Analyzing the Impact of Solar Arrays on Surrounding Vegetation in Agrivoltaic Farming for Performance Optimization

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ABSTRACT

This project investigates the impact of solar arrays on surrounding vegetation within agrivoltaic systems to enhance operational efficiency. Agrivoltaics, which combines agricultural practices with solar energy production on the same land, offers a sustainable alternative to exclusive solar installations on agricultural land. By diversifying income for farmers and addressing energy equity issues in less grid-connected areas, agrivoltaics can play a crucial role in sustainable energy and rural economic development. The study focuses on understanding the intricate balance between energy production and agricultural yield in agrivoltaic sites. Solar panels create microclimates that influence plant growth dynamics, necessitating a comprehensive analysis of these effects.

The primary research question explores the feasibility of using remote sensing tools and satellite data to assess the impact of solar arrays on vegetation health and productivity, thereby informing future agrivoltaic projects. The first step was identifying agrivoltaic sites across the United States by integrating global observer AOI data with the US Solar Photovoltaic Database (USPVDB). Then, LANDSAT satellite imagery is used to analyze these locations, leveraging NDVI, spectral wavelengths (particularly red wavelengths indicative of photosynthesis), and TCG data to monitor changes in vegetation over time from before and after solar array installation.

The data from each location is then combined to evaluate average changes across the points. The results showed an 18.5% decrease in NDVI and a 54.2% decrease in TCG, suggesting a decline in overall vegetation health and photosynthetic activity following the installation of solar panels, while the 40.6% decrease in Band 4 suggests potential for enhanced photosynthesis under certain conditions due to the solar panels. These results highlight the complex relationship between solar arrays and surrounding vegetation in Agrivoltaics and provide valuable insight into the factors to be considered for the successful implementation of agrivoltaic projects.

Background and Goals

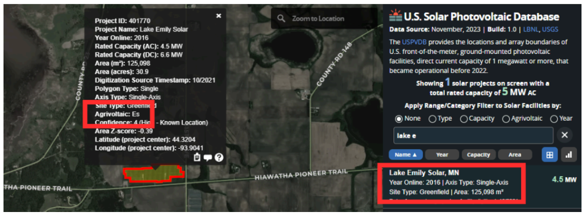
Agrivoltaics, also known as low-impact solar, is the practice of using the same land for both agriculture and solar energy production. It offers an alternative to the complete conversion of agricultural land to solar locations. This co-location practice has the potential to both address energy inequity by supplying solar energy in locations less centered on the electricity grid, while also helping farmers diversify income through land-lease payments and other business models. Agrivoltaics can keep farmland in production and sustain rural farmland economies. Especially in the United States where mounting production expenses have allowed only the biggest producers to survive, there is a growing need to support these communities. Further, only 2% of large solar array projects in the US are agrivoltaic, highlighting the potential for growth of this practice.

The success of Agrivoltaics relies on optimizing the balance between energy production and agricultural output. Solar panels can create microclimates by altering light, temperature, and moisture conditions, which can significantly affect plant growth. By understanding the impact of solar arrays on surrounding vegetation, the goal of this project is to investigate these interactions that are so crucial for maximizing the benefits of agrivoltaics. This paper asks, by using remote sensing tools and satellite data, is it possible to analyze the impact of solar arrays on surrounding vegetation health in order to inform and facilitate the future of agrivoltaic projects?

Methodology and Approach and Results

The first step was outlining the data of interest. First, Agrivoltaic solar projects in the US were identified. This was done by sorting through the GLOBE observer AOI points to identify locations with solar panels. These sites were then overlaid with the US Solar Photovoltaic Database (USPVDB) and filtered to find agrivoltaic projects.

After identifying these specific locations on the USPVDB, they were matched up with data on the LANDSAT database. By inputting these locations into the LANDSAT time observer, data from the locations of interest can be extracted.



