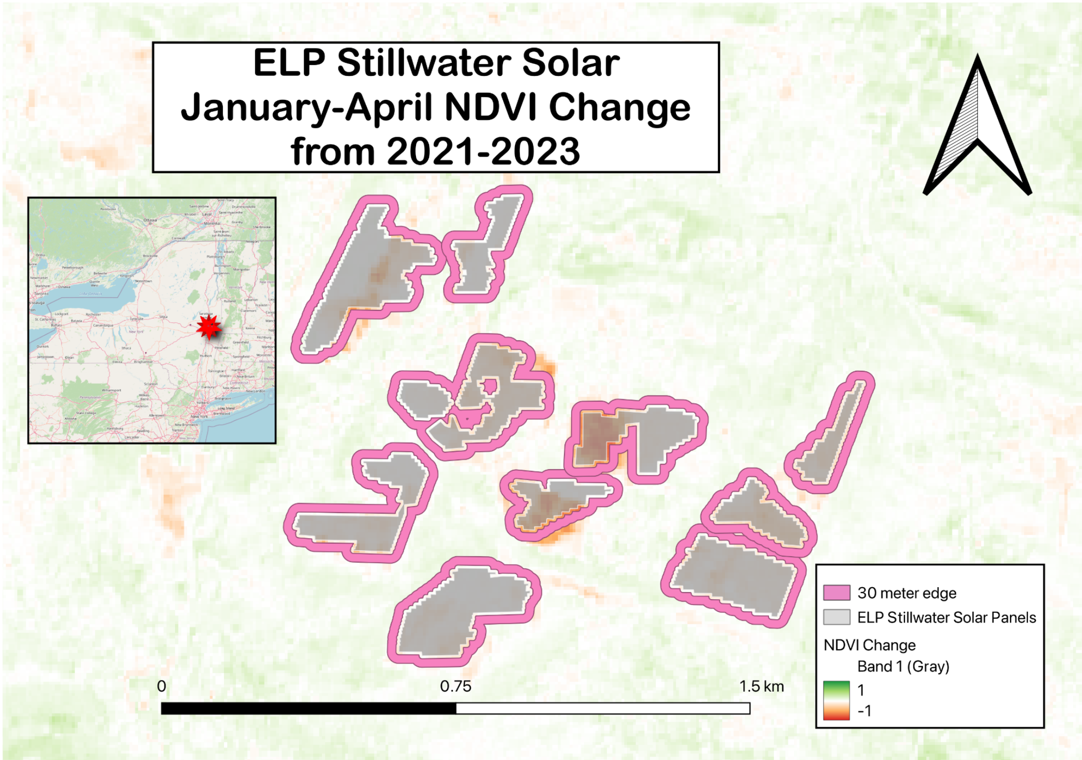


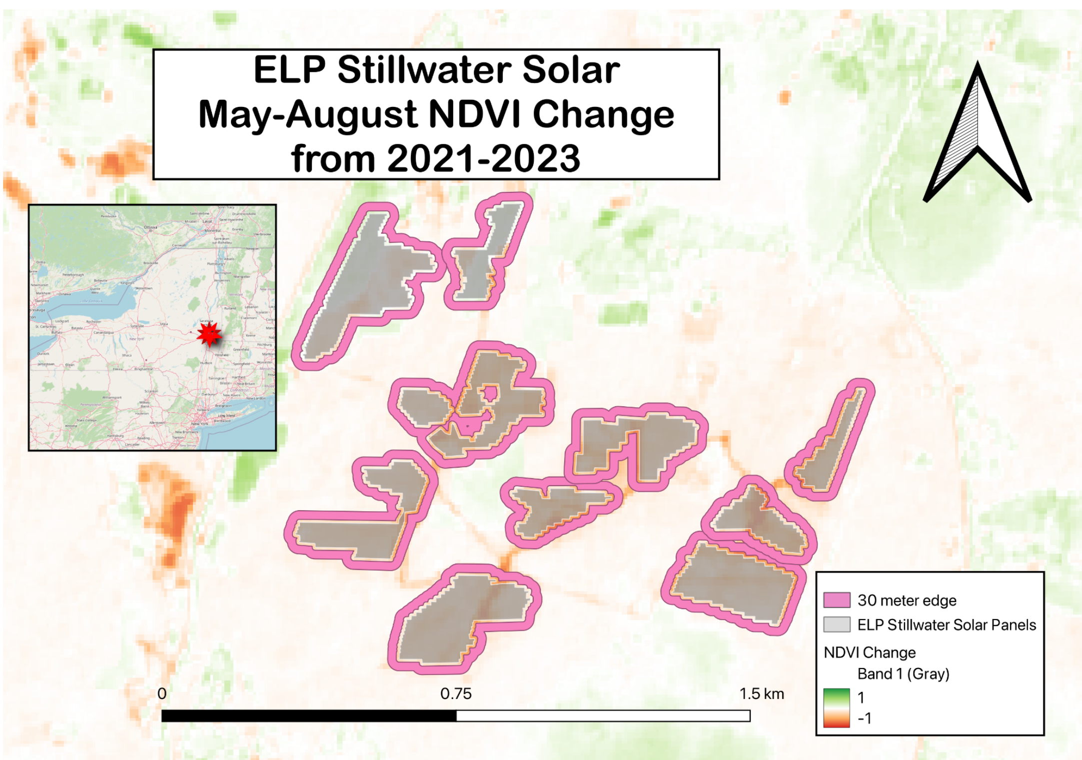
Figure 2. Maps of the 29 solar panels collections at the Tier-1 solar farms (gray), the 10-40 meter buffer (pink), and 29 randomly-selected nearby grassfield control variables (light-green).




Branscomb Solar May-August NDVI Change from 2020-2022
30 meter edge
Branscomb Solar Panels
NDVI Change
Band 1 (Gray)
1
-1
0
1
2 km


Branscomb Solar September-December NDVI Change from 2020-2022
30 meter edge
Branscomb Solar Panels
NDVI Change
Band 1 (Gray)
1
-1
0
1
2 km


ELP Stillwater Solar
January-April NDVI Change
from 2021-2023
30 meter edge
ELP Stillwater Solar Panels
NDVI Change
Band 1 (Gray)
1
-1
0
0.75
1.5 km


ELP Stillwater Solar
May-August NDVI Change
from 2021-2023
30 meter edge
ELP Stillwater Solar Panels
NDVI Change
Band 1 (Gray)
1
-1
0
0.75
1.5 km

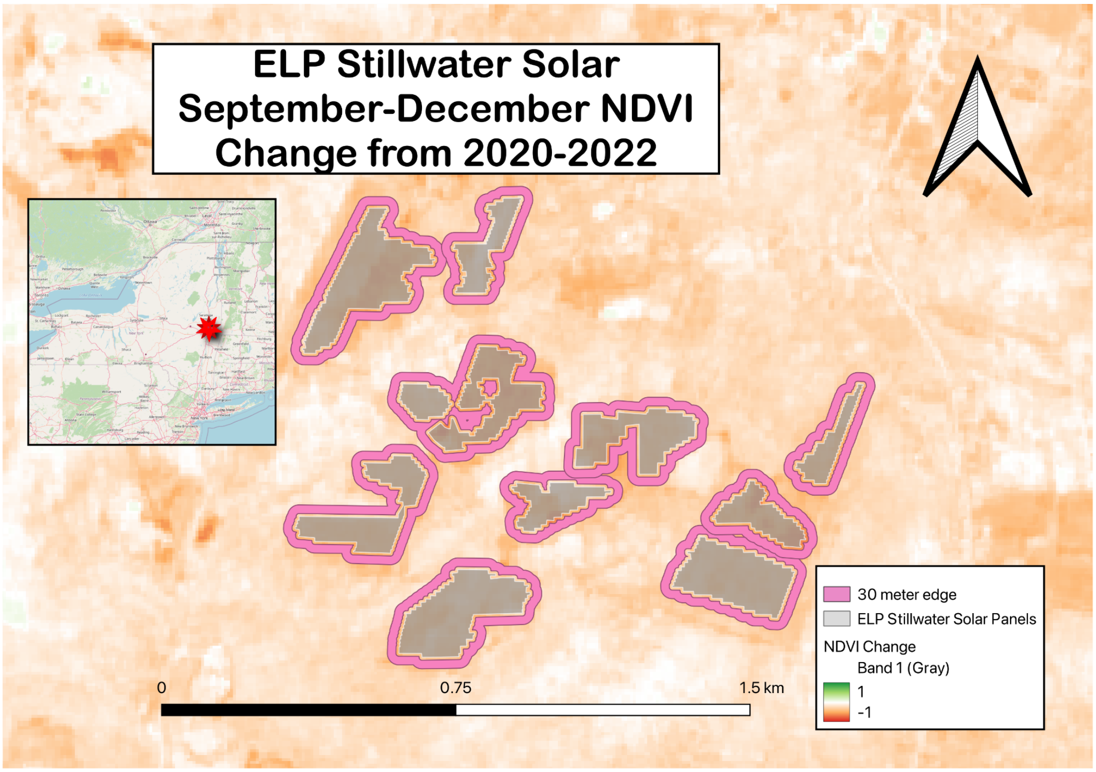


Figure 3. Spatial distribution of NDVI changes for the 3 four-month periods pre- and post-construction. Green areas are indicative of vegetation growth and health, while red areas are likely either energy or nutrient limited. Maps highlight a general trend of decreasing NDVI except during the plant growing season observed May through August.

Multiple paired t-tests are conducted for the zonal statistics NDVI in R version 4.3.1, a programming language for statistical computing and graphics[8] (R Core Team & RStudio Team, 2023). Subsequent boxplots are created to visualize paired t-tests for both Tier-1 solar panels and their respective control variables. Linear regression models are also used to determine the range of and correlation between these average NDVI of the study area and control.

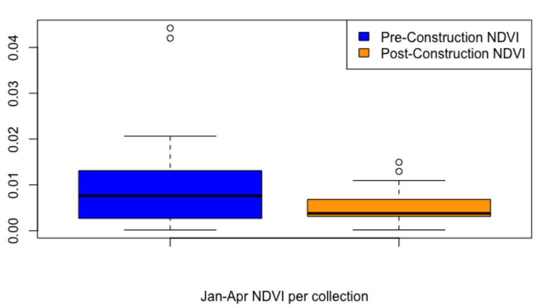
[8] R code uploaded to GitHub here: https://github.com/matthew-n-gee/NYSERDA-Tier-1-Solar-Farm-NDVI.git

RESULTS

There are detected disparities in average NDVI between pre- and post-construction vegetation along the edge of the solar facility that is not observed in the control grassfields. The boxplots and paired t-tests shown below in Figure 4 note low p-values of 0.009548 and 6.851^{-6} in the delta of average NDVI within the 30 meter solar edge for 2 four-month periods: January-April and May-August. On the other hand, the paired t-tests for the September-December solar edge NDVI, as well as all 3 four-month periods from January-December for the control variable, have a higher p-value of 0.2481, 0.1028, 0.1724, and 0.109, respectively. Using a p-value less than 0.05 to reject the null hypothesis, all solar edge data except the September-December period reflect a statistically significant difference in NDVI before and after solar farm establishment, yet the control variable is not statistically significant.