Project ID: 401770
Project Name: Lake Emily Solar
Year Online: 2016
Rated Capacity (AC): 4.5 MW
Rated Capacity (DC): 6.6 MW
Area (m²): 125,098
Area (acres): 30.9
Digitization Source Timestamp: 10/2021
Polygon Type: Single
Axis Type: Single-Axis
Site Type: Greenfie d
Agrivoltaic: Es
Confidence: 4 (Hi - Known Location)
Area Z-score: -0.39
Latitude (project center): 44.3204
Longitude (project center): -93.9041

U.S. Solar Photovoltaic Database
Data Source: November, 2023 | **Build:** 1.0 | LBNL, USGS
The USPVDB provides the locations and array boundaries of U.S. front-of-the-meter, ground-mounted photovoltaic facilities, direct current capacity of 1 megawatt or more, that became operational before 2022.
Showing 1 solar projects on screen with a total rated capacity of 5 MW AC
Apply Range/Category Filter to Solar Facilities by:
● None ○ Type ○ Capacity ○ Agrivoltaic ○ Year
lake e
Lake Emily Solar, MN 4.5 MW
Year Online: 2016 | Axis Type: Single-Axis
Site Type: Greenfield | Area: 125,098 m²

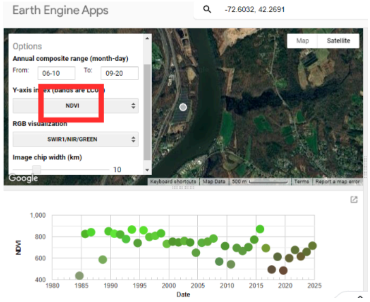
Identifying Area of Interest (AOI) using GLOBE Observer and US Solar Photovoltaic Database (1)

The LANDSAT time observer includes satellite data from 1984 through 2024 and provides information on many different variables. By identifying what year the solar panels were installed, the data can be utilized to notice significant trends before and after the installation of the panels.

Data Preparation

After identifying the desired locations and data points, the variables to collect data for were identified. These variables included the NDVI (Normalized Difference Vegetation Index) which determines the amount of vegetation in an area by comparing the greenness to the bare soil.

Matching USPVDB sites with LANDSAT Time Observer (2)



Annual composite range (month-day)
From: 06-10 To: 09-20
Y-axis index (bands are LC0
NDVI
RGB visualization
SWIR1/NIR/GREEN
Image chip width (km)
10

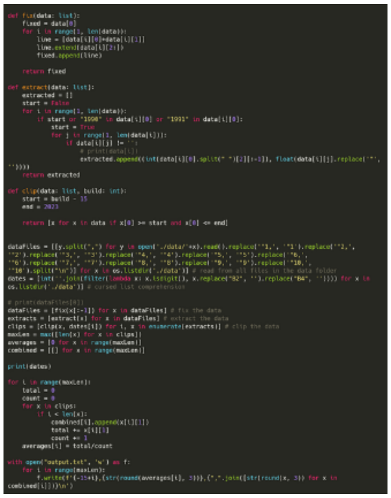
Figure 3.1

Data from TCG (Tasseled Cap Greenness), which shows the amount of greenness in an area, were also taken. Lastly, data from B4 were taken which measures the reflection of the red wavelength in an area. Figure 3.1 shows an example of a data point collected from NDVI with a graph displaying the change in NDVI value over time.

Once all the csv files from the different sites are downloaded the data needs to be combined and averaged. It starts by separating the data by measurement type. Then for each collection of CSV files the year the agrivoltaic array is found in the filename.

The data is converted to a 1 dimensional array starting 15 years prior to the construction and up to 10 years post construction. The data is then averaged across all the measurements of the same type. This effectively centers and averages the data around the construction year so analysis can be performed on it.

The public repository containing the code and data used in this project is available here. Figure 3.2 shows a code snippet of this procedure.

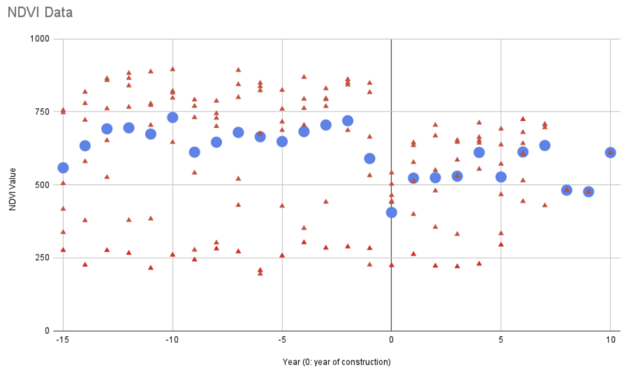


```
def fix(data: list):
    fixed = data[0]
    for i in range(1, len(data)):
        line = [data[i][0]+data[i][1]]
        line.extend(data[i][2:])
        fixed.append(line)

    return fixed

def extract(data: list):
    extracted = []
    start = False
    for i in range(1, len(data)):
        if start or "1990" in data[i][0] or "1991" in data[i][0]:
            start = True
            for j in range(1, len(data[i])):
                if data[i][j] != '':
                    # print(data[i])
                    extracted.append((int(data[i][0].split(" ")[2][:-1]), float(data[i][j].replace('"',
''))))
    return extracted

def clip(data: list, build: int):
    start = build - 15
    end = 2023

    return [x for x in data if x[0] >= start and x[0] <= end]


dataFiles = [[y.split(",") for y in open("./data/"+x).read().replace('"1,', '"1').replace('"2,',
'"2').replace('"3,', '"3').replace('"4,', '"4').replace('"5,', '"5').replace('"6,',
'"6').replace('"7,', '"7').replace('"8,', '"8').replace('"9,', '"9').replace('"10,',
'"10').split("\n")] for x in os.listdir('./data')] # read from all files in the data folder
dates = [int(''.join(filter(lambda x: x.isdigit(), x.replace("B2", '').replace("B4", '')))) for x in
os.listdir('./data')] # cursed list comprehension

# print(dataFiles[0])
dataFiles = [fix(x[:-1]) for x in dataFiles] # fix the data
extracts = [extract(x) for x in dataFiles] # extract the data
clips = [clip(x, dates[i]) for i, x in enumerate(extracts)] # clip the data
maxLen = max([len(x) for x in clips])
averages = [0 for x in range(maxLen)]
combined = [[] for x in range(maxLen)]

print(dates)

for i in range(maxLen):
    total = 0
    count = 0
    for x in clips:
        if i < len(x):
            combined[i].append(x[i][1])
            total += x[i][1]
            count += 1
    averages[i] = total/count

with open("output.txt", 'w') as f:
    for i in range(maxLen):
        f.write(f'{-15+i},{str(round(averages[i], 3))},{",".join([str(round(x, 3)) for x in
combined[i]])}\n')
```