Pre- vs. Post-Construction Change in NDVI

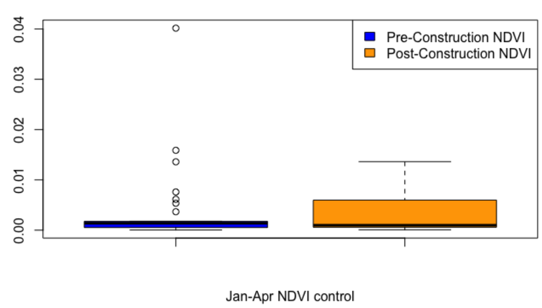
Jan-Apr: Solar Edge




```
Paired t-test

data:  Pre_Construction_Jan_Apr_NDVI_mean and
Post_Construction_Jan_Apr_NDVI_mean
t = 2.7825, df = 28, p-value = 0.009548
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 0.001201065 0.007903681
sample estimates:
mean difference
    0.004552373
```

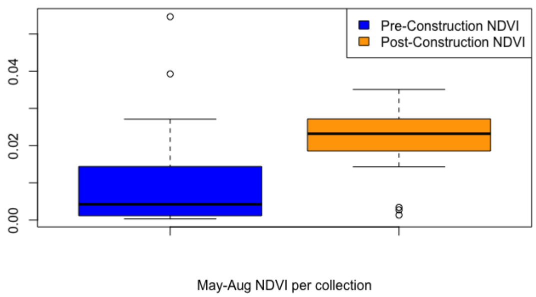
Jan-Apr: Control Grassfields




```
Paired t-test

data:  Pre_Construction_Jan_Apr_NDVI_mean_control and
Post_Construction_Jan_Apr_NDVI_mean_control
t = -1.6864, df = 28, p-value = 0.1028
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.0025771546  0.0002497868
sample estimates:
mean difference
   -0.001163684
```

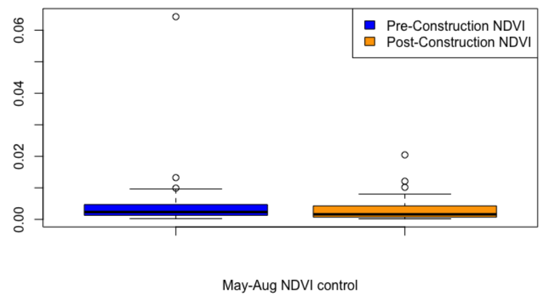
May-Aug: Solar Edge




```
        Paired t-test

data:  Pre_Construction_May_Aug_NDVI_mean and
Post_Construction_May_Aug_NDVI_mean
t = -5.5123, df = 28, p-value = 6.851e-06
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.01646445 -0.00754312
sample estimates:
mean difference
    -0.01200379
```

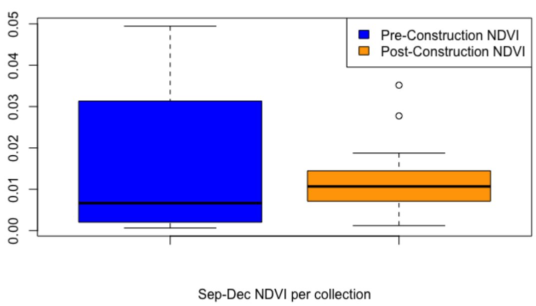
May-Aug: Control Grassfields




```
        Paired t-test

data:  Pre_Construction_May_Aug_NDVI_mean_control and
Post_Construction_May_Aug_NDVI_mean_control
t = 1.4003, df = 28, p-value = 0.1724
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.001040001  0.005533711
sample estimates:
mean difference
    0.002246855
```

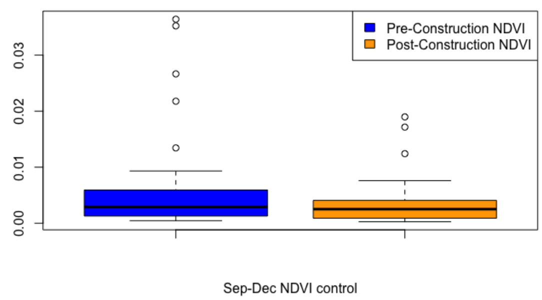
Sep-Dec: Solar Edge




```
        Paired t-test

data:  Pre_Construction_Sep_Dec_NDVI_mean and
Post_Construction_Sep_Dec_NDVI_mean
t = 1.1795, df = 28, p-value = 0.2481
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.002962196  0.011004447
sample estimates:
mean difference
    0.004021125
```