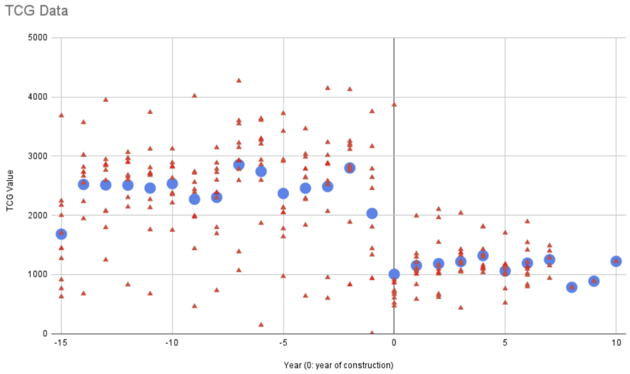
Figure 3.2

Results

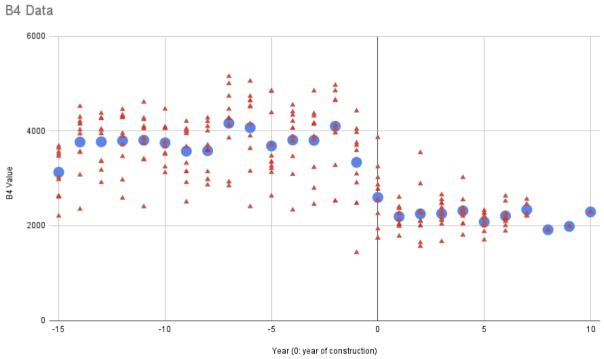
The NDVI showed a 18.5% decrease indicating a decrease in vegetation health. The output for the data showed an immediate decrease after the implementation of the agrivoltaic projects.



However, over time, the NDVI values slowly increased and returned back to the values before the agrivoltaic was created. This indicates that the agrivoltaics themselves do not have a direct impact on the NDVI of the vegetation and instead, the sudden drop in NDVI values could be due to the construction of the agrivoltaic project. The limited timespan and accessibility to the agrivoltaic projects prevents from finding the true cause for the decrease in NDVI values.



The values for TCG showed a 54.2% decrease. TCG shows photosynthetically active vegetation. Similar to the NDVI, TCG also showed an immediate decrease after the agrivoltaics were installed. However, this decrease was continuous. This indicates that the agrivoltaics do have an effect on the TCG of the surrounding vegetation and are not caused by external factors.



The B4 showed a 40.6% decrease. B4 shows the amount of red wavelength being reflected. Plants absorb red wavelengths during photosynthesis, so a decrease in B4 indicates more photosynthesis is occurring. The results from the LANDSAT time series show a sudden decrease in B4 simultaneous with the installation of the agrivoltaics, indicating that photosynthesis increases.

This increase in red light absorption can be attributed to extra light absorbed by the solar panels. This explains how vegetation decreases after the implementation of agrivoltaics because the absorption of red wavelength by the agrivoltaic shows will cause plants to receive less energy, limiting their capabilities to perform photosynthesis and lowering vegetation health.

By analyzing different data values that show unique factors, the most relevant values were identified to find correlations and explain the data taken from numerous agrivoltaic sites throughout the United States.

Conclusion and Future Goals

This study emphasizes the importance of optimizing Agrivoltaic systems. The collected data reveals an 18.5% decrease in Normalized Difference Vegetation Index (NDVI) and a significant decrease in Tasseled Cap Greenness (TCG). Both factors indicate a decline in vegetation health and photosynthetic activity following solar panel installation. This can likely be attributed to reduced sunlight absorption from vegetation, stunting growth and producing an overall decline in agricultural productivity. Conversely, a 40.6% decrease in Band 4, typically associated with near-infrared reflectance, suggests potential for enhanced photosynthesis under certain conditions.

These findings can be crucial for informing future agrivoltaic projects as understanding these dynamics can maximize energy production and agricultural output. Additionally, with only ~2% of solar farms being agrivoltaic, this research offers significant potential. In the future, this study aims to understand other factors that can cause variation in solar reflectance or photosynthetic efficiency. Using the Application for Extracting and Exploring Analysis Ready Samples (*Aρρ*EEARS), future work will aim to determine what factors like sun angle, panel area, or location can influence B4 and NDVI values.

*Aρρ*EEARS offers geospatial datasets of spatial parameters which will be directly correlated with the collected data in the NASA LANDSAT Time Series dataset. This research highlights several considerations for optimizing agrivoltaic systems such as panel orientation and spacing. Modifying these factors could mitigate observed declines in NDVI and TCG. Similarly, selecting different crops that may be more shade tolerant or absorb the reflected wavelengths can improve productivity. Accounting for seasonal variation and analyzing the microclimate beneath solar panels can also offer greater insight. Overall, while this study indicates a decline in NDVI, TCG, and Band 4, it offers a key step in optimizing solar panels for the future.

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