Sep-Dec: Control Grassfields



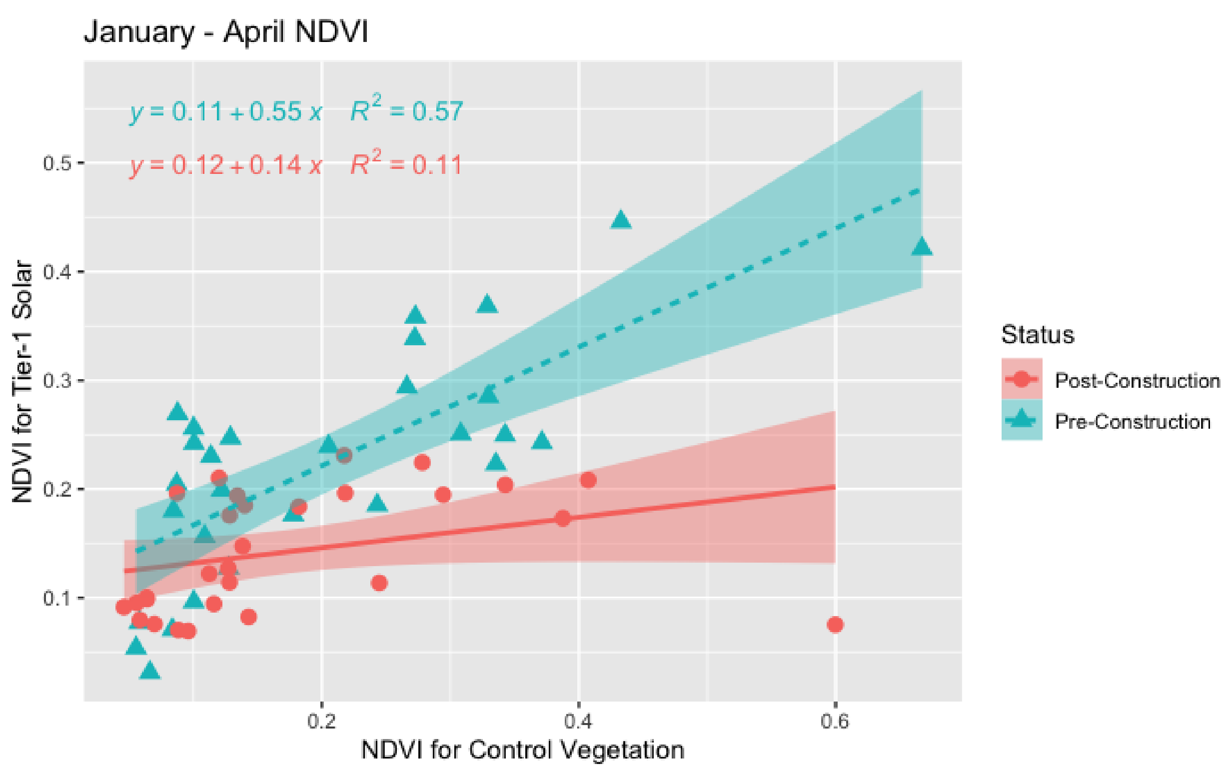

```
        Paired t-test

data:  Pre_Construction_Sep_Dec_NDVI_mean_control and
Post_Construction_Sep_Dec_NDVI_mean_control
t = 1.6555, df = 28, p-value = 0.109
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.0007045601  0.0066427112
sample estimates:
mean difference
    0.002969076
```

Figure 4. Boxplots and paired t-tests used to detect change in paired pre-construction and post-construction NDVI. Note that the solar panel collection edges (left) and control variable grassfields (right) undergo separate paired t-tests per four-month period.

Although the independent variable affects the dependent variable for 2 out of the 3 four-month periods in a statistically significant way, both periods' mean difference is opposite to one another directionally. A positive 0.004552373 mean difference for the January-April winter months indicates an decrease in NDVI, while a negative -0.01200479 mean difference for the May-August plant growing season indicates an increase in NDVI after solar farm establishment.

Linear regression models in Figure 5 further illustrate how NDVI does not differ much between the independent and control variable pre-construction, yet overall declines for the independent variable post-construction. All three models portray a lower NDVI range throughout all solar edge samples (vertically in Figure 5) but a relatively constant NDVI range for the control (horizontally in Figure 5), where no human development has occurred.



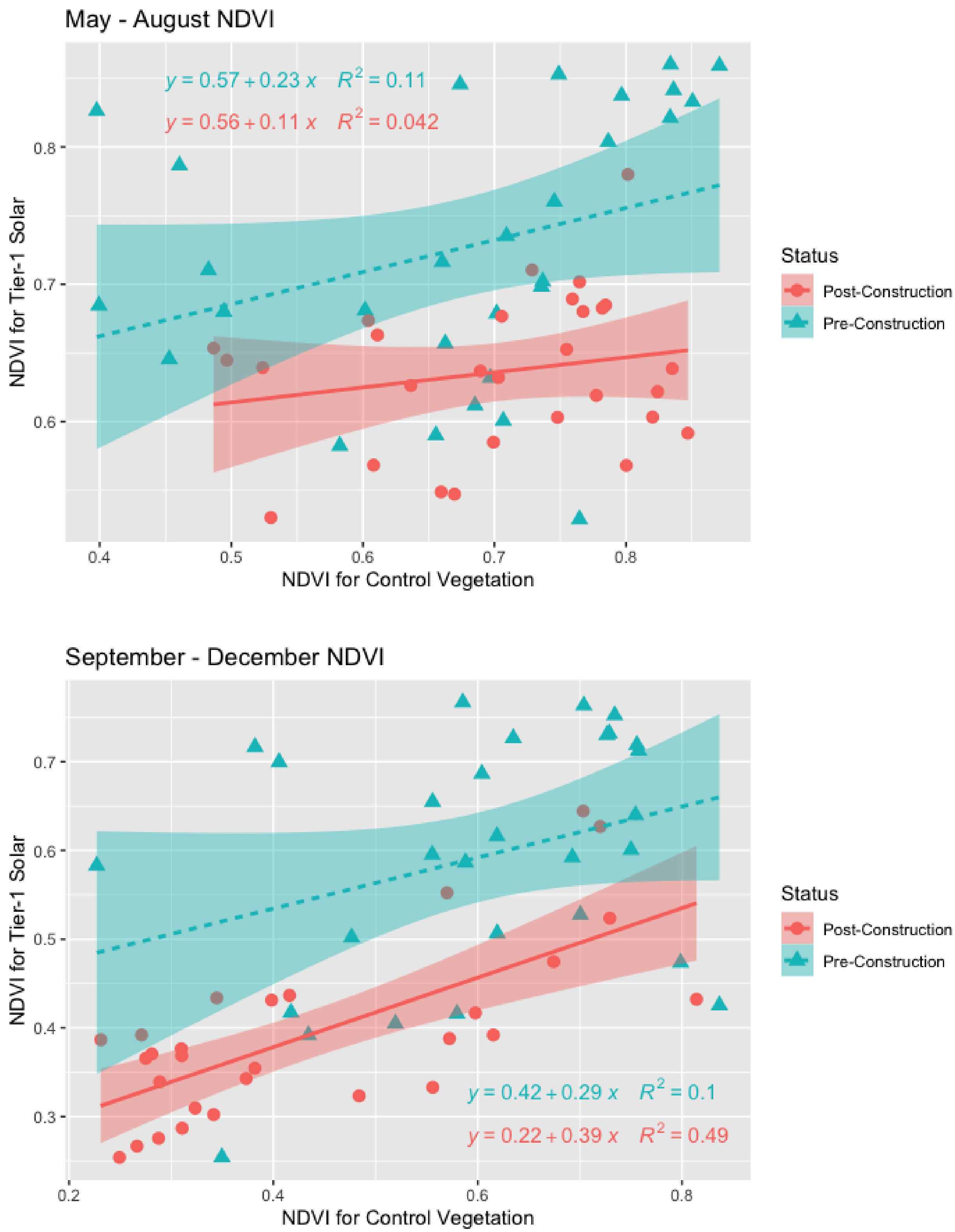


Figure 5. Linear regression models illustrate solar edge and control grassfield NDVI measurements of all 29 solar collections a year before (blue) and after (red) Tier-1 solar farms establishment per four-month period.

DISCUSSION

The insignificant statistical difference for both September-December panel collection edge and control NDVI could be due to factors other than solar site establishment, such as general plant growth rate changes between years. However, data during January through August suggests that solar panel establishment does impact vegetation health and greenness. The data from January through April does corroborate my original hypothesis: solar site establishment negatively affects vegetation health and greenness, as shown in a decreased NDVI, along the solar panel perimeter. Solar panel shading restricts accessible light for leaf photosynthesis and heat during cold winters that cause freezing and organismic tissue damage. The energy needed for a plant to grow new tissue and keep tissues active during its lifespan through growth and maintenance respiration is predicated on the plant energy balance, in which solar energy is stored for food production. Shading from solar can disproportionately affect this energy amount, such that survival will depend upon species shade tolerance.

In contrast, the increase in NDVI for the May-August growing season as seen in Figure 4 insinuates that solar sites can be beneficial to nearby vegetation growth. One likely explanation is that shade from solar panels are able to protect the vegetation from extreme thermal temperatures apparent during the summer growing months, reducing stress from desiccation. These panels also help accumulate usable water for plants as precipitation runs off the panel below.

This study does not fully support the initial hypothesis, yet does reflect the issue of land-use conflict. A resolution to this is co-location, where a certain landscape integrates both solar farms and vegetation together (Hernandez et al. 2019). Novel ideas in this field include agrivoltaics, in which vegetation is planted in the spaces between solar panels for shade and increased access to water (Fiorelli et al. 2022). Future policy-making can benefit from incorporating co-location.

While this study begins the framework for understanding the implications of solar farms on vegetation, there are several limitations in this study that could skew the data. One technological limitation includes limited access to data with finer spatial resolution than 10 meters. Lack of said precise data prevents the inclusion of module inter-row spacing measurements in between solar panels, which are roughly 3 meters, into the study. Another limitation is that due to how recent Tier-1's have been built, post-construction data for many Tier-1 solar farms spanning a year does not exist yet. Besides the seven involved in this study, a majority of Tier-1's are under development or still being planned, which therefore restricts the ability to have a larger sample size. Lastly, this study does not account for other factors that could be measured through remote sensing, such as land surface temperature or net ecosystem productivity, because their geospatial data has a coarser spatial resolution. Thus, these less detailed measurements cannot accurately quantify minute changes along the edges of solar panels. However, accounting for and evaluating said factors, likely through in-situ sampling, is likely necessary to comprehensively study the ecological effects of solar farm construction.

CONCLUSION

The current process associated with solar energy development throughout New York State has an immense impact on the vegetated biomes. The need for more land area to build expansive solar facilities fosters land-use conflict with existing grasslands and forests. While this research suggests that solar panel shading may be beneficial to nearby plants during the summer growing season, future study into this topic may be necessary. Conversely, solar farms may prove detrimental to plant growth during colder seasons possibly through being restricted by solar panel shading. Moreover, solar facility establishment that prepares land with site bulldozing can result in soil compaction that encourages nutrient runoff through weakening plant-soil infiltration rates. Thus, more in-depth scrutiny of local climate and landscape topography may be necessary to determine whether a vegetated area should be left undisturbed. Considering environmental ramifications can assist in properly informing solar companies and stakeholders on site selection, construction, and maintenance that is sustainable and long-lasting.

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